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Lessons from the United States and China

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GOVERNING ARTIFICIAL INTELLIGENCE – LESSONS FROM THE UNITED STATES AND CHINA

PhD Series 29.2022

Benjamin Cedric Larsen

GOVERNING ARTIFICIAL INTELLIGENCE

LESSONS FROM THE UNITED STATES AND CHINA

Department of International Economics Government and Business

PhD Series 29.2022

CBS COPENHAGEN BUSINESS SCHOOL
HANDELSHØJSKOLEN

Ph.D. Thesis

Governing Artificial Intelligence: Lessons from the United States and China

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Acknowledgments

Undertaking a PhD is a long and arduous but most rewarding journey. Like the Chinese saying "*crossing the river by feeling the stones*," the scientific endeavor is a stepwise encounter within a process of continuous exploration. At times the researcher is rewarded by new findings and discoveries; at other moments, disappointment ensues. In both, it is of great importance to have a supportive environment that encourages the researcher to continue crossing the river. At some point, one realizes that the end goal is not to cross the river at all, but to continue on a path of exploration, endlessly motivated, as a worthy end goal in itself.

On my journey to earn this PhD, I am most grateful to the many people who have inspired and guided me on my road. First, I thank my supervisor, Ari Kokko, for his endless wisdom, input, support, and encouraging remarks. Next, I thank my coauthor, Yong Suk Lee, a source of inspiration who has helped me grow and evolve as a scholar. I would also like to thank my colleague Kasper Ingemann Beck for sharing the journey as a fellow researcher and becoming a good friend in the process.

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AI governance has been a transformative experience for me as a researcher and has impacted me greatly as a person. I am indebted to my coauthors Mariano Florentino Cuellar, Michael Webb, and Melody Wu, for being tremendous researchers and colleagues. I would also like to thank Shazeda Ahmed for sharing her insights on China and AI, and David Stuligross for polishing my language when the dissertation was in its final stage.

Many others have influenced the terrain I have traveled over during the past few years. I have not forgotten you and look forward to thanking you personally when our paths next cross.

As I write these acknowledgments, I am reminded of words by T.S Elliot: "*We shall not cease from exploration And the end of all our exploring Will be to arrive where we started And know the place for the first time*." At this moment, I know the reward of this journey for the first time. The true reward is not the journey's end but acknowledging that true exploration never ceases. Instead, it continues to flow, much like the river that has just been crossed.

Benjamin Cedric Larsen
San Francisco, June 2022

English summary

This dissertation analyzes how artificial intelligence (AI) technologies are being governed, with an emphasis on the experiences of the United States and China. The thesis is positioned at the intersection of platform- and technology-related governance and regulation, rooted in literature emanating from disciplines such as information systems, institutional theory, and political economy. The thesis elaborates on a range of governance mechanisms for AI located across technical, organizational, and institutional levels. Drawing on the empirical cases of the United States and China, the overarching research question of the thesis inquires: how is artificial intelligence governed in the United States and China, and what are some of the broader implications for the governance of AI?

The motivation for this research question rests on the insight that the approaches to AI governance by the United States and China will inform AI governance regimes elsewhere in significant ways. While scholars from several academic fields have contributed to the existing literature on AI governance, many unfulfilled gaps have barely been dealt with. In particular, as more vigorous calls for AI regulation have emerged, little is known about the interactions between new and incoming AI regulation and firm-level behavior and innovation. Second, while AI technologies are already implemented in most sectors and industries, little is known about how discrete AI fields gain legitimacy and become institutionalized over time. Third, while a great number of national AI policies and innovation strategies have been released, how these interact with and affect AI innovation has been little studied. Finally, even though international competition in areas such as AI and semiconductors is on the rise, the effects of great power competition on technological governance and data privacy preferences have been little studied.

To address each of these gaps and answer the main research question, the dissertation employs a mixed-methods approach to the study of AI governance. The first article of this thesis examines four kinds of AI regulation in the United States. The article finds that while regulation may decrease firm managers' intent to adopt AI technologies, it increases the salience of AI-related ethical concerns. The second article looks at how AI technologies gain socio-technical legitimacy. The article finds that variations within digital and institutional infrastructure affect processes of obtaining socio-technical legitimacy. The third article focuses on China's policy initiative to create National Open Innovation Platforms for AI. The article uncovers several government mechanisms that affect the resourcing tools and securing rules of innovation platforms, all of which have broader implications

for AI innovation. The fourth article assesses how great power competition between the United States and China affects the data privacy preferences of Chinese citizens. The main finding, that tech competition shifts citizen willingness to share data, has underlying implications for the design of AI governance regimes. The findings of the thesis build on 24 months of field research in China and the United States, as well as on the analysis of 4,391 survey-based observations, 16 interviews, and more than 2,000 archival records.

Building on its theoretical and empirical findings, the dissertation advances a holistic understanding of AI governance. Specifically, this thesis, first, clarifies how governments have several mechanisms at their disposal to affect platform governance processes and associated forms of generativity, which has implications for AI innovation. Second, the thesis demonstrates that policymakers, firms, and civil society participants all are capable of influencing how AI technologies are accepted or rejected at a socio-technical level. Third, it documents the essential role AI regulation plays in fostering more ethically oriented AI solutions. Lastly, it indicates why and how competition among nations can have significant consequences for associated forms of AI governance. Based on lessons from the United States and China, national differences in AI governance are likely to have implications for AI alignment at the international level.

Keywords: artificial intelligence, innovation, governance, mechanisms, United States, China

JEL codes: K24 Cyber Law
L38 Public Policy
L51 Economics of Regulation
O25 Industrial Policy
O33 Technological Change: Choices and Consequences • Diffusion Processes
O36 Open Innovation

Danish summary

Denne afhandling analyserer hvordan kunstig intelligens (AI) bliver styret ud fra USA og Kinas erfaringer. Afhandlingen er placeret i krydsfeltet mellem platform og teknologirelateret styring og regulering, forankret i litteratur inden for informationssystemer, institutionel teori og politisk økonomi. Specialet bidrager ved at uddybe en række styringsmekanismer for kunstig intelligens der er placeret på tværs af tekniske, organisatoriske og institutionelle niveauer. Afhandlingens overordnede forskningsspørgsmål er: hvordan styres kunstig intelligens i henholdsvis USA og Kina, og hvad er nogle af implikationerne heraf for fremtidig styring af AI?

Motivationen for dette forskningsspørgsmål hviler på refleksionen af, at AI-relaterede styringsmekanismer udviklet i USA og Kina, vil have vigtige konsekvenser for andre lande. Den eksisterende litteratur omkring styringen af kunstig intelligens består af en bred vifte af akademiske discipliner, imens der er mange vigtige spørgsmål omkring AI-relateret styring der endnu ikke er blevet berørt. Forholdet mellem AI-lovgivning og AI innovation er for eksempel ikke blevet tæt studeret. For det andet, mens kunstig intelligens er blevet implementeret i mange sektorer, forbliver vores viden om hvordan kunstig intelligens opnår social-teknologisk legitimitet i høj grad ukendt. For det tredje, mens et stort antal nationale AI-politikker og innovationsstrategier er blevet frigivet, er det lidt undersøgt, hvordan disse interagerer med og påvirker AI-innovation. Til sidst, mens geopolitisk konkurrence i henhold til kunstig intelligens er stigende, har forholdet mellem af stormagtkonkurrence og teknologisk styring ikke modtaget meget opmærksomhed.

For at adressere disse områder samt at besvare det overordnede forskningsspørgsmål, anvender afhandlingen blandede metoder til at forstå social-teknologisk styring af kunstig intelligens. Den første artikel i afhandlingen undersøger fire forskellige former for AI-regulering i USA. Artiklen finder negative, men heterogene virkninger af forskellige former for AI-lovgivning på AI-adoption. Artiklen finder også, at AI-regulering øger vigtigheden af etiske spørgsmål forbundet med brugen af kunstig intelligens. Afhandlingens anden artikel ser på, hvordan forskellige AI-teknologier opnår social-teknologisk legitimitet. Artiklen konstaterer, at uensartede AI-teknologier er underlagt forskellige udviklinger inden for digital og institutionel infrastruktur, hvilket påvirker deres grad af legitimitet. Den tredje artikel fokuserer på Kinas politiske initiativ med at skabe nationale åben innovations platforme inden for kunstig intelligens. Artiklen opdager flere styringsmekanismer, der påvirker ressourceværktøjer og sikringsregler for innovationsplatforme, hvilket har implikationer for

AI-innovation. Den fjerde artikel vurderer, hvordan stormagtskonkurrence mellem USA og Kina påvirker individers præferencer for databeskyttelse. Artiklen finder, at grundet teknologisk konkurrence mellem USA og Kina er individer mere tilbøjelige til at dele deres data med kinesiske virksomheder. Disse resultater har underliggende betydninger for fremkomsten af forskellige AI-relaterede styringsregimer. Afhandlingens resultater bygger på 24 måneders feltarbejde i Kina og USA, samt 4,391 survey-baserede observationer, 16 interviews, samt analyse af mere end 2,000 artikler.

Med udgangspunkt i de teoretiske og empiriske resultater fremmer afhandlingen en holistisk forståelse af AI-styring, der er baseret på USA's og Kinas erfaringer. Afhandlingen bidrager specifikt til at afklare, hvordan regeringer har en række mekanismer til rådighed, hvilke kan bruges til at påvirke platform-relaterede styringsprocesser, hvilket har implikationer for AI-innovation. For det andet har både virksomheder, politiske beslutningstagere samt civilsamfundet forskellige mekanismer til rådighed der kan bruges til at påvirke hvordan AI-teknologier accepteres eller afvises på et socialt-teknologisk plan. For det tredje spiller AI-regulering en vigtig rolle i at fremme mere etisk orienterede AI-løsninger. Endelig kan højteknologisk konkurrence mellem nationer have vigtige konsekvenser for tilknyttede former for AI-styring. Baseret på erfaringerne fra USA og Kina vil nationale forskelle i AI-styring sandsynligvis få konsekvenser for tilpasning af bedste praksis på internationalt plan.

Nøgleord: kunstig intelligens, innovation, regeringsførelse, mekanismer, USA, Kina

JEL-koder:
- K24 Cyberlov
- L38 Offentlig Forvaltning
- L51 Økonomisk Regulering
- O25 Industripolitik
- O33 Teknologisk forandring: Valg og konsekvenser • Diffusionsprocesser
- O36 Åben innovation

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List of abbreviations

AI	Artificial Intelligence
AGI	Artificial General Intelligence
AIDP	Artificial Intelligence Development Plan
AIIA	Artificial Intelligence Industry Alliance
AIOSS	China Artificial Intelligence Open Source Software Development League
API	Application Programming Interface
BIS	Bureau of Industry and Security
CAICT	China Academy of Information and Communications Technology
CCP	Chinese Communist Party
CCPA	California Consumer Privacy Act
CESI	Chinese Electronic Standardization Institute
CFIUS	The Committee on Foreign Investment in the United States
CPU	Central Processing Unit
FRT	Facial Recognition Technology
GDPR	General Data Protection Regulation
GPU	Graphics Processing Unit
ICT	Information Communication Technology
IEEE	Institute of Electrical and Electronics Engineers
IT	Information Technology
MIIT	Ministry of Industry and Information Technology
MOE	Ministry of Education
MOFCOM	Ministry of Commerce
MOST	Ministry of Science and Technology
NAII	The National Artificial Intelligence Initiative
NAIIA	The National AI Initiative Act of 2020
NAIIO	The National Artificial Intelligence Initiative Office
NDRC	National Development and Reform Commission
NHTSA	National Highway Traffic Safety Administration
NIST	National Institute of Standards and Technology
NOIPAI	National Open Innovation Platform for AI
NSCAI	The National Security Commission on Artificial Intelligence
NSTC	National Science and Technology Council
OGD	Open Government Data
OS	Operating System
OSS	Open Source Software
OSTP	White House Office of Science and Technology Policy
PAI	Partnership on Artificial Intelligence
PIPL	Personal Information Protection Law
R&D	Research and Development
SDK	Software Development Kit
SIIO	State Internet Information Office
SME	Small and Medium-Sized Enterprise

List of key concepts

The following provides a brief overview of the key concepts deployed and explored throughout the thesis.

Artificial Intelligence (AI)

Artificial intelligence (AI) is defined as the capacity of a technology to cognitively perform functions that would ordinarily be understood to require intelligence (Russell & Norvig, 2010). This includes perceiving, reasoning, learning, interacting with the environment, problem-solving, and exercising creativity. Examples of technologies that enable AI to solve problems are robotics and autonomous vehicles, computer vision, language, virtual agents, and machine learning.

Artificial General Intelligence (AGI)

Demarcates the ability of an intelligent agent to understand or learn any intellectual task similar to that of a human being (Pei, et al., 2019).

AI Ethics

AI ethics have converged around five ethical principles: transparency, justice and fairness, non-maleficence, responsibility, and privacy (Jobin, et al., 2019).

AI Governance

AI governance is conceptualized throughout this thesis as a combination of AI innovation, AI adoption/diffusion, and AI regulation. AI governance combines and bridges understandings of AI development (e.g., industrial policy, R&D conducted in companies and research institutions) and AI regulation (e.g., laws and regulations that affect AI development and application).

AI Regulation

AI regulation includes existing laws, new rules, and evolving domain-specific regulations. The main goal of regulators is to ensure opportunity in the application and innovation of AI-based tools, products, and services while limiting negative externalities in competition, privacy, safety, and accountability.

Boundary Resources

Boundary resources are defined as "the rules and tools that serve as the interface to govern the arm's length relationship between the platform owner and different members of the platform ecosystem" (Bonina & Eaton, 2020, p. 4). Members include developer organizations of all sizes, other boundary resource owners, and regulators, as well as user communities that may be beyond any direct ability to influence a platform and its design but can nonetheless seek to affect the process of boundary resource modification through other forms of pressure (Eaton, et al., 2015).

Compute

Compute or computing refers to computer performance and specifies the amount of useful work that is accomplished by a computer system. Computer performance is estimated in terms of accuracy, efficiency, and speed of executing computer program instructions. Complex algorithms and large amounts of data tend to rely on more extensive use of compute resources.

Digital Infrastructure

Digital infrastructure is made from a multitude of digital building blocks. It is defined as the computing and network resources that allow multiple stakeholders to orchestrate their service and content needs (Constantinides, et al., 2018). Digital infrastructures are distinct from traditional infrastructures because of their ability to collect, store, and make digital data available simultaneously across many systems and devices (Constantinides, et al., 2018). Examples of digital infrastructures include the Internet (Henfridsson, et al., 2018), data centers, open standards, e.g., IEEE 802.11 (Wi-Fi), and consumer devices such as smartphones.

Digital Sovereignty

Digital Sovereignty is broadly defined as retaining national control over domestic data and strategic supply chains that include digital components such as hardware and software (Pohle & Thiel, 2020).

Ecosystems

Ecosystems comprise the platform's sponsor, i.e., platform core, plus all complement providers that make the platform more valuable to consumers (Ceccagnoli, Forman, Huang, & Wu, 2012; Gawer &

Cusumano, 2013). Platform ecosystems take a "hub and spoke" form, with an array of peripheral firms connected to the central platform via shared or open-source technologies and technical standards that are accessed via application programming interfaces (API) and software development kits (SDK).

Field Change

Institutional infrastructure reflects the embeddedness of organizations within fields and the structuration of fields that occurs through interactions and institutional activity amongst actors (Dacin, et al., 1999). Organizational fields are becoming more dynamic, and boundaries between fields have become more porous due to new digital infrastructures, such as the Internet (Powell, et al., 2017, p. 336).

Field Legitimization

Issues associated with field-level legitimization and processes of institutionalization arise when emerging AI systems are inaccurate, unsafe, or non-transparent, which erode trust across applications and causes fields' to stay fragmented. Analyzing field-level trajectories involves assessing what it takes for altered power dependencies to be conceived as legitimate practices. This process is necessary for a field to move from fragmentation or contestation towards greater alignment of digital and institutional infrastructures.

Generativity

In the context of digital innovation, generativity is referred to as "a technology's overall capacity to produce unprompted change driven by large, varied, and uncoordinated audiences" (Zittrain, 2006, p. 1980).

Innovation Platforms

Innovation platforms are defined as the "foundations upon which other firms can build complementary products, services or technologies" (Gawer, 2009, p. 54). The technical architecture of an innovation platform contains modules, or building blocks, that represent "accessible innovative capabilities" (Gawer, 2014). These modules can be accessed and combined by app developers (complementors) to build apps and services (known as platform complements) (Bonina, et al., 2021)

Institutional Infrastructure

Institutional infrastructure is established through activities such as certifying, assuring, and reporting against principles, codes, rules, and standards, as well as through the formation of new associations and networks among organizations, including official rules and regulations (Waddock, 2008).

Negative Externality

A negative externality exists when the production or consumption of a product or system results in a cost to a third party, such as civil society participants. Air and noise pollution are commonly cited examples of externalities.

Open Innovation

Open innovation is defined as "the use of purposive inflows and outflows of knowledge to accelerate internal innovation and expand the markets for external use of innovation" (Chesbrough, 2006, p. 1). Similarly, open data and open-source software (OSS) are often associated with open innovation platforms since their "free" redistribution of public goods attracts complementors from the ecosystem to the platform.

Orchestration / Governance

Orchestration refers to a set of governance mechanisms through which the Government as a Platform determines a variety of technological and institutional configurations to deliver public value. These governance mechanisms require negotiations between the regulatory regimes embedded and structured in the technological architectures and those embedded and structured in the institutional arrangements that govern different public agencies (Cordella & Contini, 2012).

Platforms

Platforms are referred to as 1) transaction platforms, e.g., e-commerce, and 2) innovation platforms, e.g., apps and services (Bonina, Koskinen, Eaton, & Gawer, 2021; Cusumano, Gawer, & Yoffie, 2019). Platforms usually have a core and a periphery established by third-party developers (Bonina & Eaton, 2020).

Socio-technical systems

Socio-technical systems describe the interaction between people and technology in the workplace and society. The term refers to the interaction between society's complex technological and digital infrastructures and how these affect and influence human behavior.

1. INTRODUCTION

Artificial intelligence (AI) has been described as a general-purpose technology (GPT) (Agrawal, Gans, & Goldfarb, 2019) that is characterized by near-ubiquitous use across a wide range of sectors and industries (Bresnahan & Trajtenberg, 1995). AI systems already operate in diverse areas, such as the stock market (Mackenzie, 2006), mortgage underwriting (Markus, 2017), autonomous vehicles (Hengstler, et al., 2016), medical devices (Davenport & Kalakota, 2019), the judicial system (Mckay, 2020), and a range of other fields.[1]

While technological use-cases are on the rise, so are national strategies and technology policies aimed at AI innovation and regulation. OECD's AI Policy Observatory provides a repository of national AI policies and strategies, which currently covers more than 700 AI policy initiatives from 60 countries, territories, and the EU (OECD, 2021).

On the one hand, countries are eager to support domestic innovation and development of AI systems and technologies to reach the economic advantages associated with a GPT. On the other, new laws and regulations aim to curb externalities that may arise from rapid AI adoption. AI-related externalities have already been documented in several areas such as job displacement (Bessen, 2018), hiring practices (Whittaker, et al., 2018), data and privacy matters (Tucker, 2017), bias, and discrimination (Lambrecht & Tucker, 2019), and so on. The potentially disruptive impacts caused by a GPT such as AI highlight the need for new laws and regulations to guide thoughtful technological expansion. The measures supporting AI innovation and regulation guiding its diffusion are in combination viewed as constituting the nascent field of AI governance.

AI governance is a multidisciplinary field comprised of various academic disciplines such as computer science, information systems, economics and management, political science, and philosophy. Some of the critical issues discussed in this emergent field focus on algorithmic development and implementation, the economics of AI, and policy- and ethical-oriented issues related to guiding the equitable expansion of AI systems and technologies. In other words, a wide range of

[1] This dissertation uses a broad definition of artificial intelligence (AI), defined as the capacity of a technology to cognitively perform functions that would ordinarily be understood to require intelligence (Russell & Norvig, 2010). This includes perceiving, reasoning, learning, interacting with the environment, problem-solving, and exercising creativity. This thesis refers to AI interchangeably as AI technologies, systems, programs, and agents.

academic fields is currently converging around various problems associated with the ongoing expansion of AI technologies. No academic discipline can single-handedly solve the breadth of pending problems associated with AI adoption and regulation, and many multipronged and multidisciplinary approaches to studying AI governance are currently emerging.

Based on these considerations, this thesis adopts a broad conceptualization of AI governance that incorporates policies, strategies, and mechanisms that enable AI innovation and development and constrain its diffusion through mechanisms such as regulation.

The three most important countries and regions that currently dominate and shape the field of AI governance are the United States, Europe, and China (Castro, McLaughlin, & Chivot, 2019). Each country or region develops independent approaches to AI governance, shaped by national policies, laws, and regulations that sometimes affect the direction and composition of AI development and shape socio-technological forms of adoption.

The European Union is a frontrunner in developing novel data and AI regulations such as the General Data Protection Regulation, which went into effect in 2018, and the proposed AI Act, which goes into effect by 2023. However, the primary focus of this dissertation rests on a comparison of the AI governance regimes that are currently emerging in the United States and China. While AI rulemaking is prominent in the European Union, the continent is not home to any of the world's largest AI innovation platforms, which in many cases drive AI infrastructure and innovation on the commercial side. While the regulatory approaches of the EU establish precedence in data and AI governance (Mökander, et al., 2021), the approaches of the United States and China hold the ability to do the same.

There are several reasons for comparing the approaches of the United States and China from a European perspective. Both countries occupy the commanding heights of the global economy, and the two countries represent different economic and political systems from market-based to state-capitalism and from a two-party liberal democracy to a one-party communist state. The United States and China are also world leaders in AI research and development and AI-related technological adoption (Zhang, et al., 2021). The United States and China are also home to the world's leading technology companies and innovation platforms such as Facebook, Amazon, Apple, Google, Microsoft, Baidu, Alibaba, Tencent, ByteDance, and Huawei. In terms of AI development, these companies and their AI innovation platforms are establishing industry-wide best practices, which significantly shape the opportunities for other companies in terms of AI-related research and development and subsequent adoption. Leading platform companies from the United States and China also impact and guide the social fabric of economies in novel ways that alter socio-technological dependencies while influencing new ways of interaction and organization. This is true for AI-powered functions from search engines to social media ranking algorithms, facial recognition in surveillance, the ordering of information, and so on. In other words, leading technology companies from both the US and China are enabling entirely new forms of digital information infrastructure that have wide-ranging consequences for most countries, companies, and individuals. In many ways, leading technology companies from both the United States and China are paving the way for reimagining how economic, organizational, and social dependencies can be restructured in novel forms of socio-technological infrastructure.

While there are essential differences and similarities to AI governance between the United States and China (discussed in Chapter 6), some of the observations made throughout the thesis can motivate similar studies to be carried out between the EU and China, and other countries.

Based on these considerations, the guiding research question of this thesis aims to clarify how artificial intelligence is governed in the United States and China, respectively, and what some of the implications hereof are for the governance of AI.

Both the United States and China have declared their ambitions to remain (US) or to become the world leader in AI (CH), which implies an underlying great power competition (Cave & ÓhÉigeartaigh, 2018). This competition has been variously described as a technological race (Capri, 2020), an AI arms race (Scharre, 2019), a new Cold War (Dupont, 2020), and technological decoupling (Han, Jiang, & Mei, 2021). Common for all these portrayals is that they do not imply any expected forms of AI alignment or deep cooperation between the United States and China. Instead, AI development and adoption are turned into integral parts of an underlying great power competition between the two nations. This competition involves economic, military, research, and application-driven conflicts that limit potential avenues for cooperation.

However, viewing AI development as a zero-sum game is neither optimal in the short term nor the long run. In the short term, fueling great power competition may cause countries to neglect to develop thoughtfully designed ethical solutions that benefit society and limit negative externalities. Countries may similarly choose to move away from global norms in terms of international data and information interoperability, which could cause digital fragmentism that results in walled gardens and information ecosystems based on diverging socio-economic values and norms. To some extent, these developments are already underway.

The free movement of goods and data and the open-source development of AI tools and systems are obstructed by budding political questions over digital sovereignty, which create new and value-based barriers to sustained global interoperability (Pohle & Thiel, 2020). The choice to use AI as a geopolitical lever that enables specific AI-governance regimes to emerge could be associated with precarious political strategies that hold potential to distort some of the broader developmental benefits of AI for humanity. This is especially true when differing socio-technical regimes are likely to emerge based on how social values are baked into technologies and how their underlying systems are utilized across use-cases. These use-cases are likely to feed into and determine a range of underlying value-based structures such as the degree of freedom of access to information, public sector surveillance, and varying forms of data centralization, to name a few.

In the long term, the advent of more robust forms of artificial general intelligence (AGI)[2] could mean that some countries will seek to exploit their newfound power and ability to the detriment of other nations. International hostility could similarly exacerbate risk-taking, embolden hostile motivations, or force unforeseen errors associated with AI development and adoption and military use of AI technologies. If left unchecked, the current AI competition between the United States and China could develop into a race to the bottom. In this scenario, mutual responsibility to formulate and install guardrails that curb the adoption and diffusion of harmful AI systems, such as those found in military applications or the spread of misinformation, could be neglected.

Until now, the great power competition on AI between the US and China has entrenched itself in an ongoing technological decoupling between the two countries. This decoupling is based on neo-mercantilist concerns related to unequal terms of competition, illegal means of technological appropriation, violation of international sanctions, and value-based concerns over public sector use and support of AI systems, such as biometric surveillance (Dupont, 2020).

The United States has been particularly active in deploying its entity list, which restricts access to American technology (Kwan, 2020). In 2016, the Chinese company ZTE ended on the entity list

[2] AGI refers to the ability of an intelligent agent to understand or learn any intellectual task similar to that of a human being (Pei et al., 2019).

as it violated US sanctions by exporting US-origin goods to Iran. In 2019, the Trump Administration added multiple Chinese entities to the list because of alleged involvement in human rights abuses, including those against the Uighurs in China's Xinjiang Autonomous Region. Most recently, the Biden administration added several of China's leading AI enterprises to the entity list for acting contrary to the foreign-policy interests of the United States. For Chinese companies dependent on American technology, such as hardware (e.g., chip technology) or software (e.g., an operating system), this can translate into severe strategic setbacks for the marketization of existing products as well as for R&D.

Currently, the US and China seek to bolster national supply chains and technological self-sufficiency (Shih, 2020) in hardware, e.g., semiconductors, laptops, surveillance cameras, data centers, and software, e.g., AI algorithms, open-source software, and AI frameworks.

While the US has used its entity list to block several Chinese companies from obtaining critical American technology, both countries have begun to outstrip and replace foreign developed technological hardware such as desktops and network equipment (Fuller, 2020). The Chinese Communist Party (CCP), for example, decided to replace all government computers that run Windows by 2022 with China's domestically developed Kylin OS (Hanson, 2020).

The Clean Network is another initiative that the former Trump Administration initiated to address long-term data privacy and security threats. The Clean Network was proposed based on human rights principled collaboration in opposition "to aggressive intrusion by malign actors, such as the Chinese Communist Party" (US Department of State, 2021).

These developments obfuscate existing technological and digital interconnections across the Pacific while limiting cooperation in joint research, student exchange, market access, ecosystem collaboration, and platform integration (Han, et al., 2021). These circumstances have significant consequences for the future of AI development and cooperation.

For Beijing and Washington, the stakes of AI development are associated with the strategic development of their respective economies. However, it is increasingly evident that each country's domestic approach to AI governance rests on critical differences that are likely to be embodied in varying forms of AI governance.

In Brussels, the European Union's specific approach to AI governance is also likely to have significant implications and consequences for international AI governance and cooperation. However, it remains to be seen how the triad of emerging approaches to AI governance from Brussels, Beijing, and Washington might influence each other.

Unless common ground for international forms of AI cooperation and governance are found, it is plausible that a diverse range of AI governance regimes could emerge in the years to come. The formation of disparate AI regimes could have wide-ranging consequences for technological application and international forms of digitally-oriented cooperation going forward.

This introduction has emphasized that AI governance should be viewed as a broad and multidisciplinary field that touches on many areas surrounding AI research, innovation, adoption, diffusion, regulation, and cooperation. Therefore, it is also clear that AI governance stretches far beyond domestic policies and mechanisms for supporting and regulating AI development and adoption. The dispersion of AI technologies is, as outlined, entangled in intricate questions and problems that are intertwined in the formulation of new rules for international interaction and engagement in areas of AI development and diffusion. How countries seek to engage with AI governance domestically will have important implications for international forms of AI governance and technological expansion. Domestic considerations regarding how AI technologies are enabled or constrained already affect how best practices are transmitted elsewhere. It is also clear that international fragmentation in digital integration and interoperability will affect the adoption and diffusion of disparate AI technologies, systems, and practices.

Based on an empirical investigation of the approaches to AI governance that are currently emerging from the United States and China, this thesis seeks to advance our current understanding and conceptualization of AI governance. By doing so, this thesis engages in a broader philosophical discussion surrounding AI governance.

1.1.Motivation

From an academic perspective, research on AI governance remains in its infancy. This thesis's main goal and motivation are to explore a variety of policy mechanisms and firm-level approaches, which in combination can contribute to informing the field of AI governance. By comparing policy mechanisms and firm-level responses from both the United States and China, this thesis addresses four gaps and areas of interest in the expanding literature on AI governance.

However, as the literature only has started to form, it may be hard to talk of concrete gaps. The field of AI governance should be viewed as a dynamic and constantly evolving research agenda that slowly has started to cement around varying issues and academic positions. This thesis is motivated by engaging with four distinct areas across AI innovation, AI regulation, AI institutionalization, and AI great power competition, which feed into the overarching field of AI governance. While each area could have been the subject of a PhD thesis, the argument for engaging with all four areas ties back to strengthening the brittle research agenda surrounding AI governance. While each of the mentioned areas is researched individually, the scholarly community is largely silent when it comes to addressing how they jointly inform the broader field of AI governance. This thesis is motivated by doing just that.

First, governments' mechanisms to stimulate AI innovation have been largely neglected in the literature. While it has been more widely documented how firms engage in AI innovation (Brynjolfsson, et al., 2017) and strategy and management processes (Fountaine, et al., 2019), including the role and organization of platforms (Bonina, et al., 2021), the link between national AI policy and innovation strategies and how these interact with and affect AI innovation has received less attention (Sousa, et al., 2019). At the same time, it is becoming clearer that core research on AI in universities and research institutions faces new challenges, such as lack of access to data and compute vis-à-vis large innovation platforms. Little research has been conducted on national policies and strategies that encourage and enable the construction of more open and inclusive AI platforms and ecosystems conducive to innovation. Therefore, a research gap is located in understanding how governments can use new mechanisms to affect the generativity[3] of AI platforms and ecosystems while engaging in public-private orchestration of the platform economy.

Second, the introduction of AI agents into new or existing fields creates altered dynamics where algorithms hold power and potential to shape the emergence of novel forms of socio-economic organization (Curchod, et al., 2020). Algorithms can be seen as non-human agents that can evaluate, rank, and reward or punish individuals' actions and positions based on pre-programmed instructions that shape social relationships (Floridi, 2014). Existing institutional infrastructure, such as internal guidelines within a business or external laws and regulations, tend to determine the scope and speed

[3] In relation to digital innovation, generativity is defined as "a technology's overall capacity to produce unprompted change driven by large, varied, and uncoordinated audiences" (Zittrain, 2006, p. 1980).

at which organizational change is allowed to occur (Hinings, Gegenhuber, & Greenwood, 2018). In terms of AI, however, this relationship has been little studied. While it is easy to understand ex-post where novel forms of AI such as facial recognition technologies may run into varying forms of contestation, it may be harder to conceive ex-ante what is needed to build inclusive and non-biased socio-technical systems and institutions. In other words, it is little understood how emerging AI-powered digital infrastructures interact with and affect human behavior and forms of organization, as well as how existing institutional infrastructures are equipped to guide varying forms of AI dispersion. Therefore, a perceived gap exists in terms of how novel forms of AI technology diffuse, shape new forms of organization in the process, gain legitimacy, and become institutionalized over time.

Third, little research has been conducted on regulating a GPT such as AI. This establishes a problem in terms of a lack of precedence in understanding how new forms of regulation may interact with and affect varying sectors that use AI differently. While AI adoption is rising, regulatory responses tend to develop much more slowly, categorized as the pacing problem (Hagemann, Huddleston, & Thierer, 2018). In other words, novel digital systems, products, and infrastructures, including artificial intelligence, tend to emerge much faster than the surrounding institutional infrastructure designated as laws and regulations that guide technological expansion (Hinings, Gegenhuber, & Greenwood, 2018). This may create extensive issues if negative externalities are associated with fast-moving technological implementation that could be at odds with existing structures or norms for specific actors or groups of society (Buolamwini & Gebru, 2018: Obermeyer, et al., 2019). The main goal of regulators is to limit negative externalities in areas such as competition, privacy, safety, and accountability while ensuring continued opportunity in the application and innovation of AI-based tools, products, services, and systems (Buiten 2019; Campbell 2021). However, the literature has barely dealt with the complex interactions between new public-sector AI regulations and their tentative effects on firm-level behavior and innovation during this process. Therefore, a gap in the research is located in the rising pressure of normative arguments surrounding AI regulation and in the number of studies that have dealt with how new and intended AI regulation could affect firm-level behavior.

Fourth, technological competition could affect AI governance by lowering demands for AI regulation to stay competitive. This is also true in terms of data, which is an essential input factor in AI innovation. However, little is known about how great power competition interacts with and possibly shapes preferences for technological governance in areas such as data privacy and AI regulation. Great power competition and questions over digital sovereignty could have important implications for how countries continue to structure hardware and software interoperability measures and data privacy and data protection practices (Floridi, 2020). These are all relevant concerns in terms of AI governance. At the same time, the impact of great power competition on demands for privacy and regulation is an area that remains little understood and accounted for in the literature. Therefore, how nationalism feeds into the degree of freedom governments have as they choose among disparate AI governance and data privacy regimes is an important research area.

Table 1. Research gaps addressed in this thesis

No.	Research gap
Gap 1	The link between national AI policies and innovation strategies and how these interact with and affect AI innovation has been little studied.
Gap 2	There is incomplete knowledge surrounding how novel forms of AI technology diffuse and how they obtain legitimacy or are obstructed in terms of institutionalization processes.
Gap 3	Little is known about the interactions between new and incoming public-sector AI regulation and firm-level behavior and innovation.
Gap 4	The implications of great power competition on regulatory and data privacy preferences have been little researched and understood.

Based on the proposed gaps, it is clear that multiple areas associated with AI governance have been insufficiently dealt with in the current literature. Furthermore, the interconnections between the mechanisms that enable AI innovation and constrain it through policy and regulation have hardly been explored and discussed at a more general level of abstraction.

1.2. Research objective and questions

This dissertation aims to increase our current understanding of AI governance based on the policies and mechanisms developed and deployed by the United States and China. The main question of this thesis explores how artificial intelligence is governed in the United States and China and what some of the implications hereof are for the governance of AI. This broad and overarching research question encompasses various governance dimensions at different levels of AI innovation, adoption/diffusion, and regulation. In order to specifically address the research gaps presented in the previous section, four sub-questions are formulated, as shown in Table 2.

Table 2. Main research questions

Level	Country	Research Question
Main RQ	US & China	How is artificial intelligence governed in the United States and China, and what are some of the broader implications for the governance of AI?
Sub-RQ1	US	How do different kinds of AI-related regulation – or even the prospect of regulation – affect firm behavior, including firm responses to ethical concerns?
Sub-RQ2	US	How are AI-induced fields subject to varying degrees of legitimacy as well as processes of institutionalization?
Sub-RQ3	China	What mechanisms can governments use to affect the boundary resources of innovation platforms, and how do these influence platform governance?
Sub-RQ4	China	How does technological competition affect data privacy preferences?

Sub-RQ1 focuses on AI regulations in the US. It examines varying forms of regulation across existing laws, new horizontal regulation, sector-specific regulation, and data-related regulation. Specifically, it assesses how regulation might cause managers to change their perception of the importance of AI ethical issues such as privacy, transparency, safety, bias/discrimination, and labor-related issues. Sub-RQ1 addresses managers' associated intent to adopt AI technologies and alter their AI-related business strategies. This perspective is important as few studies engage with the actual or potential costs of varying kinds of AI regulation.

Sub-RQ2 addresses how AI-induced fields are subject to varying degrees of legitimacy as well as processes of institutionalization, with illustrations from the US. AI agents often hold autonomy to act on (e.g., judicial evidence, road conditions) and interact with (e.g., speech recognition, chatbots) their environments. In many cases, an AI agent is likely to affect organizational structures and alter behavioral dependencies in ways that can be difficult to identify ex-ante (Curchod, et al., 2020). Looking at AI legitimization processes and understanding how these are likely to arise when emerging AI systems are inaccurate, unsafe, or nontransparent contributes to establishing new insights into processes of AI institutionalization.

Sub-RQ3 focuses on China and looks at a range of government mechanisms that are used to affect the boundary resources (i.e., governing tools and rules) of AI innovation platforms. The role of platforms in AI innovation is relevant since large technology companies often resource digital ecosystems with essential tools such as open data and open-source software and guide ecosystem behavior through rules that shape interaction (Ghazawneh & Henfridsson 2012: Yoo, et al. 2012). The third research question seeks to address how governments interact with and affect the generative boundary resources of AI innovation platforms and how this influences platform governance and AI innovation.

Finally, Sub-RQ4 seeks to determine how technological competition between the US and China may affect data privacy preferences. Nationalistic sentiment surrounding technology competition between the US and China could influence people's willingness to share data with companies and the government. Researching how and whether that is the case informs how nationalistic sentiment correlates with data privacy preferences, indicating how governments can shape varying regulatory agendas that surround and feed into disparate forms of AI governance.

By assimilating the findings from the four perspectives of AI regulation (US), AI institutionalization (US), AI innovation (CH), and AI-related great power competition (CH), this thesis establishes a multi-angle perspective (Khan, 2014) that informs the governance of AI.

1.3. Contribution of this dissertation

Following the presentation of the research gaps and research questions, this section provides a brief overview of the main contributions of the dissertation. This dissertation makes several contributions to the literature on AI governance. These are divided into empirical and theoretical contributions that are further developed and discussed in Chapter 6.

In terms of empirical contributions, the dissertation adds evidence to some of the tentative costs that are associated with varying forms of AI regulation. More specifically, this thesis finds that information about current and proposed AI regulation tends to reduce managers' stated intent to adopt AI technologies. However, information about AI regulation also raises managers' perceptions of the importance of varying AI-related ethical issues. An empirical contribution specifies how different kinds of regulation could affect industries and their ethical concerns differently due to industry-specific characteristics.

The thesis also adds empirical evidence on how great power competition between the US and China may invoke nationalistic sentiment, which increases people's willingness to share data with companies and the government. When Chinese citizens are reminded of the US–China tech competition, they also tend to lower the valuation they place on their facial image data. This finding has potential implications for the understanding of how nationalism can configure in the construction of disparate data privacy regimes. The finding has consequences for AI governance, which needs to be interpreted according to diverse socio-political forms of organization.

Theoretically, this dissertation makes specific contributions to the literature on platform- and technology-related governance and regulation, rooted in information systems, institutional theory, and political economy. In relation to the platform literature, a theoretical contribution is made by adding nuance to our understanding of the governance mechanisms that can be used to govern the boundary resources of innovation platforms. Governance mechanisms (e.g. rules and legislation) have been detailed to affect areas such as platform interoperability, software accessibility, and data sharing. Governments can utilize mechanisms to influence platform behavior, which directly and indirectly affects AI governance and innovation. Novel organizational mechanisms also include the construction of hybrid public-private platforms that may be conducive to establishing new forms of AI-associated infrastructure.

Institutional theory is advanced by presenting a novel conceptual framework that can be used to analyze and understand AI-induced field change at greater depth. The framework clarifies how an algorithm's ability to shape organizations and institutions may be restricted by existing institutional infrastructures, which hold the capacity to determine the scope and speed at which organizational change may occur. Where institutional infrastructure and governance arrangements, such as standards, rules, and regulations, are unelaborate, an AI field can evolve quickly but is more likely to run into contestation. Information systems theory is extended by incorporating the notions of technological maturity, autonomy, and data, which inform AI-induced digital infrastructures.

Table 3. Overview of articles

	Article I	**Article II**	**Article III**	**Article IV**
Title	Does Information About AI Regulation Change Manager Evaluation of Ethical Concerns?	A Framework for Understanding AI-Induced Field Change: How AI Technologies are Legitimized and Institutionalized	Government Mechanisms for Platform Boundary Resource Tuning: The case of China's National Open Innovation Platforms for AI	US–China Tech Competition and the Willingness to Share Personal Data in China
Co-authors	Mariano-Florentino Cuéllar, Michael Webb, Yong Suk Lee			Jingxin Wu, Yong Suk Lee
Article RQs	How do different kinds of AI-related regulation – or even the prospect of regulation – affect firm behavior, including firm responses to ethical concerns?	How are AI-induced fields subject to varying degrees of legitimacy as well as processes of institutionalization?	What mechanisms can governments use to affect the boundary resources of innovation platforms, and how do these influence platform governance?	How does technological competition affect data privacy preferences?
Main RQ	Sub-RQ1	Sub-RQ2	Sub-RQ3	Sub-RQ4
Key Findings	AI regulation increases manager perception of the importance of safety, privacy, bias/discrimination, and transparency issues related to AI but reduces manager intent to adopt AI technologies	Extends information systems theory associated with AI agency and infrastructure through adding the institutional perspective to understand the dispersion and legitimization of AI technologies	Extends information systems theory on boundary resources and repurposes it around government mechanisms in shaping the boundary resources of innovation platforms. Constructs the concept of hybrid platforms	US–China technology competition invokes nationalistic sentiment, which increases respondents' willingness to share data with companies and the government. This lowers the price of data as an input factor in AI innovation
Unit of Analysis	Meso: comparing managers' aggregated perceptions of, and reactions to, different AI regulations	Macro: looking at varying AI fields and their trajectories of legitimization and institutionalization	Macro: national policy level, interpreting National Open Innovation Platforms for AI	Meso: comparing citizen's data privacy preferences when reminded of US–China tech competition on AI
Status	Published in the Journal of Law, Economics, and Organization Conference paper accepted for NBER Economics of AI (2019) & ASSA (2020)	Published in Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society (AIES'21)	Submitted	Submitted

1.4. Overview of research articles

The dissertation comprises this synopsis as well as four original research articles that form the analytical body of the dissertation. As shown in Table 3, each research article is guided by its own research question; together, these questions inform the overarching research question of the thesis.

The first research article adopts a meso-oriented view. It provides empirical insights into the preferences of firm managers and how information on varying forms of AI regulation is likely to shift these preferences.

The second research article adopts a macro-oriented view and develops a novel theoretical framework that can be used to understand varying processes of AI legitimization and institutionalization.

The third research article adopts a macro-oriented view and provides both empirical insights and theory building in relation to the platform literature.

The fourth research article adopts a meso-oriented view. It provides empirical insights into the data privacy preferences of individuals and how great power competition is likely to shift these preferences.

1.5. Scope and delimitation

The scope of this thesis is delimited in several ways. In terms of geography, this thesis has chosen to focus specifically on the empirical contexts and policy approaches of the United States and China. Many countries, however, develop unique approaches to govern AI. While these are all relevant, they are largely excluded from this study. Focus is instead placed on the US and China because their approaches (along with the European Union) are more likely to establish international precedence affecting the governance of AI technologies elsewhere.

In terms of technology, the focus is strictly centered on artificial intelligence. The focus on AI was chosen due to its inherent capabilities as a GPT, which means that AI will have vast consequences for countries, firms, and individuals (Agrawal, Gans, & Goldfarb, 2019). Due to the breadth of technical use-cases and how these hold the potential to shape new forms of organization and individual practices, this thesis deploys a broad view on AI that moves across innovation, adoption, diffusion, and regulation.

In terms of actors and their segmentation, this thesis focuses primarily on policymakers and firm managers and their perceived mechanisms and processes governing AI innovation, adoption, and regulation. Actors from civil society (i.e. individuals) also play an essential role in governing AI adoption and diffusion. Their role is mentioned and discussed in Article II regarding processes of AI legitimization, and in Article IV in relation to data privacy preferences.

In terms of the temporal scope, the dissertation leans against recent and rapidly evolving events that cover a relatively short time span. Although the modern development of AI dates back to the 1950s, adoption and technological expansion were dormant for many years and only saw a real uptick with the advent of more useful deep learning techniques since the early 2010s. The advent of deep learning algorithms and essential improvements in computing have caused more widespread adoption over the last decade, forcing policymakers to think more carefully about regulating the technology. Therefore, regulation of AI is a nascent phenomenon, which only started to gain real attention in the late 2010s. This means that the foundation of inquiry laid out in this thesis covers policy, economic, managerial, and philosophical arguments that remain in their infancy. While these arguments are rapidly developing, they are by no means fully formed at this early stage of inquiry. This provides both temporal obstacles, e.g., in terms of interpreting events as they unfold, and opportunities to shape the evolving agenda on AI governance.

Finally, the level of analysis of this dissertation varies across the four articles but is mainly placed on meso and macro levels of inquiry. As AI governance includes the relationships between policymakers, firms, and civil society participants, it is crucial to consider how they interact with and affect each other. Situated on the macro and meso levels of analysis, the thesis can construct a higher level of abstraction that enables it to transcend the individual approaches of the United States and China. The limitation of this approach is that behavior at the micro-level, that is, at the level of individuals and specific firms, is not dealt with nor analyzed to a great extent.

1.6. Structure of dissertation

The dissertation is organized around six introductory chapters that jointly comprise the synopsis. The synopsis is followed by four individual research articles that encompass this thesis's main body of knowledge.

Chapter 1 presents the background, introduces the research objective and questions, and delimits the scope of the inquiry.

Chapter 2 provides a brief overview of the field of artificial intelligence, including its history and some of the main algorithms and approaches that currently dominate implementation. Next, the central AI policies and national strategies of the United States and China are outlined and then serve as the main point of reference for the rest of the synopsis.

Chapter 3 elaborates on the theoretical and conceptual frameworks deployed and used throughout the thesis. This chapter covers relevant debates on the core concepts that inform the conceptual framework of the thesis.

Chapter 4 explains the methodological choices that underlie and guide the thesis. It discusses the philosophy of science, the research strategy and design, and the data collection and analysis. The chapter gives an account of the validity and reliability of the research.

Chapter 5 summarizes the four research articles, including the contribution of each to answering the main research question of the thesis.

Chapter 6 highlights the key findings concerning the main research question and presents the conceptual, methodological, and empirical contributions. The chapter then presents managerial and policy implications and points to avenues for future research.

2. THE EMPIRICAL CONTEXT

Three factors drive the advancement of artificial intelligence. These are algorithmic innovations, data, and compute available for training and deploying AI algorithms. Each is detailed in the following section, beginning with a brief historical introduction to the field of AI.

2.1. An introduction to AI

The development of the first digital computer can be dated to 1941, when German engineer Konrad Zuse developed the world's first programmable fully automatic computer, the Z3 (Salz Trautman, 1994). With the rise of programmable computers, Alan Turing published a 1950 article on Computing Machinery and Intelligence in which he asked, "Can machines think?" (Turing, 1950). In 1956, the Dartmouth Summer Research Project on Artificial Intelligence set out to answer this question, which marks the beginning of modern research on artificial intelligence. The Summer Research Project was joined by leading American scholars who believed that "a significant advance can be made in one or more of these problems if a carefully selected group of scientists work on it together for a summer" (McCarthy, et al., 1955, p. 1). While it proved to take somewhat longer than first anticipated, different approaches to AI have since emerged (Nilsson, 1983). Varying approaches to AI development and application have been broadly categorized between symbolic AI, also is known as "classical" or "Good Old Fashioned AI" (GOFAI), and sub-symbolic AI, and statistical learning.

Classical rules-based AI is grounded in symbolic representations of problems, logic, and search and was the dominant paradigm of AI research from the mid-1950s until the late 1980s. Most of the early research followed a "knowledge-based" approach where researchers manually encoded the knowledge the AI would need to know to carry out a particular task (Marcus & Davis 2019). Subsequently, researchers would write computer programs holding that knowledge, enabling a program or a robot to carry out its intended functions in a controlled environment. One unique approach to symbolic AI is expert systems, also noted as an inference engine, which applies a network of logical rules to a knowledge base to deduce new information. Expert systems are often encoded as "If-Then" statements, determining whether the system needs any additional information to proceed with a given task or function.

By the 1980s, progress in symbolic AI had stalled. At the same time, imitating all combinations of human cognition, perception, learning, and pattern recognition proved hard to compress into a rules-based approach. Instead, the focus on sub-symbolic methods combined a rules-based approach with autonomous and self-explorative approaches to accumulate intelligence (Nilsson, 1998). During the 1980s, research on soft-computing and artificial neural networks began, along with the observation that problems often cannot be solved by relying on complete logical certainty alone. In extension, soft-computing deals with approximate models and solves complex real-life problems that are tolerant of imprecision, uncertainty, partial truth, and approximations (Ibrahim, 2016).

Since the 1990s, AI researchers have increasingly adopted sophisticated mathematical and statistical tools and models to compare and, to some degree, unify competing architectures. Compared with GOFAI, new ”statistical learning” techniques, such as neural networks, have gained higher levels of accuracy in different applied domains without necessarily acquiring a semantic understanding of the underlying datasets (Russell & Norvig, 2010).

In the early days of AI, little data existed compared to modern Big Data architectures and applications, which have been enabled by advancements in information communication technology (ICT). Today, machine learning has largely replaced the classical knowledge-based approach, which often infers relations directly from data (Marcus & Davis, 2019). This kind of learning is relatively recent and began to take off in the early 2010s when Big Data became more available and deep learning techniques matured.

2.1.1. Modern AI

One of the goals of creating artificial intelligence is to enable machines and computer systems to learn about the world and engage in complex tasks that require high cognitive capabilities. The enablement of computer systems requires both knowledge representation and reasoning capabilities for such systems to start solving complex tasks such as diagnosing a medical condition or having a meaningful dialog with a human in natural language. Knowledge representation and reasoning incorporate findings from many diverse fields such as psychology, philosophy, and biology.

Machine learning (ML) is the overarching scientific study of algorithms and statistical models. ML-based computer systems detect patterns and learn to make predictions and recommendations by processing data and experiences rather than receiving explicit programming instruction. Machine learning algorithms can adapt in response to new data and experiences, which improves the system's efficiency over time. Machine learning departs from descriptive statistics and provides probabilistic predictions of events and prescriptions and adhering recommendations (Chui, et al., 2020). Learning is usually structured in processes that can be supervised, semi-supervised, unsupervised, or related to reinforcement learning.

Supervised learning refers to a process in which large amounts of data have been pre-labeled by humans to represent specific meaning (e.g., an annotated picture of a cat), which the system can use as an input to learn from (Chui, et al., 2020). Semi-supervised learning refers to a class of ML tasks and techniques that use a smaller amount of labeled data and a more significant amount of unlabeled data. Unsupervised learning is self-organized algorithmic learning, which can detect patterns in data sets without prior labeling (Chui, et al., 2020). Reinforcement learning (RL) is an area of ML where an algorithm learns to perform a given task by maximizing the rewards it receives for its actions. RL differs from supervised learning as labeled input is not needed while the scope of the algorithm, often designated as the software agent, is to find a balance between exploration (of uncharted territory) and exploitation (of current knowledge) (Kaelbling, et al., 1996). Choosing to use either a supervised or unsupervised machine learning algorithm normally depends on the structure and volume of data and the use case of the issue (Tiange, 2019).

Deep learning (DL) architectures such as artificial neural networks, a subgroup of machine learning, have paved the way for many modern advances in AI application, associated with areas such as computer vision, speech recognition, natural language processing, and audio recognition. Deep learning structures consist of interconnected layers of software-based calculators known as "neurons," which form a neural network that can digest large amounts of input data and process it through multiple learning layers (Burns & Burke, 2021). The neural network learns increasingly complex data features across each additional layer of digression. The network can then decide about the data, learn if its assessment is accurate, and use what it has learned to make determinations about new data. For example, in computer vision, a neural network can learn what an object looks like, allowing it to recognize the same object across new images.

2.1.2. Open source

Traditionally technology and software innovation has been developed proprietarily without publicizing sensitive information. At the beginning of the 1990s, the operating system Linux changed this when it open-sourced its software (Bagozzi & Dholakia, 2006). Open-source software (OSS) releases source code under a license where the copyright holder grants users the rights to study, alter and distribute the software freely. Open-source software has brought about a culture change in which developers contribute to software development in collaborative communities, which most often are global due to the digital characteristics of the World-Wide-Web.

The same characteristics are associated with developing AI-based open-source software, implying that most AI tools, libraries, and frameworks are open and can be freely accessed, utilized, and altered. Most open-source software is posted on open-source code repositories such as GitHub, where developers can access, iterate, fork, and potentially improve and create different versions of the software.

In traditional software development, the lifecycle of an application moves from design to implementation and deployment and finishes with managing and monitoring a final product. In machine learning applications, this process is considered an infinite lifecycle characterized by constant reiteration, based on ongoing experimentation related to new data inputs that affect and potentially alter the model. One of the key features of live ML systems is that they can influence their behavior if they update over time. This makes it difficult to predict the behavior of a model before it is released. At the same time, feedback loops can be hard to detect and address if they occur gradually over time, especially in models that are updated infrequently. Dealing with changes in the external world implies that models require continuous attention and tweaking of perimeters to ensure accuracy across monitoring and testing. Manual intervention or investigation is often required when certain action limits are reached, including monitoring upstream data producers that may change significantly over time, affecting the output of an ML system. Because external changes occur in real-time, ideally, responses should also occur in real-time. This frequently requires human intervention (i.e., keeping a human in the loop) unless adjacent automated systems and procedures are in place (Sculley, et al., 2015).

2.1.3. Data

In recent years, the importance of data in the economy has increased. Due to the sheer number of transactions and activities conducted online, firms, governments, data aggregators, and other parties are enabled to observe, record, structure, and analyze data about consumer behavior at new levels of detail and computational speed (Varian, 2010). While aggregate data have been previously known, technology has enabled the recording of individual transactions, allowing far richer datasets to emerge based on micro-observations. As a result, the digital economy is contingent on the organization of large amounts of unstructured data that facilitate the targeting of product offerings by firms to individual consumers. Search engines, for instance, rely on data from repeat and past searches to improve search results, sellers rely on past purchases and browsing activities to make product recommendations, and social networks rely on selling data to marketers to generate revenue (Acquisti, Taylor, and Wagman, 2016). Data has therefore become an essential resource in the digital economy, while the proliferation of Internet-based digital services and smartphones have made the creation and collection of data more accessible and cheaper than before. In 2013 IBM estimated that 90% of the world's data had been created in the past two years alone (Esteramorperez, 2020), while data from Statista reveals an exponential growth of created, captured, copied, and consumed data worldwide from 2010 to 2025 (Statista, 2022).

The production and consumption of increasing data also mean that more use-cases in training algorithms are generated. One of the most widely known datasets for training machine-learning algorithms is administered by ImageNet, which has more than 14 million images that humans have labeled. Since 2010, the ImageNet project has run an annual Large Scale Visual Recognition Challenge (LSVRC), where software programs compete to classify and detect objects and scenes. The accuracy of algorithmic programs has increased rapidly, while some computer programs achieved 95% accuracy in 2015, which is equal to human performance ability. By 2017, accuracy had climbed above 97%, and progress is continuing. While these improvements have been made on one particular dataset, the results feed into more extensive technological advancements that correlate to better performance on other specific tasks, such as analyzing security camera footage or spotting animals in nature. Similarly, for the field of speech recognition algorithms that can accurately transcribe speech, performance on one primary benchmark has increased from 84% in 2011 to 95% in 2017 (Shoham, et al., 2017).

2.1.4. Markets for data

Besides many publicly available datasets that can be used for machine learning training, data is also monetized meaning that it is sold and collected on markets for data. Data brokers usually collect information about individuals from available sources across public records, including census data, address records, vehicle and driving records, bank details, social media sites, web browsing history, and so on (Dixon, 2013). The accumulated data is aggregated to create individual consumer profiles that can be sold on markets for data. Consumer profiles comprise thousands of pieces of information such as a person's age, race, gender, height, weight, marital status, religious affiliation, political affiliation, occupation, household income, net worth, homeownership status, investment habits, product preferences, health-related interests, and so on. Data brokers can sell this kind of data and related consumer profiling, often for use in targeted advertising and marketing-related activities (Dixon, 2013). Due to data's growing role and importance, it has been popularly described as the "oil of the digital economy."

Markets for data have been enabled by increased connectivity between devices and increases in compute coupled with decreases in the costs of storing data. In connection with IoT, higher levels of connectivity mean that data travels through a higher number of digital devices, leaving behind a "digital trail" or "digital exhaust" across many different platforms and services. In terms of markets for data, a product from Google Home, for example, could be connected to a Nest thermostat connected to a telecommunications company that shares data with insurers, contractors, and sub-contractors.

The European Commission has estimated that markets for data were worth up to $116 billion in 2020 (Ram & Murgia, 2019). As machine learning is more accurately developed depending on the number of inputs and the richness of details in data, data labeling also feeds into markets for data and is projected to triple between 2019 and 2023, reaching $5 billion (Kshetri, 2021). As human data labeling is a labor-intensive job, it is often outsourced to developing countries such as India, Vietnam, and the Philippines, where salaries are lower than in the United States, for instance.

New regulations such as the European Union's General Data Protection Regulation (GDPR), California's Consumer Privacy Act (CCPA) and China's Personal Information Protection Law (PIPL), have changed some of the governing mechanisms of markets for data while altering company practices for handling and storing data. Under the GDPR, for example, consumers can request their data in downloadable and readable formats, which has required many companies to re-engineer their IT architectures related to data handling and storage processes, potentially driving up costs related to infrastructure and administration.

The landscape for data and ownership and the governance and regulation hereof is constantly evolving as IT technology and practices change and mature. While the current information infrastructure has morphed into a monetized model where consumers generally have little control over their data, alternatives that allow consumers to regain a sense of ownership over their data are being innovated. These solutions can enable individual data owners to permit external apps or companies to read or write to different parts of their data, which hands power back to individual owners, i.e., producers of personal data (Mansour, et al., 2016).

2.1.5. Compute

A Central Processing Unit (CPU) is the most common microprocessor and is responsible for executing the instructions of a computer program on most computers. Compute is an enabling factor of AI-related algorithmic processing, and exponential advancements in compute have paved the way for new AI capabilities to emerge. Since 1965, Moore's law has observed that the number of transistors in an integrated circuit (i.e. chip, microprocessor, semiconductor) has doubled approximately every two years. Previously, compute used to be a limitation to the development of AI, for example, in terms of testing deep learning theories and methods in practice.

The Big Data revolution of the early 2010s has, along with GPUs (Graphics Processing Units), become one of the enabling building blocks for providing the processing power behind modern AI advances. GPUs were initially developed for video games in the 1970s but have been applied to neural networks since the early 2000s. While a CPU consists of a few cores that have been optimized for sequential serial processing, a GPU has a massively parallel architecture consisting of thousands of smaller and more efficient cores designed for handling multiple tasks simultaneously. As deep learning requires high levels of computational power, GPUs have proved to accelerate the training process of neural networks.

Besides traditional semiconductor manufacturers (e.g., Intel, NVIDIA, Qualcomm, ARM, NXP), software companies (e.g., Amazon, Alibaba, Google, Baidu, Microsoft, Huawei) have developed proprietary semiconductors that enable faster processing within their data centers. For example, Google's Tensor Processing Unit (TPU) has been developed specifically for neural network machine learning based on Google's AI framework TensorFlow. The new breed of microprocessors is called AI accelerators, explicitly designed for AI applications such as neural networks, machine learning, and machine vision. Companies such as Amazon (Inferentia), Baidu (Kunlun), Alibaba (Pingtouge Hanguang), and Huawei (Ascend, Atlas) are all developing similar solutions.

Companies can choose to buy individual semiconductors and establish proprietary information infrastructure, or they may choose to buy and access compute and associated information infrastructure through virtual machines offered by cloud providers. The largest cloud providers are known as hyperscalers and usually have a range of AI solutions attached to their cloud and AI platforms. AI platforms operate as vertical technology stacks that third parties can access and utilize through application programming interfaces (API). AI platforms are built on cloud computing services that enable customers to access and utilize AI tools and technologies without building and investing in their hardware and IT infrastructure. Earlier, technology stacks had to be built from scratch, whereas services since have been modularized into specific AI and ML solutions.

The AI-related technological landscape is rapidly evolving and some capabilities have begun to migrate from the cloud towards edge applications. This means that ML, compute, and algorithmic inference are moving closer to where data is being gathered and created, such as mobile devices. These developments relate to upgrading efficiency, speed, privacy, and security while enabling data to be processed in real-time (Haas & Davies, 2020). This migration towards edge applications is accelerated by the emergence of the Internet of Things (IoT), which is enabled by advancements in 5G networks that allow for an increase in data to travel between devices. New and interconnected devices are currently being developed in areas such as autonomous vehicles, healthcare, smart cities, and the Industrial Internet of Things (IIoT).

2.1.6. AI governance

Two distinct but connected forms of AI governance are currently emerging. One is soft law governance, which functions as self-regulation based on non-legislative policy instruments. This group includes private sector firms issuing principles, guidelines, and internal audits and assessment frameworks for developing ethical AI. Soft law governance also entails multistakeholder organizations such as The Partnership on AI, standard-setting bodies such as the International

Organization for Standardization, and interest organizations such as the Association for Computing Machinery. Actionable mechanisms by the private sector usually focus on developing concrete technical solutions, including the development of internal audits, standards, or explicit normative encoding. This means that soft-law governance and associated mechanisms already play an essential part in setting the default for how AI technologies are governed (AI Ethics Impact Group, 2020). Hard law measures, on the other hand, entail laws and legally binding regulations that define permitted or prohibited conduct. Regulatory approaches generally refer to legal compliance, the issuing of certificates, or the creation or adaptation of laws and regulations that target AI systems (Jobin, et al., 2019). Policymakers are currently contemplating several approaches to regulating AI, which broadly can be categorized across existing laws and legislation, new horizontal regulations, domain-specific regulations, and data-related regulations.

Table 4. AI governance overview

	Soft law governance	**Hard law governance**
Definition	Self-regulation based on non-legislative policy instruments	Legally binding regulations that are passed by the legislatures to define permitted or prohibited conduct
Examples	Private sector firms issuing principles and guidelines for ethical AI	Horizontal Regulation, e.g., Algorithmic Accountability Act, EU AI Act
	Stakeholder organizations such as The Partnership on AI	Sector-specific regulations, e.g., NHTSA on autonomous vehicles
	Standard-setting bodies such as The Institute of Electrical and Electronics Engineers (IEEE)	Data-related regulations, e.g., CCPA (US), GDPR (EU), PIPL (CH)
Mechanisms	Development of concrete technical solutions, including the adoption of assessment framework, audits, and standards	Regulatory approaches generally refer to legal compliance, the issuing of certificates, or the creation or adaptation of laws and regulations to accommodate the specificities of an AI system (Jobin, et al., 2019).

2.2.The United States AI policy landscape

This section gives an overview of AI policy in the United States. It presents AI policy at the federal, state, and local levels before giving an overview of current trends in AI regulation. Next, AI ethics and forms of self-regulation by private sector enterprises are introduced before developments in technology and national security policies are elaborated. In summary, AI policy in the United States is progressing at a slow and incremental pace at the national level, while data and algorithmic governance policies often are fragmented at the state level.

In the United States, AI policy was first debated in 2016, when President Obama and the White House Office of Science and Technology Policy (OSTP) launched a series of workshops and established a Subcommittee on Machine Learning and Artificial Intelligence. The subcommittee was established to monitor advances in AI while coordinating federal activity in the area.

In May 2018, President Trump and the White House held a Summit on Artificial Intelligence for American industry that included key American technology companies.[4] Priorities included funding for AI research, removing regulatory barriers to deploying AI-powered technologies, training the future American workforce, achieving strategic military advantage, leveraging AI for government services, and working with allies to promote AI R&D (The White House, 2018).

In June 2018, The White House announced plans to help provide US companies with new data sources and establish a Select Committee on Artificial Intelligence to help government agencies adopt AI technologies and consider partnerships with industry and academia (The White House, 2018).

In a July 2018 memo from the Executive Office of the President, US leadership in AI was clarified as the second-highest R&D priority after the security of the American people.

In February 2019, President Trump signed Executive Order 13859, announcing the American AI Initiative, which serves as the US national strategy on AI.

In August 2019, the National Institute of Standards and Technology (NIST) submitted the report "U.S. LEADERSHIP IN AI: A Plan for Federal Engagement in Developing Technical Standards and Related Tools" prepared in response to Executive Order 13859 (NIST, 2019). NIST plan recommends that the Federal government commits to deeper, consistent, and long-term engagement in AI standards development activities that help the United States speed up AI development. Specifically, the plan recommends that the Federal government should:

- foster AI standards-related knowledge, leadership, and coordination among Federal agencies

[4] E.g. Alphabet, Facebook, Amazon, Ford Motor Co, Boeing Co, MasterCard and Microsoft Corp

- promote focused research to advance and accelerate broader exploration and understanding of how aspects of trustworthiness can be practically incorporated within standards and standards-related tools
- support and expand public-private partnerships to develop and use AI standards and related tools to advance reliable, robust, and trustworthy AI. Advance non-traditional collaborative models for standards development, such as open-source efforts and Federal open data initiatives
- strategically engage with international parties to advance AI standards for US economic and national security needs

In 2020, President Trump's Executive Order 13859 was ratified as The National AI Initiative Act of 2020 (NAIIA), which became law in January 2021. As the United States national strategy on AI, the mission of The National Artificial Intelligence Initiative (NAII) is to:

- ensure continued US leadership in AI R&D
- lead the world in the development and use of trustworthy AI systems in public and private sectors
- prepare the present and future US workforce for the integration of artificial intelligence systems across all sectors of the economy and society, and
- coordinate ongoing AI activities across all Federal agencies to ensure that each informs the work of the others (NAIIO, 2022)

The National Artificial Intelligence Initiative Office (NAIIO), located in the White House Office of Science and Technology Policy (OSTP), is charged to coordinate and support the NAII. The NAIIA also relies on the National Science and Technology Council (NSTC) Select Committee on Artificial Intelligence to coordinate the initiative. All executive departments and agencies that are developing or deploying AI, providing educational grants, or regulating or guiding AI are required to adhere to six strategic objectives that include:

- promoting sustained investment in AI R&D
- enhancing access to Federal data, models, and computing resources
- reducing barriers to the use of AI technologies

- training American AI researchers, and
- promote an international environment supportive of American AI innovation, and
- embrace trustworthy AI for government services and missions

Federal agencies are instructed to prioritize AI investments in their R&D assignments while making federal data, models, and computing resources more available to American researchers and industry. These efforts happen in concert with implementing the Open, Public, Electronic, and Necessary (OPEN) Government Data Act, which mandates federal agencies to publish all their information as open data, using standardized, non-proprietary formats (Murray, et al., 2017). The OPEN Government Data Act was passed in the House of Representatives in November 2017 and builds on President Obama's May 2013 Open Data Policy.

Government support measures and the quest for digital sovereignty is a political agenda that has been rapidly building in the US. In January of 2021, Congress passed the Creating Helpful Incentives to Produce Semiconductors (CHIPS) for America Act as a part of the National Defense Authorization Act (NDAA) for the Fiscal Year 2021 (HR 6395, 2020). The CHIPS Act aims to promote the research, development, and fabrication of semiconductors within the United States. On February 4, 2022, The House of Representatives passed CHIPS Act investments totaling $52 billion as part of the America COMPETES Act.

2.2.1. State and local AI policy

At the State and local levels, several AI-related bills have been introduced. In 2017 the New York City Council passed an algorithmic accountability bill that established the New York Algorithm Monitoring Task Force. The group studies how city agencies use algorithms to make decisions by understanding how AI systems and procedures potentially affect the citizens of New York (Stoyanovich, et al., 2020).

In California, the State Senate passed a resolution supporting the Asilomar AI Principles in August 2018, which are 23 guidelines that guide the safe and beneficial development and use of AI (California State Senate, 2018). The California Consumer Privacy Act was passed in June 2018 and required informing people about how their personal information is being used while allowing people to opt out of having their data sold to third parties (Pardau, 2018). In 2019, California also passed a bot disclosure law that makes it unlawful to use a bot without disclosing that it is not a human if used to incentivize a commercial transaction or influence a vote in an election (Lamo & Calo, 2019).

Other State initiatives include an AI Task Force established in Vermont in May 2018, which makes recommendations about government use of AI and state regulation. A Future of Work Task Force was established in Washington in March 2018 to navigate automation and shifting skills requirements.

Local policies also include several bans on facial recognition technology used by local agencies, passed in cities like San Francisco, Oakland, Berkeley, and Sommerville, Massachusetts (Spivack & Garvie, 2020).

2.2.2. AI regulation

In the United States, the use of AI is implicitly governed by a variety of common law doctrines and statutory provisions, such as tort law, contract law, and employment discrimination law (Cuéllar, 2019). This implies that judges' rulings on common law-type claims already play an essential role in how society governs AI. Existing law (e.g., tort law) may, for instance, require that a company avoid any negligent use of AI to make decisions or provide information that could result in harm to the public (Galasso & Luo, 2021). Likewise, current employment, labor, and civil rights laws imply that a company using AI to make hiring or termination decisions could face liability for its decisions involving human resources.

While common law often involves decision-making that builds on precedent, federal agencies also engage in important governance and regulatory tasks that may affect AI across various sectors of the economy (Barfield & Pagallo, 2018). In the spring of 2019, the Food and Drug Administration (FDA), for example, released a "Proposed Regulatory Framework for Modifications to AI/Machine Learning-Based Software as a Medical Device" (FDA, 2021). The FDA's approach to regulating AI aims to examine and pre-approve the underlying performance of a firm's AI products before they are marketed and post-approving any subsequent algorithmic modifications. The proposed regulatory framework considers a total product lifecycle approach in which AI technologies and products will remain open to real-world learning and adaptation through continuous algorithmic updating while ensuring that standards for safety and efficiency are met.

Horizontal AI regulations include the Algorithmic Accountability Act, first proposed in 2019 and reintroduced in 2022 in an amended form. If passed, the regulation will regulate large firms with gross annual receipts of $50 million or more over the last three consecutive years or possess or control personal information on more than 1 million consumers (Congress, 2019). If passed, the Algorithmic Accountability Act would regulate large firms through mandatory self-assessment of their AI systems, including disclosure of their usage of AI systems, development process, system design, training, and the data gathered and in use. The act would also require companies to conduct impact assessments for bias, effectiveness, and other factors when using automated decision systems to make critical decisions. The act also proposes establishing a public repository of varying AI systems at the Federal Trade Commission and hiring 75 new commission staff to enforce the law.

In October 2021, the Biden administration proposed developing an AI-centered "bill of rights" to mitigate any adverse consequences of technological expansion. The proposed bill of rights would, for example, be used to protect US citizens against AI-powered surveillance, discrimination, and other forms of harm. The legislation would ensure that US citizens would be free from "pervasive or discriminatory surveillance" in their homes, communities, and workplaces, and citizens whose rights have been violated by an automated system would be able to seek new ways of redress (Gutierrez, et al., 2021).

2.2.3. AI ethics and self-regulation

AI is currently being governed by a range of multistakeholder organizations, which along with standard-setting bodies are examples of soft-law governance (Wallach & Marchant 2018). One example is the Partnership on AI (PAI) established in 2016 by companies such as Apple, Amazon, Google, Facebook, IBM, and Microsoft. The Partnership on AI was established as a multistakeholder forum to study and formulate best practices on AI technologies, advance the public's understanding of AI, and serve as an open platform for discussion and engagement about AI and its influences on people and society (Sanchez, et al., 2019).

In January 2017, the non-profit Future of Life Institute organized the Asilomar Conference on Beneficial AI, bringing together a broad group of AI researchers from academia and industry (FLI, 2017). At the conference, leaders, and researchers across diverse fields from computer science, economics, law, ethics, and philosophy established 23 principles on beneficial AI. The Asilomar AI

Principles move across issues associated with research, ethics, and long-term impacts. The Principles have been endorsed by the state of California through ratification of bill ACR-215 (California State Senate, 2018).

Many private-sector firms also engage in a variety of self-regulation measures that, in many cases, are predicated on AI principles. Google, IBM, Intel, and Microsoft have, among others, published AI principles that guide corporate development and implementation. AI principles relate to areas such as accountability (e.g., that AI developers are responsible for considering AI design, decision processes, and outcomes), value alignment (e.g., that AI are aligned with norms and values of users), explainability (e.g., that an algorithms decision process is understandable), interpretability and transparency (e.g., details on the decisions made by an algorithm such as features included for making a prediction), fairness and inclusivity (e.g., that AI is designed to minimize bias and be inclusive), user data rights, privacy and security (e.g., that an AI is designed to protect user data) and reliability and safety (e.g., quality assessments).

Examples of AI-related self-governance by private-sector corporations in the US have notably been witnessed in response to nationwide protests against police brutality and racial profiling in the spring of 2020. Several companies (IBM, Amazon, and Microsoft) announced that they would stop providing facial recognition technologies (FRT) to law enforcement agencies. IBM called for "a national dialogue on whether and how facial recognition technology should be deployed by domestic law enforcement agencies" (Krishna, 2020, p. 1). Amazon announced a one-year moratorium on police use of its facial recognition technology, giving policymakers time to set appropriate rules around its use. Microsoft declared that it would not sell FRT technology to police departments in the United States until a federal law that regulates the technology is formulated.

2.2.4. Technology and national security

In recent years the US has broadened the use of its entity list under the Bureau of Industry and Security (BIS), which restricts the export of certain sensitive technologies and components to foreign organizations. The entity list was created in 1997 to address risks related to the proliferation of weapons of mass destruction, and its expanded use has since transformed it into a general tool for protecting US security and foreign interests. In October 2019, BIS announced that it had added 28 Chinese government and commercial organizations to its entity list, implicated in human rights violations against Uighur Muslims in the Xinjiang region of China (Federal Register, 2019). Chinese entities on the list have expanded under the Biden Administration, which added 34 Chinese entities in January 2022. The entity list restricts many Chinese AI companies such as Hikvision, iFlytek, SenseTime, Yitu, Huawei, and Megvii from access to American technology.

The Committee on Foreign Investment in the United States (CFIUS) is another mechanism used to block international mergers and acquisitions due to concerns over national security. CFIUS was established in 1975, while its jurisdiction was broadened in July 2018 through passing the Foreign Investment Risk Review Modernization Act. CFIUS comprises members of the State, Defense, Justice, Commerce, Energy, and Homeland Security Departments and is led by the Treasury secretary (Yoon-Hendricks, 2018). CFIUS typically sends its findings and a recommendation to the president, who has the power to suspend or prohibit the deal. CFIUS has, for example, forced the Chinese mobile company Kunlun to sell its American dating app Grindr in 2020 due to concerns over national security associated with data protection (E. Wang, 2020). CFIUS was also engaged in reviewing the Chinese social media platform TikTok under the Trump administration.

The US Securities and Exchange Commission is also engaged in efforts to ban foreign companies listed in the US if their auditors do not comply with requests for information from American regulators. The delisting of some Chinese companies became a strategic priority in November 2020 when President Trump signed an executive order "Addressing the Threat From Securities Investments That Finance Communist Chinese Military Companies." The executive order has been further extended under the Biden administration. It claims that "the use of Chinese surveillance technology […] facilitates repression or serious human rights abuse" and constitutes an "extraordinary threat" (White House, 2021a). These developments have, among others, caused Chinese companies such as China Mobile, China Unicom, and China Telecom to delist from US Stock Exchanges.

2.3. China's AI policy landscape

This section gives an overview of AI policy in China. It presents AI policy at the national, provincial, and local levels before giving an overview of current trends in AI regulation. Next, AI ethics and forms of self-regulation by private sector enterprises are introduced before developments in technology and national security policies are elaborated. In summary, AI policy in China has developed rapidly since a national strategy for AI was adopted in 2017. AI policy in China is perceived as a coherent set of strategies that emanate from the State Council and ministries and trickle down to the provincial and local levels of government and industry.

While modern research on AI in China tends to take 2017 as a starting point, China has a much longer history of AI research and development that often is unacknowledged in the literature. The Chinese Association for Artificial Intelligence (CAAI), for example, dates back to 1981, when it was established under the Ministry of Civil Affairs to foster talents in AI (CAAI, 2020). Basic research and funding into AI began in 1986 when the National Natural Science Foundation of China (NSFC) and the 863 programs began to fund research in AI in areas such as hardware and software for intelligence, human-computer interaction (HCI), intelligent application systems, neural networks, genetic algorithms, machine learning, natural language processing, computer vision, and robotics (Zhu, et al., 2018). The long-term goal of the 863 program was to realize "strategic transitions from pacing front-runners to focusing on 'leap-frog' development" (MOST, 2020b) while making China independent of any financial obligations for foreign technologies (Hequan, 2000). The 863 program contributed to establishing some of China's current AI champions, such as the voice-recognition company iFlytek, which received state funding in the early 2000s.

After the year 2000, China's Ministry of Science and Technology (MOST), the National Natural Science Foundation of China (NSFC), and other central governmental agencies, as well as local governments, including Beijing, Shenzhen, and Hangzhou, began to increase their funding towards AI (Xue, 2018). This enabled Chinese researchers to attend international conferences and become more involved and integrated with international research communities (Zhu, et al., 2018).

Since then, many industrial policies that have indirect but essential implications for AI development have emerged. China's 10th five-year plan, from 2001 to 2005, made software development a critical pillar of economic development. In 2006, the State Council's "National Medium and Long Term Plan for the Development of Science and Technology (2006–2020)" began to prioritize R&D in frontier technologies such as sensors, semiconductors, robots, and virtual reality, which according to the plan, should have reached a mature stage of development by 2020 (Sun & Cao, 2021). In 2008, MOST launched the "China Open Source Software Competition" and the "Contest of Open Source Software Innovation and Enterprise Application" to commercialize open-source software in China's domestic industry. In 2009, the State Council released the "Strategic Emerging Industries" plan and selected New Generation Information Technology as one of ten industries to be prioritized for development (Kenderdine, 2017). In 2012, the Ministry of Science and Technology released its 12th five-year plan (FYP), which included Intelligent Smart Manufacturing as an area for targeted development. In 2014, the "National Guideline for the Development and Promotion of the IC Industry" was released by the State Council to stimulate development in integrated circuits and accelerate the pace of China's semiconductor industry to catch up with international leaders (State Council, 2014). In May 2015, the ten-year plan "Made In China 2025" further identified smart manufacturing, including related aspects of sensors and IoT connectedness, as crucial areas of development associated with turning China into a modern manufacturing power. The "Big Data Development Action Plan" was released by the State Council in 2015 and articulated that insufficient openness and sharing of government data and lagging legal and regulatory measures needed attention (State Council, 2015). The scope of the Big Data Development Plan was to promote the opening of public data resources incrementally while accelerating the construction of a unified open platform and management system for national government data.

Since 2016 a more direct focus on AI development has resulted in the formation of multiple concrete AI policy plans. In July 2016, the State Council released the Guiding Opinions on Actively Rolling out the "Internet-Plus" Initiative, which identified AI as one of eleven priority areas to accelerate information communication technologies in conventional industries. China's 13th five-year plan from 2016 to 2020 was released in April 2016 by the National People's Congress and included a strong presence of AI. In the 13th FYP for National Science and Technology Innovation, robotics and AI were recognized as a new generation of information technologies (He, 2017). In January 2017, the National Development and Reform Commission's (NDRC) "Guiding Catalogue for Important Products and Services in Strategic Emerging Industries" included allocating resources to AI innovation and technological application while allowing policymakers to start formulating growth trajectories and governing mechanisms for China's AI industry (He, 2017). These developments highlight that AI over the years has matured and been brought to the attention of the upper echelons of China's Communist Party (CCP), which has hailed AI as an essential driver for the modernization of China's society and economy.

In July 2017, the State Council released "A New Generation Artificial Intelligence Development Plan"[5] (AIDP), which marks a clear turning point in the importance of AI policy in China. The AIDP

[5] 新一代人工智能发展规划 (New generation artificial intelligence development plan)

established a range of concrete goals for AI-related R&D, industrialization, talent development, education and skills acquisition, standard-setting and regulations, ethical norms, and security for the entire AI industry. The three-step action plan outlines China's ambitions of becoming a world leader in AI by 2030.

- The first step is to make China's AI industry "in line" with competitors by 2020
- The second step is to reach "world-leading" capabilities in some AI fields by 2025, and
- The third step is to become the "primary" center for AI innovation by 2030

By 2030, China's government aims to have cultivated an AI industry worth 1 trillion RMB (USD 158bn), with related industries worth 10 trillion RMB (USD 1,577tn). The plan also lays out the government's intention to recruit the world's best AI talent, strengthen the training of the domestic AI labor force, and lead the world in laws, regulations, and ethical norms that promote the development of AI. The latter includes the intent to participate in and lead the global governance of AI.

The notion of "National Open Innovation Platforms for New Generation Artificial Intelligence"[6] and China's National AI Team[7] was added in November 2017, when China's Ministry of Science and Technology (MOST) selected four companies and endorsed these to construct open AI platforms across four distinct areas of AI application. In a testament to the success of the initial strategy, MOST further expanded the initiative in August 2019 to include a total of fifteen National Open Innovation Platforms for AI.

China's Ministry of Industry and Information Technology (MIIT) has also been heavily engaged in promoting the country's AI industry. In December 2017, MIIT released the "Three-Year Action Plan to Promote the Development of New Generation Artificial Intelligence Industry" accompanying the State Council's AIDP. The Three-Year Action Plan's objective was to accelerate the development of advanced manufacturing and integrate AI with the real economy between 2017 and 2020 while contributing to the objectives of the "Made In China 2025" plan (MIIT, 2017).

By November 2018, MIIT's "Three Year Action Plan" was accompanied by the "Working Plan for the Key Tasks of Innovation in the New Generation of Artificial Intelligence Industry." The Working Plan exemplifies four prioritized areas of AI development, as shown in Table 5.

[6] 国家新一代人工智能开放创新平台 (National Artificial Intelligence Open Innovation Platform)
[7] 人工智能国家队 (Artificial Intelligence National Team)

Under the Working Plan, MIIT has broadly called on leading technology companies and research institutions to participate in the formation of China's National AI Team by applying for a government-sponsored program on the webpage aibest.org.cn, which aimed to achieve pre-specified technological breakthroughs by 2020 (MIIT, 2017).

To implement the State Council's AIDP and MIIT's Three-year Action Plan, MIIT's Department of Information and Software Services, and the Chinese Electronic Standardization Institute (CESI) formulated a 2018 draft on supporting the establishment of "China Artificial Intelligence Open Source Software Development League" (AIOSS, 2018). Members of the AIOSS have similarly been recruited as "national enterprises"[8] that can engage in scientific and technological breakthroughs and standard-setting.

Table 5. MIIT working plan

Working Plan for the Key Tasks of Innovation in the New Generation of Artificial Intelligence Industry	
(1) Smart Products	**(2) Core foundation**
1. Intelligent network car	9. Smart sensor
2. Intelligent service robot	10. Neural network chip
3. Intelligent drone	11. Open source, open platform
4. Medical image assisted diagnosis system	
5. Video image identification system	
6. Intelligent voice interaction system	
7. Intelligent Translation System	
8. Smart home products	
(3) Intelligent manufacturing of key technical equipment	**(4) Support system**
12.Intelligent manufacturing of key tech-equipment	13. Industry Training Resource Library
	14. Standard Testing and Intellectual Property Platform
	15. Intelligent network infrastructure
	16. Network Security System
	17. Other

The Artificial Intelligence Industry Alliance (AIIA), a government-sponsored industry body, was launched in October 2017 by the MIIT's China Academy of Information and Communications Technology (CAICT), CESI, and the National Industrial Information Security Development Research Center. AIIA comprises 471 members from government, industry, and research institutions and carries out work from evaluation and certification to open-source software, semiconductor, security development, and work on ethical concerns related to AI application.

[8]本联盟面向全国企业招募联盟成员单位 (The alliance recruits members from national enterprises)

In 2018, the Ministry of Education (MOE) also released an AI Innovation Action Plan for colleges and universities to drive the proliferation of AI-related educational programs across China. The plan has three interrelated objectives: to optimize the existing innovation framework for AI development, cultivate high-caliber talent in AI, and commercialize research outcomes (MOE, 2018).

Table 6. Industrial and technology policies that target AI development

Year	Plan	Objective	Stakeholder
2016	Guiding Opinions on Actively Rolling out the "Internet-Plus" Initiative	Identifies **AI** as one of eleven priority areas to accelerate information communication technologies in conventional industries.	State Council
2016	Implementation Plan for "Internet Plus" **Artificial Intelligence** 3-Year Initiative	Outlines nine key engineering areas in **AI** technology development between 2016 and 2018.	NDRC, MIIT, MOST and SIIO
2016	"**Artificial Intelligence** 2.0"	Added to a list of 15 "Sci-Tech Innovation 2030 Megaprojects". Demonstrates how **AI** was added to megaproject status.	Chinese Academy of Engineering
2016	13th five-year plan (FYP)	**AI** is mentioned extensively throughout the FYP. Identifies **AI** as a significant objective for the central government to pursue.	National People's Congress
2017	Guiding Catalogue for Important Products and Services in Strategic Emerging Industries	Highlights the allocation and pooling of resources from both public and private sectors in affecting **AI** innovation and technological application.	NDRC
2017	2017 Mass Entrepreneurship and Innovation Plan	Sets aside $320 billion to support entrepreneurs to drive a structural shift from an industrial to a service-based economy. Strengthens the link between **AI** and China's start-up scene,	State Council
2017	A Next-Generation **Artificial Intelligence** Development Plan	Sets forth initiatives and goals for R&D, industrialization, talent development, education and skills acquisition, standard-setting and regulations, ethical norms, and security for the entire **AI** industry.	State Council
2017	Three-Year Action Plan to Promote the Development of New-generation **Artificial Intelligence** Industry	To accelerate the development of advanced manufacturing and integrate **AI** and the real economy while furthering the objectives of MIC2025.	MIIT
2018	**AI** Innovation Action Plan for College and Universities	To optimize the innovation framework for **AI** development, cultivate talent, and promote the commercialization of research on **AI**	MOE

2.3.1. Provincial and local AI policy

National policy plans are complemented by regional development initiatives that embody a decentralized approach to implementing national policy guidelines. Elaborated, this means that disparate initiatives and clusters are emerging all over China, often focusing on varying areas of AI technology and information infrastructure development. While national AI guidelines and policy plans are formulated in a top-down approach, local policymakers usually guide actual implementation based on economic factors and existing industrial needs and conditions. Provincial politicians are usually promoted based on economic performance, which creates an incentive to follow central government strategies and guidelines (Li & Zhou, 2005).

The first province-level AI policy came out in 2009, and there has since been a steady increase in the number of local government policies on AI (Xue, 2018). Several cities and local governments focus on developing specific technologies related to areas such as algorithmic R&D, semiconductors, cloud storage and infrastructure, IoT, Big Data, smart manufacturing, smart grid, smart agriculture, information security, and precision medicine (Xue, 2018).

In Beijing, for example, existing advantages build on the city's multiple research institutions, which has turned the city into a strong cluster for AI-related R&D. Non-profit research institutes such as the Beijing Academy of Artificial Intelligence, established in 2018, seek to promote greater collaboration between academia and industry.

Regional disparities mean that provinces such as Beijing and Jiangsu, for example, are more concerned with basic AI R&D due to the existing comparative advantages of universities and academic institutions (Xue, 2018). While the province of Guangdong has fewer universities than some of its northern counterparts, the province is more concerned with applications of AI across the fields of manufacturing and robotics, for instance (Xue, 2018).

Leading clusters of AI development have since been forming around the three mega-regions of Beijing, Tianjin, Hebei (Jing-Jin-Ji), Shanghai, Jiangsu, Zhejiang (Yangtze River Delta), and Guangdong, Hong Kong, Macao (Greater Bay Area) (Xue, 2018).

Regional approaches to AI development also include the formation of AI pilot zones that experiment with the implementation of novel AI technologies and systems. In February 2019, the Office for Promoting the Construction of Beijing as a Science Technology and Innovation Centre announced the establishment of the Beijing New Generation Artificial Intelligence Development National Experimental Zone (MOST, 2020a). Beijing’s AI National Experimental Zone is expected to play a vital role in the three main areas of AI talent creation, industry development, and piloting institutional reforms.

In May of 2019, the Shanghai (Pudong) Artificial Intelligence Innovation Application Pilot Zone was approved by the MIIT. Like Beijing, the zone is the first AI Innovation Application Pilot Zone.

It is built to diffuse and commercialize new AI technologies and products while strengthening the link between AI implementation and the real economy (Xinhua, 2019).

The establishment of pilot zones follows China's industrial and economic development blueprint of testing economic and regulatory reforms in regional corridors before being replicated and expanded nationwide. Plans exist to expand the National Experimental Zone initiative to 20 cities across China (Economic Information Daily, 2019).

2.3.2. AI regulation

China has been quick to devise new rules in some areas of algorithmic oversight. In 2019, the State Council released a plan on "Promoting the Platform Economy – Guiding Opinions on Standardizing Healthy Development" (State Council, 2019). The plan specifies that room should be left for developing new regulations, while supervision should be tailored according to new business solutions in order not to stifle innovation. Regulatory oversight should, accordingly, be devised in concert with leading platform operators (State Council, 2019).

In terms of AI regulation, the Cybersecurity Administration of China (CAC) passed the "Internet Information Service Algorithm Recommendation Management Regulations" On December 31, 2021. The regulations are scheduled to take effect on March 1, 2022, and target the use and misuse of recommendation algorithms (CAC, 2021). Personalized recommendation algorithms are used extensively by social media apps for content recommendation and targeted advertising and by E-commerce companies and service platforms, such as food delivery apps. The regulation aims at increasing transparency regarding how recommender systems operate while giving users more control over their data. Under the regulation, algorithmic operators have to update their technology to comply with technical requirements, from auditing to allowing users to access and control their data. Regulations, however, go beyond addressing individual user rights by mandating that operators of recommender systems follow an ethical code for cultivating "positive energy" online while preventing the spread of undesirable or illegal information (Huld, 2022).

In September 2021, the CAC and nine co-regulators[9] released a three-year roadmap governing all algorithms used in online settings. The roadmap aims to build an algorithmic supervision system

[9] State Internet Information Office, Central Propaganda Department, Ministry of Education, Ministry of Science and Technology, Ministry of Industry and Information Technology, Ministry of Public Security, Ministry of Culture and Tourism, State Administration for Market Regulation, State Administration of Radio and Television

while gradually establishing audit-based mechanisms for algorithmic security assessments (Sheehan, 2022).

AI is also governed by the China Academy of Information and Communications Technology (CAICT) (Sheehan, 2022). CAICT is focused on developing tools for measuring and testing AI systems and released China's first white paper on developing "trustworthy AI" in July 2021 (CAICT, 2021). CAICT is also working with China's AI Industry Alliance (AIIA) to test and certify different AI systems. In November 2021, the CAICT issued its first batch of trustworthy AI certifications for facial recognition systems (Sheehan, 2022).

The Ministry of Science and Technology has also encouraged self-regulation through private companies' adherence to ethical guidelines. In July 2021, MOST published guidelines that called for universities, research labs, and private sector companies to set up internal review committees to oversee and resolve ethical issues related to AI (MOST, 2021b). In October 2021, MOST released additional guidelines on "A new generation of artificial intelligence ethics code" (MOST, 2021a) which specifies ethical norms for using AI in China. The norms include reference to protecting personal information and human control and responsibility in terms of AI adoption and use (MOST, 2021c).

Many issues such as discriminatory data practices, opaque recommendation models, and labor violations are also addressed by other legislation, such as the Personal Information Protection Law (PIPL), which regulates the use of personal data in China. The PIPL came into effect on November 1, 2021, and explicitly prohibits price discrimination and other discriminatory practices for automated decision-making processes (MOST, 2021c). The PIPL, along with China's existing Cybersecurity Law (CSL) and Data Security Law (DSL), is intended to establish a broader framework for governing cybersecurity and data privacy protection in China.

2.3.3. AI ethics and self-regulation

In terms of AI ethics, the "Beijing AI Principles" for research, development, use, governance, and long-term planning of AI were released in May, 2019, by a joint multistakeholder coalition of the Beijing Academy of Artificial Intelligence, Tsinghua University, Peking University, the Chinese Academy of Sciences, and leading enterprises such as Baidu, Alibaba, and Tencent. In terms of R&D, the principles focus on benefitting humanity and the environment while serving human values such as privacy, dignity, freedom, autonomy, safety, inclusivity, and openness. In terms of use, the principles focus on the application and limits of AI technologies, informed consent, user rights, and education and training. In terms of governance, the principles highlight a need to optimize employment while being adaptive to constant changes in terms of technological capabilities and regulatory measures. Last, the principles take into consideration long-term planning for advanced AI systems and the potential risks of developing and deploying artificial general intelligence.

In 2019, members of AIIA also released a joint pledge to secure self-discipline in AI across ethical, safety, and standard domains. The draft of the pledge is divided into four chapters covering a set of general provisions stating that AI should be human-centered, enhance well-being, be fair and avoid harm. The principles relay that AI should be secure, safe, controllable, transparent, explainable, protect privacy, clarify responsibilities and focus on diversity and inclusivity. AIIA members should also focus on asserting self-discipline and self-governance, formulate standards, promote open-source sharing, and provide universal education while furthering technological development.

Private sector companies have also released AI principles. For instance, Tencent's principles, released in 2018, state that AI should be available, reliable, comprehensible, and controllable (Tencent Research Institute, 2020). Facial recognition company Megvii also released a set of Core Principles in 2019, including commitments not to weaponize its technology, prevent discrimination, and ensure human oversight, robustness, accountability, and data privacy (Newman, 2020). In terms of international collaboration on AI principles, Baidu was the only Chinese member of the US-led Partnership on Artificial Intelligence. However, amid heightened tensions between the US and China, the company left PAI in 2020, citing membership costs for leaving.

2.3.4. Technology and national security

In September 2020, China's Ministry of Commerce (MOFCOM) published its own "unreliable entities" rules targeting foreign enterprises. The MOFCOM regulations were issued one day after the United States announced plans to ban US businesses from transacting with the Chinese-owned apps WeChat and TikTok (Bradshaw, et al., 2020). China first announced the creation of an "unreliable entities list" in May 2019, after the US had added Huawei and many of its global affiliates to the US Commerce Department's entity list. Chinese policymakers have clarified that the unreliable entities list is established to combat unilateralism and trade protectionism that interrupt supplies to Chinese firms. Like the United States, China's entities list seeks to protect China's national security and economic interests by penalizing any foreign enterprise, organization, or individual who endangers China's national security or development. This includes firms that cease to do business with Chinese companies "in violation of normal market transaction principles" or that discriminate against Chinese companies and consumers (MOFCOM, 2020). Any foreign entities added to the list can be subject to fines, import-export bans, investment restrictions, travel prohibitions, and reputational damage (Bradshaw, et al., 2020).

3. THEORETICAL AND CONCEPTUAL FRAMEWORK

Theoretically, this thesis draws on multiple literatures positioned at the intersection of platform- and technology-related governance and regulation, rooted in information systems, institutional theory, and political economy. To analyze how artificial intelligence is governed in the United States and China, and understand some of the broader implications for the governance of AI, this chapter reviews relevant theoretical literature that informs the conceptual framework of the thesis.

By drawing on multiple theoretical approaches, this thesis seeks to strengthen an understanding of AI governance that operates across several distinct socio-technical levels. These include the technical (AI innovation), organizational (AI adoption), and institutional levels (AI diffusion). This distinction is important as separate governing mechanisms can be discerned at each socio-technical level. For these reasons, I consider it unfeasible to rely on one theoretical framework to inform the broader empirical inquiry of the thesis. Instead, the broad nature of the applied theories serves to operationalize governing mechanisms across meso and macro levels of analysis, which allows for a more granular perception of AI governance to emerge. By adopting this approach, the thesis seeks to build a holistic interpretation of AI governance. An overarching conceptual framework that guides the empirical analysis of the individual research articles is presented at the end of this chapter.

3.1.Literature review

The following literature review has been divided into three separate parts. The first part elaborates on the notion of digital infrastructure borrowed from information systems theory. Digital infrastructure is used as an overarching construct to signify elements that feed into and enable varying forms of AI innovation. This includes digital building blocks and platforms as technical and organizational constructs that guide AI innovation, adoption, and diffusion processes. The role of the public sector in orchestrating these processes is also highlighted in this section. The second part of the literature review goes over institutional infrastructure and elaborates on how AI technologies are adopted and gain socio-technical legitimacy. Institutional theory is applied to understand how varying logics are embedded in AI systems and the actors that work to impact processes of socio-technical legitimacy. The third and last part of the literature review looks into regulation and governing mechanisms that establish new rules targeting the ongoing expansion of AI systems and technologies.

3.1.1. Digital infrastructure

Information systems theory informs valuable concepts such as digital building blocks, modularization, and platforms and ecosystems. These are considered digital infrastructures that inform AI-related innovation (technical level) and new forms of organization (organizational level). The theoretical concepts and constructs elaborated from an information systems perspective function as the technical foundation of inquiry throughout the thesis.

Digital infrastructure is defined as the computing and network resources that allow multiple stakeholders to orchestrate their service and content needs (Constantinides, et al., 2018). Digital infrastructures are distinct from traditional infrastructures (e.g., roads, utility networks, trains) because of their ability to collect, store, and make digital data available across many systems and devices simultaneously (Yoo, et al., 2012). Examples of digital infrastructures include the Internet (Henfridsson, et al., 2018; Rai, et al., 2019); data centers; open standards, e.g., IEEE 802.11 (Wi-Fi), as well as consumer devices such as smartphones (Hinings, et al., 2018).

Henfridsson, et al. (2018, p. 90) refer to "digital resources" as entities that serve as building blocks in creating and capturing value from information. Digital building blocks are transformational due to the innovative patterns established through "use-recombination" (Henfridsson, et al., 2018). Digital building blocks are also associated with generativity, which is defined as the "capacity to produce unprompted change driven by large, varied and uncoordinated audiences" (Zittrain, 2006, p. 1980).

AI technologies exemplify a novel form of digital building blocks that are distinguishable from traditional software systems (e.g., ERP, CRM) due to new kinds of inherent agency, which render these as "organizers," "predictors," or "controllers" of data flows that are captured by digital infrastructures (Russell & Norvig, 2010). Novel AI agents embody distinct logics and cognitive functions that are partially derived from and impact the social system and environment in which they operate (Floridi & Sanders, 2004).

Most digital building blocks are made accessible through online platforms such as transaction platforms, e.g., e-commerce, and innovation platforms, e.g., apps and services (Bonina, Koskinen, Eaton, & Gawer, 2021; Cusumano, Gawer, & Yoffie, 2019). Transaction platforms act as intermediaries between two or more groups of agents, for example, in the form of multi-sided platforms (MSP) to organize economic transactions (Hagiu & Wright, 2015). Examples include app stores, e-commerce platforms, dating platforms, and social media platforms. Innovation platforms emphasize the technical and organizational “foundations upon which other firms can build complementary products, services or technologies” (Gawer, 2009, p. 54). This process occurs as digital building blocks and modules are made accessible for novel forms of innovation (Gawer, 2014). Examples include Microsoft Azure, Amazon Web Services, and Google Cloud. Digital building blocks and modules can be accessed and combined by app developers (complementors) to build apps and services (known as platform complements) (Bonina, et al., 2021).

While many forms of AI are used on transaction platforms, the central organizational construct of interest in this thesis is innovation platforms, as these increase the accessibility of AI technologies for SMEs. In terms of organization, innovation platforms are characterized by having platform owners (Boudreau & Hagiu, 2009) responsible for governing the innovation of modules in the core architecture and the innovation activities of third-party developers at the periphery (Bonina & Eaton, 2020). The relationship between core and periphery is often contextualized through the notion of ecosystems, which are made up of the platform sponsor as well as providers of complements that make the platform more valuable to consumers (Ceccagnoli, Forman, Huang, & Wu, 2012; Gawer & Cusumano, 2013). Platform ecosystems take a “hub and spoke” form, with an array of peripheral firms connected to the central platform via shared or open-source technologies and technical standards (application programming interfaces (API), software development kits (SDK)). By connecting to the platform, complementors can generate complementary innovation and gain access to other members or costumers of the platform’s broader ecosystem (Ceccagnoli, et al., 2012; Cennamo & Santalo, 2013).

Innovation platforms are often associated with open innovation, defined as “the use of purposive inflows and outflows of knowledge to accelerate internal innovation and expand the markets for external use of innovation” (Chesbrough, 2006, p. 1). Similarly, open data and open-source software (OSS) are often associated with open innovation platforms since their “free” redistribution of public goods attracts complementors from the ecosystem to the platform.

3.1.1.1.Platform governance

In terms of platform governance, Ghazawneh & Henfridsson (2010) developed the theory of boundary resources to explain how platforms govern the inherent tension between openness and control. Boundary resources evolve through governance of the production function, which refers to the rules and tools that are used to constrain or enable the generativity of ecosystems (Eaton, et al., 2015; Ghazawneh & Henfridsson, 2010; Henfridsson & Bygstad, 2013; Yoo, Henfridsson, & Lyytinen, 2010). The concepts of resourcing and securing refer to the “software tools and regulations that serve as the interface for the arms-length relationship between the platform owner and the application developer” (Ghazawneh & Henfridsson, 2013, p. 174). Resourcing is the process by which the scope and diversity of a platform are enhanced, which contributes to expanding the ecosystem of actors around the platform by increasing the supply of new resources, knowledge, and capabilities (Iansiti & Levien, 2004). Examples of tools are APIs and SDKs that give developers access to the modular core of the platform and enable them to build software services. Securing is the process by which the platform's control is increased and contributes to governing a community of third-party developers. Platform integrity is maintained by providing rules for controlling the quality of third-party apps and services developed for the platform. One example of rules is those established by software and data licensing agreements (Boudreau & Hagiu, 2009). If rules are broken, the platform owner can take a range of actions, such as suspending a developer from using or accessing the platform (Bonina & Eaton, 2020). Resourcing tools and securing rules are critical components of platform governance (Ghazawneh & Henfridsson, 2013).

While the information systems literature has detailed several aspects of private sector platform governance, the literature has barely dealt with the ways governments can affect platforms resourcing tools and securing rules.

3.1.1.2. Platforms and the public sector

More recently, the public sector has embraced the platform-based organizational construct, e.g., to encourage new forms of innovation (Mergel, 2018). Public sector agencies have, for example, started to embrace a range of market-inspired open innovation initiatives (Bommert, 2010). Open innovation approaches are relevant to the government because, arguably, many challenges are too complex or inconvenient for the public sector to embark on or solve (Sørensen & Torfing, 2011). In embracing the open innovation model, public sector organizations have, for example, started to make public data and records available on platforms, thereby facilitating open innovation through open government data (OGD) initiatives (Zuiderwijk & Janssen, 2014). OGD can be perceived as cross-boundary information sharing between the government and the public, including businesses and individuals (T. Yang, et al., 2015).

The use of platforms in the public sector can either be considered in terms of proprietary government platforms that deliver services directly to citizens or as hybrid public-private platforms. In hybrid platforms, infrastructure and governing mechanisms are shared between one or more parties from the public and private sectors (Klievink, et al., 2016). For example, in public healthcare, hybrid platforms can link anonymized medical data with third-party developers such as universities, pharmaceutical companies, or start-ups, allowing these to innovate and engage in the production of new types of treatment and services (Kallinikos & Tempini, 2014). Hybrid platforms are also used to inform public infrastructure upgrades, using, for example, real-time traffic flow data gathered by a ride-hailing platforms that collects real-time data on traffic flows (Jacobides, et al., 2019). While hybrid platform arrangements and AI-induced experimentation are currently emerging across various sectors, the organizational concept has been little elaborated or discussed in the literature (Klievink, et al., 2016).

In terms of hybrid public-private platforms, a challenge for cooperation is that alignment needs to be secured between private sector business models and public objectives and forms of organization (Janssen, et al., 2008). Apart from the formal governance instrument, a collaborative form of governance is needed, as traditional modes of governance such as hierarchical, authoritative, and contract-based forms may be counterproductive in making the platform successful (Gawer, 2014). Therefore in the governance of hybrid public-private platforms, there typically exists a formal relationship and a responsibility by private actors to report to the government on areas such as progress, standards, and interoperability (Klievink, et al., 2016). The hybrid platform also needs to offer the opportunity for government agencies to capitalize on these developments or to transform how the government interacts with businesses, which implies that government agencies are active stakeholders with both agenda and instruments that can affect platform-related generativity as well as facilitate new forms of business-to-government exchange (Klievink, et al., 2016). Striking a balance between autonomy and control is central in hybrid arrangements, where it is crucial to consider how new business models can align with public sector interests. For governments, it is therefore important to uncover a broader range of mechanisms that can be used to affect AI-induced generativity in the digital economy. This includes a focus on how governments can enable or constrain varying forms of platform innovation and how these innovations diffuse and affect SMEs or civil society participants at a broader level. These aspects have been little dealt with in the literature.

3.1.1.3. Digital institutional infrastructure

As large technology platforms usually are the leading innovators of a field, these also carry weight in how new technologies and associated standards emerge and are governed (Pisano & Teece, 2007). Typically private actors orchestrate ecosystems and associated digital infrastructures, which brings issues to the forefront, such as the challenge of establishing a governance system, reproducing social order, and incorporating aspects of value appropriation and control (Hinings, et al., 2018, p. 54). These issues are also crucial for policymakers to consider when supporting or regulating the digital economy.

Literature on public value theory (Panagiotopoulos, et al., 2019) considers how data and AI technologies (Janssen, et al., 2020) align with public sector priorities and how advances in government data science and AI can deliver new benefits and use cases to governments, regulatory agencies, and citizens (GOV.UK, 2019). Cordella and Paletti (2019) refer to "the role of ICTs as enablers for a new organizational configuration to produce and deliver public services that enable the creation of public value" (p. 2). This implies a focus on novel forms of organization where public value also encompasses digital resources such as open-source software and open data and how these are redistributed and orchestrated across public, private, and hybrid platform arrangements. Traditionally, the kind of public value associated with open data and open-source software has fallen outside the scope of governments, while these resources are becoming of strategic importance due to their intrinsic long-term industrial impacts. This includes creating broad spillover effects to the rest of the economy (Aghion, Jones & Jones, 2017; Furman & Seamans, 2019). In developing proprietary government solutions, some underlying digital components are now considered critical information infrastructure that has implications for national security and ought to be more tightly protected (e.g., 5G) (Assaf, 2008). In other areas, the government may actively encourage opening previously proprietary government data to invite greater participation in public sector innovation (T. Yang, et al., 2015). These perceived trade-offs often remain unclear and are little articulated in the literature on platform governance and innovation.

Panagiotopoulos, et al. (2019) argue that public officials can create digital infrastructures that stimulate public value creation in more or less deliberate ways (e.g., ease of online access, data distribution, mobile applications). Public agencies may also take on new roles where they orchestrate but do not maintain complete control of value creation processes (Janssen & Helbig, 2016; Linders, 2012). Cordella & Paletti (2019) refer to orchestration as a set of governance mechanisms through which the government contributes to determining various technological and institutional configurations to deliver public value.

Governing mechanisms that are borrowed from private sector platform governance, however, require a renegotiation of the regulatory regimes that are embedded and structured in the digital infrastructure, e.g., building blocks, with those that are embedded and structured in the institutional infrastructure, e.g., social acceptance of new technologies or public sector regulation of these (Cordella & Contini, 2012). This means that while a digital building block may be subject to individual forms of legitimacy, collective legitimacy is equally necessary for a new institutional arrangement to emerge. For example, it may be that a platform-based building block holds legitimacy (e.g., a cloud-based AI facial recognition system) because it performs within a predefined level of technical accuracy. However, for the organizational or broader institutional arrangement to gain legitimacy, the embeddedness of the building block into a socio-technical context needs to be accepted at a much broader level of implementation.

While information systems theory has been conducive to understanding a range of underlying concepts associated with AI innovation, platform governance, and digital infrastructure, conceptual issues over how AI systems gain legitimacy and become institutionalized over time remain unanswered. Therefore, concepts from institutional theory are added to describe the processes and governing mechanisms associated with AI adoption and diffusion at a broader societal level of socio-technological change.

3.1.2. Institutional infrastructure

Institutional theory helps elaborate on how AI-enabled digital infrastructure conceptually emerges, diffuses, and gains legitimacy through fields and organizations. Several studies have engaged with how external factors influence technological diffusion and associated processes of legitimacy (Anderson & Tushman, 1990; Nelson & Winter, 1982). Early institutional theory, for instance, connected the idea of institutional legitimacy to the notion of isomorphism (DiMaggio & Powell, 1983). In this strand of theorizing, coercive legitimacy signifies societal legitimacy, which can be achieved through legislative processes. Normative legitimacy is viewed as the appropriate professional standards and social acceptance of new technologies (Hinings, et al., 2018).

Aldrich and Fiol (1994) have similarly defined socio-political legitimacy as related to existing and changing cultural norms and political influences that include processes by which key stakeholders accept or embrace change, given their pre-existing norms. Geels (2002) and Geels and Schot (2007) have provided a multi-level perspective for evaluating new technologies and how they evolve within socio-technical systems (STS). They describe a life-cycle in which a new technology is first applied incrementally at the micro-level. From there, the technology grows and diffuses at the meso level before creating a new socio-technical landscape that supplants the previous one at a macro level. Hall, Matos, and Martin (2014) suggest that the STS approach implies that a new technology establishes legitimacy at two distinct levels. These include technical legitimacy as a technology's performance improves and socio-economic legitimacy as its use expands. Therefore, a distinction can be made between social and technical bias (Mittelstadt, et al., 2016), also referred to as structural and functional risks (Nuno, et al., 2021). Functional risks refer to technical areas such as the design and operation of an AI system, including datasets, bias, and performance issues. Structural risks refer to the ethical implications of an AI system, including the societal effects of automated decisions.

In order to understand the concept of legitimacy in the context of AI systems and technologies, this thesis draws on concepts related to institutional fields, logics, and work. These concepts provide a foundation for understanding the rationalities and practices of public sector actors that devise novel AI policies, private sector actors that implement novel AI systems, and how AI agents themselves can influence existing practices and forms of organization.

Institutional fields specify the area in which individuals and organizations participate in creating shared meaning systems through frequent forms of interaction (Scott, 2014). Institutional logics define a field's "socially constructed, historical patterns of material practices, assumptions, values, beliefs, and rules" (Reay & Hinings, 2009, p. 804). Institutional work refers to the "category of purposive action aimed at creating, maintaining, and disrupting institutions and businesses" (Lawrence & Suddaby, 2006, p, 218). Institutional work further describes how individuals and organizations work to "accomplish the social construction of rules, scripts, schemas, and cultural accounts" that change existing structures and forms of organization (Lawrence & Suddaby, 2006, p, 218). When the two approaches are combined, they refer to the institutional infrastructure of a field. Institutional infrastructure is established through activities such as certifying, assuring, and reporting against principles, codes, and standards (Waddock, 2008).

The institutional lens is relevant for understanding institutionalization processes associated with AI agents that operate in systems that embody distinct logics and cognitive functions (Floridi & Sanders, 2004). While the functional aspects of a model are defined by human actors such as engineers, AI agents remain subject to different degrees of autonomy. AI agents have the autonomy to act on (e.g., judicial evidence, road conditions), as well as interact with (e.g., speech recognition, chatbots) their environments in ways that cause AI systems to emerge as a new actor that drives organizational change.

In terms of digital infrastructure, digital building blocks such as an AI system or a dataset that have been used to train it, are created by engineers that may be subject to individual biases (Parasuraman & Manzey, 2010). This means that the designer's values can be "frozen into the code, effectively institutionalizing those values'' (Lash, 2007, p. 158). At a broader level, bias in computer systems relates to (1) pre-existing social values found in the "social institutions, practices and attitudes" from which technology emerges, (2) technical constraints, i.e., issues with the architecture, and (3) emergent aspects that arise through usage, which only can be known ex-post (Friedman & Nissenbaum, 1996).

In terms of legitimacy, problems arise when biased or otherwise flawed algorithms (and datasets) are subject to rapid technological implementation processes paired with limited institutional oversight mechanisms (e.g., audits, assessment frameworks, and regulations).

The institutional lens helps provide a nuanced conceptualization of how algorithms, viewed as non-human agents, are endowed with the ability to evaluate, rank, and reward or punish individuals' actions and positions based on pre-programmed instructions that shape social relationships (Curchod, et al., 2020, p. 648; Floridi, 2014). The reliance on algorithms as instruments for regulating social interdependencies translates into a novel form of AI-driven organizational influence that can alter existing power dependencies in unanticipated ways. Algorithms can be implicated in the constitution and reproduction of power asymmetries that regulate individuals' behaviors and ensure their compliance with predefined (e.g., platform-based) standards. How this happens has broad consequences for humans and organizations that remain little understood and accounted for in the literature (Curchod, et al., 2020). AI algorithms also alter economic practices and forms of organization in ways that create new power dependencies, e.g., between workers and machines or between new and traditional forms of organization (Frank, et al., 2019). As algorithms hold power to affect how humans conceptualize the world and further embody the capacity to modify socio-political forms of organization (Floridi, 2014), it is vital to understand how this happens in recursive ways across the technical, organizational, and institutional levels.

Since field-level advancements in AI are context-dependent, the existing organizational and institutional infrastructure tends to determine the impact an AI technology or AI agent is allowed to have in a particular socio-economic context. The concept of institutional legitimacy is helpful in terms of clarifying how AI-related systems may be conceived or constructed differently across varying socio-political contexts. Therefore, the flexibility of digital infrastructure is argued to be contingent on and restricted by technical, organizational, and regulatory mechanisms.

At this point, several essential interconnections between digital infrastructure and institutional infrastructure have been made. The process that renders digital infrastructures institutional occurs when innovators infuse specific norms, values, logics, and forms of governance and technological control into the infrastructure, and as the infrastructure becomes more widely adopted and used over time (Garud & Karnøe, 2003; Yoo, Henfridsson and Lyytinen, 2010). This may happen at technical or organizational levels as values are infused into the operation of a specific system or structure. Digital institutional infrastructure can therefore be viewed as the integration of digital infrastructure and institutional infrastructure, which is defined as “standard-setting digital technologies that enable, constrain and coordinate numerous actors’ actions and interactions in ecosystems, fields, or industries” (Hinings, et al., 2018, p. 54).

Institutional theory has been beneficial in informing how AI legitimacy may be obtained at the technical, organizational, and institutional levels. However, the legislative mechanisms that influence and govern this process have yet to be operationalized at a more concrete level. Concepts from political economy are helpful in this regard.

3.1.3. Regulation and governance

In political economy, regulation refers to the attempt of the state to steer the economy by imposing a set of economic controls on the behavior of private businesses. Regulation includes targeted rules accompanied by mechanisms to monitor and enforce varying compliance measures. The original justification of government intervention in economic interactions was linked to public interest, based on the assumptions that markets fail because of problems associated with natural monopolies, externalities, public goods, asymmetric information, moral hazard, or transaction costs (Meade, 1949; Lewis, 1949).

While liberal economics have relied on competition and private sector self-regulation to limit negative externalities, Coase (1960) argues that where markets were unsuccessful in addressing failures, impartial courts would step in and enforce contracts and common law for torts. As long as courts enforce contracts, equilibrium outcomes are expected to be efficient. Economists have since pointed out that there may be a range of transaction costs associated with imposing and enforcing new regulations. Costs can be associated with ineffective policy tools and regulations that harm social or economic welfare. Stigler's theory of regulatory capture (Stigler, 1971), for instance, argues that the political process of regulation typically is captured by industry and that regulatory efforts to promote social welfare rarely succeed. Nonetheless, public interest assumptions consider that governments can correct market failures through regulation that aims to control prices otherwise dictated by monopolies or by imposing safety standards to prevent accidents (Shleifer, 2005).

Contrary to the notion of regulatory capture, more recent research on environmental regulation argues that regulation can support innovation, for example, by raising emission requirements, which forces firms to implement new solutions (see, e.g., Hascic, et al., 2009). Aragón-Correa, Marcus, & Vogel (2020) have found that regulation, or even the uncertain anticipation of future regulation, has encouraged firms to invest in otherwise neglected areas while attracting additional investments to these areas. Regarding the environment, regulation has been argued to trigger the discovery of cleaner technologies and better environmental protection by making production processes and products more efficient. The Porter hypothesis argues that regulation can enhance firms' competitiveness and reinforce innovative behaviors (Porter & Van Der Linde, 1995).

In terms of AI, externalities are already evident in biased hiring and incarceration algorithms (Cowgill & Tucker, 2019), inaccurate facial recognition tools, and unsafe automated driving systems

(Lambrecht & Tucker, 2019; Veale & Binns, 2017). These externalities have caused government, industry, and civil society actors to call for stricter mechanisms to address rapid forms of AI adoption and diffusion.

According to regulatory theory, if the production of unsafe products is made sufficiently expensive, firms would be encouraged to innovate and produce safer products (Baumol & Blackman, 1991). Regulation can therefore reduce the divergence between business ethics and economic incentives while encouraging and enhancing socially responsible businesses behavior in the long term (Kulshreshtha, 2005). Regulations could further require firms to allocate some inputs (labor, capital) to develop and deploy ethical AI systems that limit unfair practices while protecting data and privacy.

3.1.3.1. Regulating data

Regarding data-related regulation, microeconomic theory of privacy suggests that some elements of privacy protection increase economic efficiency in a marketplace, while others decrease it. Shared personal information can become a public good and its analysis can reduce inefficiencies and increase economic welfare (Acquisti, 2014). When personal information is abused, however, it can transfer economic wealth from data subjects to data holders. When firms own data, they may overuse it and not adequately respect consumer privacy. Acquisti (2014) finds that it is unlikely that economics will be able to answer what the "optimal" distribution of privacy and disclosure is for an individual or a society. However, economics literature contributes to analyzing the specific trade-offs involved. Most theoretical economic models classify privacy as an intermediate good, implying that an individual's desire for data privacy depends on how likely the individual is to anticipate that data's effect on future economic outcomes (Tucker, 2017). If a consumer is experiencing higher prices due to the behavior captured in their data, then consumers are likely to appreciate a higher degree of privacy. Much of the policy debate revolves around whether consumers can make a sound determination of the suitable trade-off between privacy and data.

The positive externalities data holders gain from sharing their data include free content and services, reduced search costs, and more efficient interactions with commercial platforms (Goldfarb & Tucker, 2011; Lenard & Rubin, 2009). Other positive externalities relate to firms' improved targeting of consumers, which reduces marketing investments and potentially lowers product prices (Deighton & Blattberg 1991). The aggregation of web searches of many individuals could also help detect disease outbreaks (Wilson & Brownstein, 2009), and the aggregation of location data could be used to improve traffic conditions and reduce road congestion. In other words, the aggregation or centralization of private data could generate new public goods, with societal benefits accruing from big data (Acquisti, 2014). The degree to which personal data are expected to become a public good is therefore up to policymakers to determine, which means that geographical variation will occur as new solutions are debated and implemented at local and national levels. Similarly, when data are handled locally, there could be a higher chance of developing indigenous capabilities in digital services and associated AI technologies that can analyze and assess the localized data (Bauer, et al., 2016). In a world without restrictions on the flow of such data, the alternative might be that data streams will continue to flow to regional centers where such capabilities are developed (e.g., Silicon Valley, London, and Beijing).

3.1.3.2. AI ethics, firms, and regulation

In terms of AI technologies and contingent areas of data and privacy, optimal policy solutions are guided by ethical considerations shaped by institutional logics, which become more salient to the public as new AI technologies permeate existing practices.

Ethical concerns, however, are also of great importance to business leaders, even if firms are not forced to internalize the cost of complying with ethical norms by outright regulations. Managers, for example, have to make day-to-day decisions and longer-term decisions, with highly incomplete information, including decisions about exploiting new and untested technological and market opportunities (Teece & Leih, 2016). This forces some managers to exhibit present-biased preferences, which entails that managers may choose to put off AI investment in profitable but otherwise costly opportunities, as the cost of innovation occurs now, while the benefits accrue at a later stage (Ambec & Barla, 2006). In the absence of clear legislation, firm managers could be faced with a predicament in when they should release new products or systems that potentially could create or exacerbate new or existing social harms.

The difficulty with many AI products or systems is that ethical or responsible behavior could be costly, e.g., concerning the use of data or increased time associated with developing and marketing an ethically-tested product. At the same time, the returns to the additional investments are not guaranteed, which could reinforce present-biased preferences. Regulations could help managers overcome this self-control problem by requiring ethics-related consideration through increasing awareness of ethical issues (Ambec, et al., 2013). While this could impose an added cost on firms and delay adoption and innovation in the short term (Jaffe, et al., 1995; Majumdar & Marcus, 2001), over the longer term, firms likely would reorient innovation to meet regulatory and consumer demand for more transparent and trustworthy AI systems.

For businesses that internalize new managerial standards and practices that detail AI liability under varying circumstances, essential feedback loops in enhancing more ethically-oriented forms of AI innovation could be present. Internal audit and assessment mechanisms could, for example, provide more information for managers, which would help reduce managerial uncertainty and aid the development of AI products and services subject to higher ethical and legal, and policy standards. While calls for AI regulation are currently being made, the complex interactions between AI adoption and regulation remain little understood.

3.2. Conceptual framework: AI governance

As established in the literature review, AI governance is comprised of a patchwork of literatures that spans several academic disciplines. A theoretical and conceptual challenge is associated with covering and assembling diverse strands of literature. However, the perceived strength of this approach is that it informs a holistic interpretation of AI governance as a field. Conceptually, the interpretation of the governance of AI that is established and applied in this thesis moves across the technical (innovation), organizational (adoption), and institutional (diffusion) levels.

At the technical level, AI governance relates to the innovation of AI systems. The technical level refers to a broad network of interrelated technologies (algorithms, data, hardware) and architectures (e.g., innovation platforms), conceptualized as digital infrastructure. These are governed by mechanisms such as standards, audits, assessment frameworks, humans in the loop, and other forms of oversight that work to ensure reliability, safety, unbiased data, and forms of application.

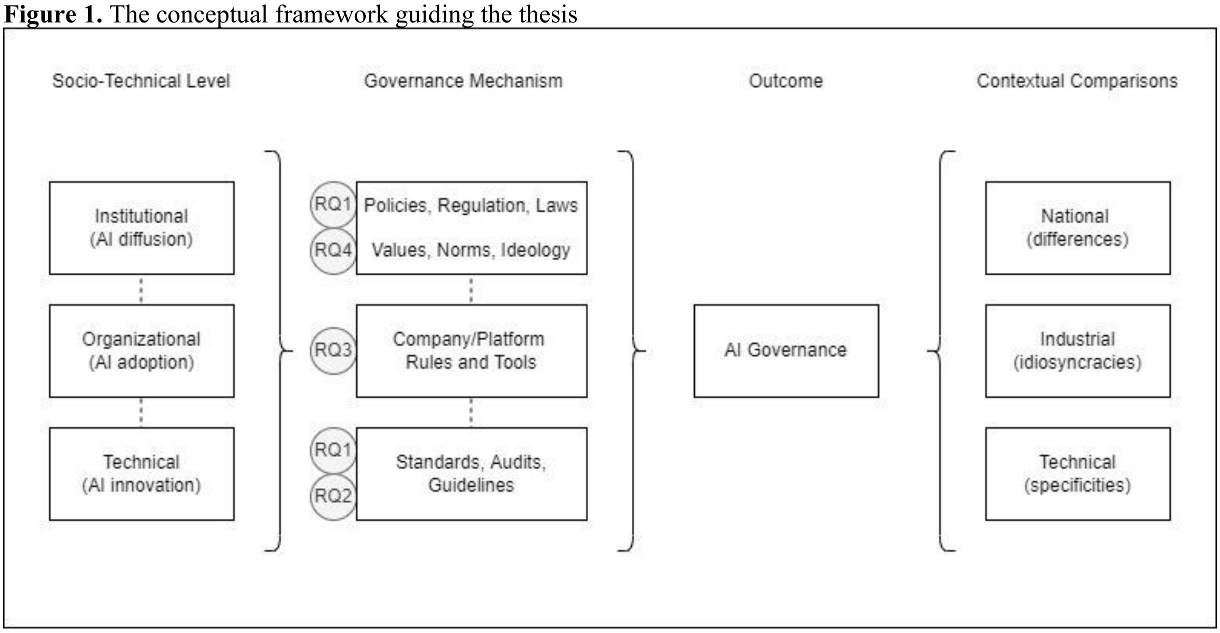
At the organization level, AI governance refers to the adoption of AI systems. This thesis has delimited its organizational area of focus to platforms as these are considered to influence AI innovation and shape adoption practices at the broadest level. Platform governance mechanisms include resourcing tools and securing rules that guide platform behavior and ecosystem interaction.

At the institutional level, AI governance refers to the diffusion of AI systems. The institutional level encompasses logics and the work of actors such as AI agents, individuals, firms, and policymakers. Infrastructure at this level is established by governing mechanisms such as certifications, audits, standards, laws, and regulations, and is elaborated through norms, values, and ideologies.

The conceptual framework places special attention on the interplay between the technical (AI innovation), organizational (AI adoption), and institutional (AI diffusion) levels, as well as between the governing mechanisms at each level. This paves the way for understanding AI governance as a holistic process of interacting dynamics that are empirically grounded in different socio-economic contexts.

Each Article of this thesis deals with one or several of these levels and their interactions. This lays the groundwork for engaging in contextual comparisons that include potential differences at the national, industrial, and technical levels. The outlined conceptual framework guides the analysis and helps clarify how AI is governed in the United States and China, respectively. The conceptual framework is also useful in gauging accompanying implications for the governance of AI.

Figure 1. The conceptual framework guiding the thesis



4. METHODOLOGY

This chapter explains the methodological considerations of the dissertation. The chapter begins with a description of the underlying philosophy of science, followed by a presentation of the research strategy and design, data collection, and data analysis.

4.1. Philosophy of science

In the philosophy of science, ontology refers to the assumptions that the researcher makes about the nature of reality. Epistemology informs the researcher's beliefs about how new knowledge concerning reality is best derived. And, methodology informs the researcher about the specific tools and techniques that can be used to justifiably establish new knowledge about social phenomena (Saunders & Lewis, 2017). This thesis builds on a mixed-methods approach that combines quantitative (Articles I & IV) and qualitative (Articles II & III) methodologies informed by a critical realist perspective.

According to critical realism, the world can be conceived based on what we see and experience, which relates to a set of underlying structures of reality that influence what is observed. Central to critical realism is that knowledge about the social world only can be derived once we understand some of the underlying social structures that impact the phenomena under study. This means that research in the critical realist tradition seeks to explain observable organizational events by looking at causes and mechanisms that give rise to and inform the social structures that influence and shape organizations (Bhaskar, 2008). For these reasons, historical analysis of social and organizational structures and their emergence and evolution is central (Reed, 2005). This implies a sense of epistemological relativism (Reed, 2005), recognizing that knowledge is historically situated, which implies that knowledge is both a product of and remains specific to a given period in time (Saunders, et al., 2019). Therefore, prior experiences, norms, and values influence scientific knowledge. This implies that social facts are social constructions that have been mutually agreed upon to varying extents rather than being subject to independent existence (Bhaskar, 2008). Causality, therefore, cannot be reduced purely to statistical correlations and quantitative methods, while critical realist thought instead gives rise to a range of accepted methods (Reed, 2005). As a result, critical realism is conducive to both inductive and deductive forms of reasoning that involve drawing general conclusions from a set of specific observations (Ketokivi & Mantere, 2010).

In embracing a critical realist ontology of the social world, this thesis emphasizes the complementarities of a mixed-methods approach to inform the study of AI governance. In this thesis, mixed methods refers to the combination of quantitative survey-based data with qualitative interview-based data, which pave the way for integrated findings (Tashakkori & Creswell, 2007). The thesis is modeled after a convergent mixed-methods design, where quantitative and qualitative results are merged and compared (Creswell & Plano Clark, 2018). A mixed-methods approach is considered an optimal solution, as the approach paves the way for extensive interpretations of complex social phenomena (Creswell, 2003).

When looking at the phenomenon of AI governance while assessing and comparing governance approaches and associated capabilities, it is essential to consider multiple ways of seeing and making sense of the world (Greene, 2007). For the study of AI governance, this implies that quantitative and qualitative approaches can mutually inform the emergent contours of the field (Chomanski, 2021; Schneider, Abraham, & Meske, 2020). Quantitative studies can include economic and technical measures such as patents and publications (Leusin, et al., 2020; Zhang, et al., 2021), while qualitative approaches may be better situated to understand processes, structures, and outcomes (Tie, et al., 2019). Both approaches, however, are subject to limitations. In purely quantitative studies, comparisons of key metrics (e.g., AI patents or publications) tend to capture a static moment in time that neglects the sense of dynamism that is inherent in rapidly evolving digital infrastructures and constantly changing AI-driven forms of socio-technical organization. Furthermore, at the international level, AI innovation is subject to competition and abstract forms of technological (de)coupling, which are politically motivated and historically contingent. The application of varying AI technologies also tends to be value-dependent, while underlying processes of adoption and diffusion make AI governance a phenomenon that is unfeasible to be understood from a strictly quantitative angle. Qualitative and conceptual approaches to the study of AI governance are also limited in several ways. For example, important trade-offs are inherent in every decision, strategy, policy, or regulation that is implemented. Managers, policymakers, and individuals may face trade-offs, e.g., between AI adoption and regulation, that may be hard to to understand purely from a qualitative basis. Due to these considerations, this thesis embraces a mixed-methods approach that combines both qualitative and quantitative methods and thereby seeks to improve the validity and reliability of the findings in this thesis.

4.2. Research strategy and design

To understand the complex processes associated with the governance of artificial intelligence technologies – in a comparative light, this thesis combines survey-based research with interview-based case studies. In order to ensure a high level of validity and reliability, the thesis is based on a variety of quantitative and qualitative data that was collected over four years and includes a total of 24 months of field research, with 12 months conducted in China and 12 months in the United States.

Table 7. Overview of the four articles

Article I	Article II	Article III	Article IV
Context: AI Regulation	Context: AI Legitimization / Institutionalization	Context: AI Innovation	Context: Tech Competition / Data Privacy
Country: The United States	Country: The United States	Country: China	Country: China
Method: Survey / AB Testing	Method: Conceptual	Method: Case-study	Method: Survey / AB Testing
Unit of analysis: managerial preferences	Unit of analysis: AI fields	Unit of analysis (Case): National Open Innovation Platforms	Unit of analysis: individual preferences

4.2.1. Survey: AB testing

A growing literature in economics and political science (see, e.g., Brynjolfsson, Collis & Eggers, 2019; Di Tella & Rodrik, 2019; Pan & Xu, 2018) relies on online survey companies such as SurveyMonkey, Amazon Mechanical Turk, and Qualtrics to conduct online surveys and experiments. Though the respondents identified through these companies are not necessarily representative samples of the population, the companies are capable of filtering potential respondents in a way that creates a statistically meaningful sample of a specific subset of the population.

To address Sub-RQ1 and Sub-RQ4,[10] this thesis adopts a randomized online survey experiment designed to study the effects of different treatments (i.e., managers' perceptions of AI regulations and individuals' data privacy preferences). Experiment participants (managers and individuals) are

[10] Sub-RQ1: how do different kinds of AI-related regulation – or even the prospect of regulation – affect firm behavior, including firm responses to ethical concerns?
Sub-RQ4: how does technological competition affect data privacy preferences?

randomly assigned to "treatment" and "control" groups, and the differences in the survey responses between the groups can be attributed to the treatments (Berengut, 2006; Mason, Gunst & Hess, 2003; Visser, et al., 2000). Controlled experiments embody a good scientific design for establishing a causal relationship between changes and their influence on user-observable behavior (Kohavi, et al., 2009, p. 1). The distribution between control and treatment groups is randomly assigned, meaning that participants are not systematically distributed across the groups (Weiss, 1997). Based on the collected observations, an Overall Evaluation Criterion (OEC) can be established for each control and treatment group (Roy, 2001). Therefore, the only observable difference should be the change between the control and treatment, which means that any difference in the OEC is due to the assignment, which establishes causality (Weiss, 1997, p. 215). Metrics of interest are explicit changes in stated behavior captured by the collected survey data. Statistical tests can then be conducted on the collected data to evaluate whether there are any statistically significant differences between the variants. This allows the researcher to accept or reject the (null) hypothesis that there is no difference between the variants. Further regression analysis allows the researcher to understand which subpopulations show significant differences (Kohavi, et al., 2009).

In this thesis, each treatment has been designed in the form of a small news article or snippet. The main paragraph is followed by a randomly assigned vignette from the control or one of several treatment conditions. The vignettes are similar in length and mirror the structure of actual online articles (sometimes with illustrative pictures added to increase the salience of the vignettes). Following each vignette, manipulation checks are included to ensure that respondents pay sufficient attention to the experiment, which increases the reliability of the findings. The control group is designed to be "neutral" while conveying broad facts or information (about AI and data).

In Article I, we chose to survey firm managers to inform the policy debate on how new or intended forms of AI regulation potentially interacts with and affect managerial preferences regarding AI ethics and AI adoption. The survey design of Article I can be found in Appendix A1. In Article IV, we chose to survey individuals to determine how great power tech competition in AI potentially interacts with and shifts individuals' data privacy preferences. Therefore, the two surveys of this thesis have been designed to examine the intent of managers and individuals. The survey design of Article IV can be found in Appendix A2.

Two types of choice experiments are included at the end of one of the surveys (Article IV). The first is a single-binary discrete-choice (SBDC) experiment (Carson, Groves, & List, 2014) that involves consumers making a single choice between two options.[11] The second measures individuals' willingness to accept (WTA) valuations, i.e., the monetary compensation needed to compensate for various goods (Brynjolfsson, et al., 2019).[12] Choice experiments help elicit consumer preferences based on hypothetical scenarios and markets.

Some literature on how surveys affect behaviors has pointed to mere measurement and self-prophecy effects, where the act of measuring itself can induce subsequent changes in respondents' behavior. (Morwitz, et al., 1993). However, other literature has found that stating one's intent to engage in behavior often is associated with an increased likelihood of subsequently engaging in the behavior (Levav & Fitzsimons, 2006). The literature also discusses "experimenter demand effects," which is the possibility that respondents change their behavior since they know they are subjects in an experiment (Zizzo, 2010; Di Tella & Rodrik, 2019). A recent paper by De Quidt, et al. (2018) has tried to bind experimenter demand effects in a series of common tasks, concluding that any potential biases are likely to be modest.

4.2.2. Case study: selection and design

To address Sub-RQ3,[13] this thesis adopts an explorative case-study design (Yin, 2009). A case study is considered an appropriate method for studying new and emerging phenomena (Eisenhardt, 1989; Yin, 2003) and is especially suitable for exploring complex processes and emerging paradigms (Birkinshaw, Brannen, & Tung, 2011, p. 575). A case study is also a helpful method for developing theory inductively (Eisenhardt, 1989). A grounded approach to theory building is considered relevant when little is known about a phenomenon (Eisenhardt, 1989). Grounded theory is an appropriate methodological approach to uncover underlying processes inherent to the substantive area of inquiry (Tie, et al., 2019). A case study is therefore considered an appropriate method for investigating social phenomena within a real-life context (Yin, 2009) that allows for a rich, detailed, and in-depth

[11] Respondents in the experiment are asked whether they would be willing to provide their data to different entities (company, government), if these were willing to pay them for their data.
[12] Respondents in the experiment are asked how much monetary compensation they would ask each of the entities in exchange for their data.
[13] Sub-RQ3: what mechanisms can governments use to affect the boundary resources of innovation platforms, and how do these influence platform governance?

interpretation (Berg, 2007, p. 283) of processes, conditions, and mechanisms as well as associated outcomes (Patton, 2015).

The case of National Open Innovation Platforms for AI (NOIPAI) in China was chosen because of its ability to inform more general questions related to how public actors can influence innovation platforms' processes of boundary resource tuning. The policy and platform initiative was also chosen because it seems to be a novel model of public-private platform orchestration related to AI innovation processes.

4.3. Data collection and analysis

The dissertation draws on multiple data collection techniques and data sources. Primary data is comprised of two large-scale surveys consisting of 1,245 and 3,146 respondents or a total of 4,391 survey-based observations, as well as 16 semi-structured interviews. Secondary data includes more than 2,000 archival records and documents, categorized systematically over five years using Mendeley software. Table 8 and Table 9 provide a detailed overview of the combined data sources and how they have been used in the four articles of the thesis.

Table 8. Primary and secondary data sources of research articles

Article	Primary data	#	Label	Secondary data	#	Label
I	Survey	1,245	S1	Archival records and documents	80	A1-7
II	Archival records and documents	112	A1-7	Participant observations	8	O1-3
III	Interview	16	I1-2	Participant observations	12	O1-4
IV	Survey	3,146	S2	Archival records and documents	35	A1-7

4.3.1. Surveys

Two surveys have been used to gather a total of 4,391 observations. The first survey targeted managers in businesses of at least 50 employees in the United States. The survey was launched in August 2019 through the survey-firm SurveyMonkey Audience. Firms with more than 50 employees were targeted because their managers are expected to be more aware of the types of AI technologies that are being used in their businesses, including their expected involvement in decision-making surrounding AI adoption. Responses were received from business owners and partners, C-level executives, and senior and middle managers. Initially, 2,610 responses were collected. About 20.9% came from non-managers, and about 33.8% came from businesses with less than 50 employees. We excluded these and respondents who indicated they did not devote full attention to answering the questions (about 9.9%). We also dropped responses from those who finished the survey unreasonably short, i.e., the first percentile of response time. Applying these restrictions, we end up with a sample of 1,245 managers. The average response time in this sample was about 7.3 minutes.[14]

The second survey targeted individual internet users in China. Internet users were targeted since these are a representative sample of the general population who utilize websites, apps, and information technology products and services and are likely to be somewhat aware of data privacy issues. The survey was launched in October 2021 through the survey-firm Qualtrics, and over seven weeks, close to 4,000 responses were collected. After excluding those who did not pass the attention checks, stopped before the end of the survey, or finished the survey in an unreasonably short time (i.e., the first percentile of response time), we ended up with a final sample of 3,146 individuals.[15]

4.3.2. Semi-structured interviews

Sixteen semi-structured interviews were collected from February 2018 to March 2019 during 12 consecutive months of fieldwork in China. A list of interviews can be found in Appendix A3. The interviews have been divided into an explorative phase, subject to familiarization with the topic (February–July 2018), and an investigatory phase, where the topic was reassessed from multiple angles (August 2018 – January 2019). During the two phases, interview partners were located and selected according to relevant criteria such as being engaged in AI innovation, their position (i.e., decision-makers), and experience (in-depth AI industry/firm knowledge). Potential interview partners were contacted through various channels such as e-mail, LinkedIn, or in-person at conferences. Respondents included CEOs, directors, and managers from domestic and international technology companies and AI start-ups located and operating in China and software engineers and developers engaged in building and maintaining AI platforms. Direct access to policymakers with responsibilities related to National Open Innovation Platforms for AI (the substantive area of study) could not be

[14] While our sample is not representative of all businesses and all industries operating in the United States, we note that comparable surveys reflect similar results in terms of firms' rate of AI adoption (Mckinsey, 2019).

[15] While our sample is not representative of all individuals in China, we aimed to get a representative sample of internet users in China, which is the more relevant population for the question we study.

established. The reasons for this may be several, including the sensitive nature of industrial policies in China.

Before each interview, questions were carefully assembled based on the subject's knowledge area and expertise in AI. The previously combined questions guided the interview process and minimized potential power imbalances between the interviewer and interviewee (Berry, 2002). All interviews took place in person and were conducted at the interviewee's office or in a public space. Most interviews were recorded and transcribed, while some were conducted in note-form due to the collected data's sensitivity or concern for the respondent's anonymity. The interviews consist of open-ended questions focusing on AI innovation in China and the role of National Open Innovation Platforms for AI. All of the interviews were conducted in English, although a translator was offered on some occasions. The duration of interviews ranged from 24 to 123 minutes.

All interviews have been transcribed and coded in NVivo software. The interviews were coded inductively through two rounds (Strauss & Corbin, 1998). The first round of coding sought to trace underlying policy- and firm- justifications at a high level of abstraction. In the second coding round, first-order codes were clustered into more abstract second-order codes that synthesized how the perceived government interactions influenced platform boundary resources. A few core categories emerged at this stage and were subsequently formed into more concrete concepts and relationships surrounding the process of boundary resource tuning. This refined first-order codes and paved the way for a more fine-grained categorization of government mechanisms for boundary resource tuning to emerge.

Triangulation methods were applied to ensure a high level of internal validity (Meijer, et al., 2002). Some interview partners were, for example, interviewed twice over 12 months, which enabled a cross-examination of their statements. Interview transcriptions were also complemented with extensive information from secondary data, which was used to scrutinize the gathered statements.

Table 9. Specification of data collection

	Label	**Data source**	**Specification**		**Examples**
Interviews			Country	Period	
	I1	Interviews #1	CN	Feb18-Jul18	Alibaba, SenseTime, Oracle
	I2	Interviews #2	CN	Aug18-Jan19	JD.com, Meezao, Microsoft,
Surveys	**S1**	Survey 1	US	Aug19-Sep19	
	S2	Survey 2	CN	Oct21-Nov21	

	A1	Policy Plans and Guidelines	The White House, The State Council, The OECD
Archival records and documents	**A2**	Academic and Industry reports	Center for the Governance of AI, Partnership on AI, AI Now Institute, Berkman Klein Center for Internet and Society
	A3	Company reports	Google, Tencent
	A4	Company websites	Baidu, Alibaba, Tencent, OpenAI
	A5	Technical and consultancy papers	McKinsey, CBI Insights
	A6	Newspapers and magazines	Xinhua, China Daily, Financial Times, MIT Technology Review, Harvard Business Review
	A7	Research articles	AI & Society, Government Information Quarterly, MIS-Q, Technovation, Technological Forecasting, and Social Change, Org. Science
Participant observations	**O1**	Conferences	MIT Technology Review EmTech (Beijing 2018), NBER Economics of AI (Toronto 2019)
	O2	Workshops	IE3 Forum (Industrial Engineering, Innovation Entrepreneurship, and Industrial Ecology) (Cambridge 2018)
	O3	Seminars	Governance of AI (Stanford 2019)
	O4	Company visits	DiDi (Beijing), JD.com (Beijing/Mountain View)

4.3.3. Archival records and documents

Secondary data has been collected from various sources such as policy documents, academic and industry reports, company reports and websites, technical documents and consultancy papers, newspapers and magazines, and research articles. Table 9 provides a detailed overview of documents used to inform the data collection process of this thesis. Secondary data serve multiple purposes, such as triangulating survey and interview data and providing context on varying levels of AI governance across technical, organizational, and institutional levels.

Secondary data has been especially relevant in informing the empirical field of inquiry associated with AI policies and governance mechanisms in the United States or China. Secondary policy documents have been used to identify the latest trends in AI governance from a public policy perspective. As policy plans and guidelines are regularly updated, only the most essential policy plans have been singled out. These policies and plans are considered highly influential in setting national strategic objectives for industry and society. Key documents have been retrieved from various government websites such as China's State Council (www.gov.cn/), the United States White House (www.whitehouse.gov), and the OECD AI Policy Observatory (www.oecd.ai/en/). These websites provide access to several government policy documents (e.g., plans, opinions, notices).

Academic and industry reports on some of the most recent developments in AI have also been included as secondary sources. These provide a means for staying up to date on the latest industrial developments associated with AI innovation, adoption, and diffusion. Publicly available data such as press releases, tech blogs, and developer forums have also been scrutinized. These are considered important sources for studying platform-based phenomena, especially as secrecy usually surrounds large platforms, making reliable first-hand data on governance and design decisions hard to come by (De Reuver, et al., 2018).

In detail, secondary data has informed Article I regarding the latest developments in the United States AI policies and regulations. In Article II, secondary data has been used to inform the latest discussion on AI and data use connected to processes of AI legitimacy. In Article III, secondary data has been used to inform the latest developments of China's central and regional AI policies explicitly connected to the National Open Innovation Platforms for AI initiative. In Article IV, secondary data has informed some of the most recent developments connected to US–China competition on AI and elements associated with technological decoupling and China's data privacy regime.

4.3.4. Participant observation

The last data source included in this thesis refers to participant observation, which is used as a method of gathering indirect, contextual data. Participant observation has been defined as "the systematic description of events, behaviors, and artifacts in the social setting chosen for study" (Marshall & Rossman, 2016, p. 78). This includes participation in AI conferences, summits, seminars, workshops, and company visits. Extensive participation in AI conferences across academia and industry was conducted in China and the United States from 2018 to 2020. Participation in these events informed the researcher's ontology regarding problems and opportunities at the frontier of AI innovation, adoption, and regulation. Participation in workshops and seminars has also led to an expansion of local networks, which has been beneficial in growing an insider's perspective on relevant questions to ask while also networking with potential interviewees. Including participant observation as a source of data ensures a high level of construct validity and consistency between conceptual constructs and how these have been operationalized throughout the thesis (Bryman, 2016).

4.4. Remarks on validity and reliability

Several techniques were adopted to ensure that the findings of this thesis have a high level of validity and reliability. Validity explains how well the collected data covers the actual area of investigation (Ghauri & Gronhaug, 2005), while reliability conveys the extent to which the results can be reproduced (Saunders, et al., 2012).

Internal measurement validity of survey-based data was established through several steps, including face validity and content validity. Face validity refers to a researcher's subjective assessments of the presentation and relevance of the measuring instrument, which should be relevant, clear, and unambiguous (Oluwatayo, 2012). Face validity was established by running several pilot surveys. The content and flow of the surveys were tested in terms of feasibility, readability, consistency, formatting, and clarity of the language used (Taherdoost, 2016). Content validity was established through extensive literature reviews that informed the surveys' core concepts, followed by several rounds of survey evaluation by colleagues and survey experts, which eliminated any undesirable items associated with the constructs (Straub & Gefen, 2004). Reliability was established by adding several attention checks throughout the surveys. This improved the robustness of the questionnaire while ensuring that consistent findings may be found at different times and under different conditions and sample groups. Reliability of the survey-based data was further ensured by dropping some of the collected samples, e.g., those who completed the survey unreasonably quickly. These measures help ensure that the selected data collection techniques and analytic procedures would produce consistent findings if replicated at another time.

In terms of the interview-based data, internal validity was established through extensive triangulation with various sources (Denzin, 2012). This process includes having spent a considerable amount of time carrying out fieldwork in China. Additional forms of triangulation have been conducted through seminar and conference presentations and going through several rounds of peer review. Reliability was established by documenting coding procedures in NVivo, which added transparency to the coding procedure.

5. SUMMARY OF ARTICLES

5.1. Article I

The first article, "Does Information about AI Regulation Change Manager Evaluation of Ethical Concerns and Intent to Adopt AI?" assesses potential trade-offs between AI regulation and AI adoption. The case of AI regulation in the United States was selected due to the growing salience of AI regulation. Four kinds of AI regulation were chosen covering: existing laws, data-related regulation, sector-specific regulation, and horizontal AI regulation, all of which have domestic and international implications for developing regulatory best practices.

The article departs from the observation that AI technologies have wide-ranging impacts. Therefore, it is interesting to consider whether firms are likely to embrace measures of self-regulation based on ethical or policy considerations and how decisions of policymakers or courts affect the adoption of AI systems. While potential impacts of AI technologies are regularly examined (see, e.g., Agrawal, et al. 2019; Frank, et al. 2019), we know little about the consequences of public-sector responses designed to regulate firm behavior, and even less knowledge exists concerning how managers might respond to implemented or intended regulatory changes. Both policies and firm practices associated with AI development and adoption hold important ethical concerns and considerations that are likely to affect human behavior.

Based on these observations, the empirical analysis of the article is guided by the following research question: how do different kinds of AI-related regulation – or even the prospect of regulation – affect firm behavior, including firm responses to ethical concerns? The article surveys 1,245 managers from the healthcare, automotive, and retail industries to examine this question. In a randomized online survey experiment, treatment groups were informed of the core contents of four regulatory treatments. The degree to which managers change their intent to adopt AI processes was measured and managers' perceptions of the importance of ethical issues related to privacy, transparency, safety, bias/discrimination, and labor-related issues was assessed.

The results indicate that exposure to information about AI regulation increases the importance managers assign to various ethical issues when adopting AI. All four regulatory treatments increase managers' interest in enhancing safety and minimizing accidents related to AI technologies. A trade-off is located, however. Managers' heightened awareness of ethical issues is offset by a decrease in managers' stated intent to adopt AI technologies. Furthermore, the article finds that the trade-off between AI ethics and adoption is more pronounced in smaller firms, which are more resource-constrained than larger firms are. When comparing the healthcare, automotive and retail industries, the article discerns heterogeneity in the results, indicating that regulation information is likely to affect industries differently due to industry-specific characteristics.

The relevance of this article in the context of the overall research puzzle is its provision of empirical evidence on how the AI regulatory landscape is currently emerging in the United States. Evidence is added to the literature that examines the broader effects of technology-related regulations on social and economic activity. Also, the article's implications for managers and organizational decision-making contribute to the literature on business ethics. The article shows that ethical guidelines, both internally within firms and externally through regulations, are likely to significantly influence decision-making concerning the implementation of novel AI systems and technologies, which has implications for AI governance.

5.2. Article II

The second article, "A Framework for Understanding AI-Induced Field Change: How AI Technologies are Legitimized and Institutionalized," utilizes institutional theory to conceptualize varying forms of AI (e.g., FRT, autonomous vehicles, recommender engines) as fields that diffuse through society and organizations. The article assesses what it takes for varying AI systems to gain legitimacy during technological adoption and institutionalization processes.

The article departs from the observation that the action potentials inherent in most AI systems imply a shift in agency from human actors to AI agents, which significantly impacts individual practices and organizational behavior. The socio-economic embeddedness of AI systems means that social and organizational practices are changing, while change may be subject to varying degrees of social acceptance and legitimacy. This issue is often confounded, as technological implementation moves faster than the institutions that regulate them, commonly referred to as the pacing problem (Hagemann, Huddleston, & Thierer, 2018). This is problematic when AI-induced externalities have unintended consequences for some actors or groups in society (Buolamwini & Gebru, 2018; Obermeyer, et al., 2019)

Based on these observations, the article is motivated to answer the research question: how are AI-induced fields subject to varying degrees of legitimacy as well as processes of institutionalization? The article combines institutional- and information systems (IS) theory to signify digital and institutional infrastructure's relative elaboration and coherence. Digital infrastructure includes assessing an AI system’s perceived degree of technological maturity, its use of data, and the system’s autonomy, to act on or interact with its environment, including the possible ramifications of those actions. Institutional infrastructure is used to elaborate on certification, standards, audits, and official rules and regulations that guide more thoughtful technological expansion (Waddock, 2008). The developed framework builds on Zietsma, et al.’s (2017) notion of pathways of change, which describes how a field moves between states from emerging/aligning to fragmented, contested and established, depending on the elaboration and coherency of digital- and institutional infrastructure.

The article finds that issues with AI legitimization generally occur when AI systems upend existing dependencies and power structures between humans, machines, and organizations in new and unintended ways. Additional issues related to non-transparent use and data centralization give rise to information asymmetries. And, most issues with legitimization occur when existing institutional infrastructure is unable to address externalities associated with rapid technological adoption.

The relevance of this article in the context of the overall research puzzle is its nuanced interpretation of how AI technologies move and gain legitimacy across varying AI fields. The article relates to the overall research question by extrapolating the need for more adaptive forms of organization to emerge that are better equipped to govern complex socio-technological changes caused by a GPT such as AI (Taeihagh, et al., 2021). Proposed measures of institutional adaptation include enhanced algorithmic auditing carried out by companies (Zarsky, 2016), third-party auditors (Clark & Hadfield, 2019), or external regulators (Tutt, 2016).

5.3. Article III

The third article, “Government Mechanisms for Platform Boundary Resource Tuning: The case of China’s National Open Innovation Platforms for AI,” looks into the platform-based organizational construct and how it affects AI innovation. The article focuses on the empirical case of China’s National Open Innovation Platforms. The case shows how China’s government uses a unique policy strategy that incorporates a range of governance mechanisms that affect private sector platform governance and AI innovation through the orchestration of open data and open-source software.

The article departs from the observation that the role of digital platforms in the economy has grown substantially over the last decade. Government interest in controlling digital information infrastructures, such as hardware and software components, has also increased. At the same time, few studies have engaged with the platform literature to understand some of the mechanisms that governments have at their disposal to enable or constrain platforms. The mechanisms governments have at their disposal to affect digital innovation, competition, and sovereignty are often distant from those assessed in studies on platforms governance of digital resources.

Based on these observations, the research question of this article asks: What mechanisms can governments use to affect the boundary resources of innovation platforms, and how do these influence platform governance? Information systems theory concerning platform architecture, ecosystems, and governance is adopted to address the research question. Applying this theoretical perspective has several strengths. First, it sheds new light on the role of varying actors across public and private settings and how these jointly impact platform innovation and governance. Second, it explains the distinct mechanisms, i.e., the rules and tools used by public and private actors, and how these enable or constrain platform generativity. Finally, it enables a more granular assessment of differing national and strategic approaches to platform innovation and governance. The article adopts an explorative case analysis of China's National Open Innovation Platforms for AI, which is considered an appropriate method for studying new and emerging phenomena (Eisenhardt, 1989; Yin, 2003).

The article locates several government mechanisms that can be used to inform private sector platform boundaries. The article extends information systems theory on boundary resources by elaborating on a range of governance mechanisms that may be used to affect the generativity of platforms in areas such as data availability, software accessibility, and digital interoperability. The article clarifies how governments can utilize mechanisms to orchestrate the platform economy, which has implications for policymakers and managers.

The relevance of this article in the context of the overall research puzzle is to provide context on the governance of AI ecosystems in China, which is different from AI governance and state-market relations in the United States. Empirical context and clarity on China's approach to AI governance are obtained, which contributes to answering the main research question of the thesis.

5.4. Article IV

The fourth article, “US–China Tech Competition and the Willingness to Share Personal Data in China,” examines how great power competition between the US and China influences data privacy preferences. Data privacy policies establish boundaries for how firms and governments collect and process individuals’ data. Therefore, data privacy policies are crucial in deterring firms' ease of access to and costs associated with handling data, which has implications for AI innovation. While the European Union’s GDPR has set a precedent for how data should be handled, it is clear that governments can design unique data privacy regimes based on different conceptualizations of the optimal distribution between data and privacy.

The article departs from the observation that data is fundamental for the development of digital technologies and artificial intelligence and that China’s central government is in a unique position to influence public opinion on data collection and data privacy practices (Chen & Xu, 2017; King, Pan, & Roberts, 2017). As tech firms become global, the tension between data collection and data privacy has moved beyond consumers and firms within a country towards tensions between nation-states based on varying ideas of digital sovereignty. At the same time, economic and technology-related disputes between the United States and China have spiraled into a technology war, referred to as the “great tech decoupling” (Johnson & Gramer, 2020).

Based on these observations, the research question of this article asks: how does technological competition affect data privacy preferences? The article examines how technological competition affects people’s sense of nationalism and their perception of data privacy. The article reports the results of a survey of 3,146 individuals in a representative sample of China’s internet population. Through a randomized online experiment, respondents’ willingness to share data with companies and the central and local governments is assessed.

The article finds that invoking nationalistic sentiment increases people’s willingness to share their data with private companies. In other words, reminding people of the technology race with the US invokes nationalistic sentiment, which increases respondents’ willingness to share data with Chinese companies and their trust in these to handle their data responsibly. Respondents also believe that access to personal data will help Chinese companies to take the lead in the global competition to develop AI technologies. When people are reminded of the US–China tech competition, they also decrease the valuation they place on their facial image data, which makes data a cheaper input factor in AI innovation.

The relevance of this article in the context of the overall research puzzle is its assessment of China's approach to AI governance and data governance. In terms of technological governance, a distinct model of digital authoritarianism is emerging from China (Khalil, 2020). By assessing public opinion on data privacy, the article engages with how competition between the US and China possibly influences public sentiment towards data collection and data privacy practices, which constitutes an essential element of AI governance. Therefore, the findings have implications in the context of emerging and converging data privacy regimes and how these are constructed at the international level.

6. CONCLUSION

This thesis investigates how artificial intelligence is governed in the United States and China and combines the gathered experiences from Articles I–IV to assess the broader implications for the governance of AI. In doing so, this thesis advances the conceptualization of AI governance as a field. It re-situates AI governance in an international framework where it is critical to account for national differences, industrial idiosyncrasies, and technical specificities across countries and regions. This final chapter summarizes the key findings concerning the main research question, presents the scientific and practical implications, and discusses future research avenues.

6.1. Key findings

The first Sub-RQ, "how do different kinds of AI-related regulation – or even the prospect of regulation – affect firm behavior, including firm responses to ethical concerns?" was addressed in Article I. Overall, four key findings emerged from the article. First, exposure to information about AI regulation increases the importance managers assign to various ethical issues when adopting AI. Second, managers' increased awareness of ethical issues is generally offset by a decrease in manager intent to adopt AI technologies. Third, exposure to information about AI regulation significantly increases expenditure intent for developing AI strategy, which includes a budget for assessing ethical impact and internal strategy development. Fourth, when comparing the responses of several industries (healthcare, automotive, retail), heterogeneity in the results indicates that regulation information is likely to affect industries differently due to industry-specific characteristics. In summary, AI regulation could slow innovation by lowering AI adoption while fostering new solutions that improve consumer welfare through heightened attention to AI-related ethical issues.

The second Sub-RQ, "how are AI-induced fields subject to varying degrees of legitimacy and institutionalization processes?" is answered in Article II. Three key findings emerged from the article. First, the autonomy of AI agents can affect existing power dependencies, which may cause friction when AI agents gain the authority to make decisions that affect human and organizational actors on the basis of analyses that are difficult for humans to replicate. This transfer of autonomy is contingent on systemic trust, which is based on conceptualizations of technological maturity and expectations that machine-augmented perceptions operate at or above human cognitive levels. Issues with field-level legitimization and nascent processes of institutionalization are likely to arise when emerging systems are inaccurate, unsafe, or non-transparent, as well as when institutional logics are incoherent, all of which erode trust across applications and cause AI fields to fragment. Second, an incentive for data centralization is inherent in most digital infrastructures and forms of organization. A lack of transparency during data collection leaves people unaware of where and how their data and information is being used, stored, and traded and for what purposes. Therefore, the legitimacy of AI agents is highly contingent on the collection, use, and ownership of data, which can be a source of dispute that causes field-level disintegration. Third, public and private forms of institutional infrastructure must be elaborated before externalities start to erode systemic and institutional levels of trust, which causes a field to grow fragmented. Public pushback forces central actors from the private sector to engage in new self-regulation measures, which in some cases means scaling back digital infrastructure until new legislative provisions fill a policy vacuum. In summary, AI governance will improve if more adaptive institutional infrastructure emerges in forms of organization that can consider how AI systems influence and shape existing practices and forms of behavior.

The third Sub-RQ, "What mechanisms can governments use to affect the boundary resources of innovation platforms, and how do these influence platform governance?" is answered in Article III. A case study from China was chosen as China's government has broader scope to act and orchestrate the digital economy than most governments. Three key findings emerged from the article. First, the article details how several government mechanisms can be utilized to affect the governance and generativity of innovation platforms, i.e., their boundary resources. Second, government mechanisms can be used to influence how platforms organize varying aspects of data governance (i.e., availability), AI open-source software governance (i.e., accessibility), as well as integration (i.e., interoperability), which has implications for AI innovation. Third, the notion of hybrid platforms is adopted to clarify a new organizational structure conducive to public-private AI innovation and governance. In summary, a range of government mechanisms, some of which are unique to the case of China, can be used to enable or constrain AI platforms; this finding has consequences for the orchestration of domestic AI innovation and international forms of digital integration.

The fourth Sub-RQ, "how does technological competition affect data privacy preferences?" is answered in Article IV. Three key findings emerge from the article. First, reminding Chinese citizens of the technology race with the United States invokes nationalistic sentiment, which increases willingness to share data with Chinese companies and their trust in these to handle their data responsibly. Second, when people are reminded of the US–China technology competition, they also decrease the valuation they place on their facial image data, which makes data a cheaper input factor in terms of AI innovation. Third, males are more willing to share their data with private companies and the central and local governments. In summary, technology competition on AI between China and the United States may shift nationalistic sentiment, impacting data privacy preferences and making people more willing to share their data with companies and the government.

This leads us to the main research question guiding this thesis: "how is artificial intelligence governed in the United States and China, and what are some of the broader implications for the governance of AI?" The question is answered in terms of how the US governs AI and how China does so, and, most importantly, some implications for the governance of AI are derived. The conceptual framework developed in Section 3.2 is used to compare the approaches to AI governance by the US and China. Special attention is placed on AI innovation, adoption, regulation, and closing considerations regarding differing socio-technical values.

6.1.1. AI Governance in the United States

The United States approach to AI governance (Articles I & II) is summarized as fragmented and overly reliant on forms of self-regulation (Cath, et al., 2018). In terms of AI innovation, policymakers have focused on creating an environment free of heavy regulation. Maintaining US leadership in AI has been associated with removing "overly burdensome" regulations that otherwise create "barriers to innovation" (The White House, 2018). Government regulation has been proclaimed to hamper innovation and American competitiveness in policy plans such as the "Guidance for Regulation of Artificial Intelligence Applications" and NIST standards report on "U.S. Leadership in AI" (NIST, 2019; Vought, 2020). Government support measures include new industrial policies such as the CHIPS for America Act, which works to return the manufacturing of semiconductors to American soil (Kharpal, 2021). These policies are linked to matters of digital sovereignty and demarcate a shift in US industrial policy spurred by concerns over retaining American technological leadership in the face of growing competition from China. While new industrial policies have been embraced, American policymakers have stressed the importance of continued reliance on market-based innovation as the best strategy for staying ahead. Heightened geopolitical competition on AI development between the US and China could cause US policymakers to become less inclined to regulate AI. While China and the European Union are devising and implementing new rules to curb AI-induced externalities, US policymakers seem to be stuck by fears over restraining AI innovation.

In terms of AI adoption, the use of AI in public sector domains has witnessed pushback by varying actors, including civil society organizations, think tanks, and companies. Several companies have established moratoriums on the use of facial recognition technologies for public sector law enforcement until more explicit regulations emerge. These developments are symptomatic of America's current approach to AI governance, which is fragmented and contested among varying actors, while policymakers have taken a nominal approach to formulating new rules. These developments can be contrasted with China, where the state has become a heavy adopter of FRT, while civil society organizations play a minuscule role due to their limited capability to voice dissent and push back on public sector use and AI adoption.

In terms of AI regulation, the United States takes a different approach than China and the European Union. While the US Algorithmic Accountability Act was reintroduced in 2022, the Act has a long way to catch up with China's regulation of recommender engines, which went into effect in March 2022, as well as with the European Union's AI Act, which is scheduled to go into effect in 2023. The US cautious approach to AI regulation has made self-regulation the de facto mode of AI governance. However, AI regulation has started to gain some traction at the sectoral level. Sector-specific regulations gradually establish a patchwork approach to AI governance that develops incrementally. In data regulation, no national policy on data privacy has been devised. Instead, California's Consumer Privacy Act has become the de jure regulation of data in the United States due to the importance of California's local economy and solid concentration of technology companies in Silicon Valley. Regarding regulation of content and information on online platforms, these continue to be largely protected from legal repercussions due to Section 230, which outlines that liability falls on the individual as the content creator (Citron & Wittes, 2018). The global reach of some platforms (e.g., Facebook, Twitter) and their power to enhance, restrict, or ban people from operating coincide with nascent expectations of what it means to enhance democratic forms of platform oversight, transparency, and control. Algorithms, such as recommender algorithms, which rank, organize, and determine the visibility of certain information, also produce socio-technical outcomes that remain subject to vague forms of transparency. Like the too-big-to-fail notion in the financial industry, platforms' use of AI and orchestration of information have morphed into systemically important global information infrastructures. As these infrastructures have the potential to "fail" in ways that create externalities, they must be endowed with rigid forms of transparency, oversight, and control in ways that are yet to be devised.

In terms of values, the growing importance and focus of "American values" in AI governance gives rise to an ideological mechanism that justifies America's current approach to AI regulation while stressing a human rights-centered approach to AI governance. In terms of AI governance, the United States has positioned itself as a "champion and defender of core values of freedom and human rights" (White House, 2021b). American values, however, are also used to define geopolitical opposition to China, especially in the area of AI adoption and development. The National Security Commission on Artificial Intelligence (NSCAI) Final Report, published in March of 2021, defines AI competition as a value-based competition where China should be viewed as a direct competitor (NSCAI, 2021). The NSCAI recommends creating "choke points" that curtail China's progress (Kharpal, 2021; Nellis, 2021). These developments entail that international forms of AI governance are becoming embroiled in great power competition between the US and China. The innovation and adoption of AI is beginning to turn into a strategic arena of competition that endangers existing forms of collaboration. In September 2021, the US–EU Trade and Technology Council (TTC) stressed that the US and EU are opposed to uses of AI that do not respect human rights requirements, which include "rights-violating systems of social scoring" (TTC, 2021). The TTC has also clarified that the US and EU "have significant concerns that authoritarian governments are piloting social scoring systems with an aim to implement social control at scale" (TTC, 2021). China's social credit system is the implicit focus of the statement and signals that the approaches to AI governance by the US/EU and China are growing incompatible due to departing ideological and socio-technical considerations of what constitutes a good AI society.

6.1.2. AI Governance in China

China's approach to AI governance (Articles III & IV) is summarized as rapidly accumulating and subject to development and guidance based on centrally formulated plans and policies. In terms of AI innovation, policymakers have begun to strengthen partnerships with private-sector technology and AI companies, which establishes a new approach to industrial policymaking and guidance of China’s digital economy. Several leading AI companies have been elevated to national champions or National AI Team members (Jing & Dai, 2017) responsible for strengthening China’s AI ecosystem. However, technology companies such as Baidu, Alibaba, and Tencent are not traditional national champions but are private platform companies that have grown into the strategic heights of China’s centrally planned economy. Due to the importance of these companies for the future of China’s socio-economic development, China’s central government has started to implement new mechanisms to bring them closer to the CCP's strategic objectives and visions for the future of Chinese society. Mechanisms include mixed-ownership reforms (Ingeman, 2021), taking minority stakes and controlling board seats (Y. Yang & Goh, 2021), and prohibiting sectors that do not align with the long-term priorities of the Party (Koty, 2021). While the US has started to implement industrial policy plans, such as the CHIPS Act, industrial policy plans and government-guided investment funds are far more explicit in China, as outlined in Section 2.3.

In terms of AI adoption, state-led procurement of AI technologies has been an essential factor in turning China into a world leader in some areas of AI, such as facial recognition technologies (Beraja, et al., 2021). China’s central government has implemented FRT on a massive scale and is experimenting with new forms of AI-augmented social governance in areas such as its social credit system (Cao, et al., 2021). As mentioned, both forms of AI usage are opposed by the US and the Europan Union, on ethical grounds.

In terms of AI regulation, China’s implementation of the AI Development Plan has been an essential step in transforming the country from having a lax governance regime towards establishing far stricter enforcement mechanisms associated with data and algorithmic oversight. For example, China’s regulation of recommender engines, which went into effect in March 2022, is the first of its kind globally. The regulation goes further than focusing strictly on content moderation by requiring private companies to actively promote “positive” information that follows the Party line. This includes promoting content that is considered patriotic, family-friendly, and that focuses on positive stories in line with the core socialist values of the CCP (Huld, 2022). Content such as extravagance, over-consumption, anti-social behavior, excessive adoration of celebrity idols, and political activism are subject to stricter scrutiny and regulatory intervention (Huld, 2022). China takes a different approach to AI and content-related regulation than the United States and the EU. It places the responsibility of moderating, prohibiting, and promoting certain content on private sector companies, and steps in directly if the companies fail to meet the government’s expectations. In the US, the regulation of content and information is, as mentioned, governed by Section 230, which means that liability falls on the individual and not the platform. However, China's regulation of recommender engines could be complicated for companies to implement and for regulators to enforce due to arbitrary interpretations of the law. For companies that operate in China and internationally, the regulation could result in further decoupling of domestic and international operations in order to comply with divergent AI governance and regulatory regimes.

In terms of values, AI governance in China is embodied by Chinese characteristics that shape AI-related socio-economic practices. China’s AIDP and most recent Five-Year Plan establishes that the goal of technological development is to promote social stability (State Council, 2017; Xinhua News Agency, 2021). The AIDP has also stated that AI serves as a social control tool in the “great rejuvenation of the Chinese nation” (State Council, 2017), implicating that a balance between social control and innovation should be maintained (Hine & Floridi, 2022). This includes relying on the market to allocate resources and drive efficiencies while depending on the central government to direct the economy through public planning and industrial guidance (State Council, 2017). China’s model of fragmented authoritarianism, reliance on state guidance, enlisting of public and private actors, and more stringent control of the flow of information are in combination, argued to embody an approach to AI governance that is radically different from that of the United States. The meaning of social control and maintaining “harmony and stability,” e.g., through data points on individual behavior, makes China’s AI governance regime depart from similar approaches and characteristics in the United States and Europe. The role of the central government in China is viewed as an orchestrator of industrial scale innovation as well as online content and information that underlines China’s unique approach to AI governance. China is considered as pioneering a distinctive paradigm of AI governance that hybridizes elements of industrial policy with new forms of governing data and artificial intelligence at the intersection of public and private interests and forms of organization. In China’s emergent paradigm of AI governance, the role of the private sector is changing as digital companies are compelled to cooperate with policymakers in order to align with the CCP’s vision of a harmonious society. During this process, the role of private-sector AI companies is changing as these are expected to play a critical function in cooperating with public sector agencies in areas from

R&D to standards and regulation of online content. The responsibility of private-sector technology companies can therefore be viewed as slowly transforming to better align with the CCPs vision for the future of China. In the United States and Europe, the extent to which technology companies are expected to exhibit stronger democratic practices and forms of oversight and control remains to be seen.

6.1.3. Implications for the governance of AI

Based on the findings associated with the United States and China's respective approaches to AI governance, several implications for the governance of AI are deliberated. Varying forms of AI adoption and wider diffusion of, e.g., facial recognition technology and AI in social credit systems, are starting to give rise to disparate AI governance regimes at the international level. This means that varying approaches to AI governance (AI innovation and regulation) will be based on diverse logics and assumptions about what constitutes appropriate forms of AI innovation and application. At present, value-based ideological ruptures have started to emerge across the US/EU and China, which could have consequences for the governance of artificial intelligence.

Current trends towards technological decoupling and digital sovereignty are symptomatic of a broader entrenchment of strategic digital capabilities and resources flowing in the direction of nation-states. Control and self-sufficiency over strategic resources such as AI, data, and semiconductors are currently of the highest importance for national leaders. These developments could foster an era of heightened international tension, distrust, and competition in the digital space. As technological decoupling deepens, China will endure its move towards achieving self-sufficiency and technological independence, especially from US-originated goods. US actions, such as placing Chinese companies on its entity list and restricting them from obtaining American technology, further legitimize and incentivize China's push to obtain self-sufficiency. While the intentions may be linked to slowing the rise of China, the actions also portray that China cannot rely on strategic technological inputs from the US as a part of its economic growth strategy. Arguably, the erratic nature and politicization of strategic supply chains foster strong incentives for achieving self-sufficiency in a range of digital infrastructures. Unless reversed, these developments privilege perspectives that view AI-related technological development as a zero-sum competition.

At present, the United States and China pursue very different approaches to AI innovation, where one is based on market-driven incentives while the other is influenced by top-level guidance. For the US, the big question is whether its continued reliance on market-based forms of planning and innovation will be enough to counter China's rapid acceleration in AI development. For China, the big questions are whether continued government intervention in the digital sphere will deter private investment and innovation, and whether private sector opportunities will cede to less efficient state-run firms over the medium to long term.

Based on an integration of the combined findings of this thesis, along with a careful extrapolation of current events, an argument is made that two departing forms of AI governance potentially could emerge. In the US, AI governance is ideologically anchored in a free-market liberal democracy; in China, AI governance is ideologically anchored in a state-capitalist and communist model of socio-economic development. The underlying values and ideologies of each socio-economic regime are already spilling over into varying conceptualizations of what a "good" AI-driven society looks like (Cath, et al., 2018; Hine & Floridi, 2022; Roberts, Cowls, Hine, et al., 2021; Roberts, et al., 2020). This implies a sense of path dependency, meaning that what is done now will have consequences for future choices. This is especially true in terms of how AI is used to govern societies, which could have path-departing implications.

The prospects for finding a middle ground to AI governance in the European Union's proposed approach to AI regulation are considered implausible. Like the US, the EU's approach to AI governance is based on conceptualizations of human rights, which are operationalized to condemn AI usage for social monitoring and control purposes.

At a technical level, however, international alignment of best practices could potentially be found in the application of common governing mechanisms, such as audit-based frameworks or how recommender systems are governed, for example, which establish a foundation for international harmonization of practices. These developments are of great importance for long-term issues in AI governance associated with AI alignment and the advent of AGI. Therefore, how AI governance is aligned at the international level could prove to be one of the greatest challenges for the 21st century.

6.2. Scientific implications

This dissertation makes specific contributions to the literature on platform- and technology-related governance and regulation, rooted in information systems, institutional theory, and political economy. These can be divided into theoretical/conceptual, methodological, and empirical contributions across the four articles, as shown in Table 10. While the contributions were introduced in Section 1.3, this section advances a discussion of the novelty of the core contributions.

First, this thesis makes a theoretical contribution that advances the literature on platform governance at the organizational level. Doing so contributes to elaborating on information systems theory that surrounds platform governance. Existing platform theory on boundary resources is extended by clarifying contextual factors as a range of concrete government mechanisms used in the tuning of platforms boundary resources (Bonina & Eaton 2020; Eaton, et al., 2015; Ghazawneh and Henfridsson 2010, 2013). Government mechanisms are located in areas that affect how technical resources are generated and distributed on innovation platforms. This includes affecting data availability, software accessibility, and infrastructural interoperability. Government mechanisms for tuning platform boundary resources have theoretical implications for how governments seek to affect measures of AI innovation while adopting a platform induced way of thinking and organization (Brown, et al., 2017; Cordella & Paletti, 2019; Ju, et al., 2019; Klievink, et al., 2017; Zhao & Fan, 2018). In delineating new and existing government mechanisms, this thesis contributes to establishing a research agenda around the emergent ways governments seek to structure and orchestrate the platform economy. Doing so contributes to reorienting the platform literature towards how resourcing tools and securing rules are shaped by the interplay of public and private governance mechanisms (Cordella & Paletti, 2019; Gorwa, 2019; Raunio, et al., 2018). Conceptual contributions are also made regarding platform architecture and digital infrastructure by elaborating on hybrid platforms as an important structure for affecting AI-induced generativity (Constantinides, et al., 2018; Klievink, et al., 2016; Tilson, et al., 2010). Hybrid platforms also have important implications for novel governance mechanisms such as AI standards, which are shaped at the intersection of public and private collaboration and forms of organization. Hybrid platforms are consequently found to be a critical organizational mechanism for governing AI technologies in new ways at the intersection of public and private interests.

Second, this thesis makes a conceptual contribution by advancing a novel framework for analyzing AI-induced socio-technical legitimacy and field change. In outlining the framework, the thesis advances information systems theory by adding the institutional perspective to understand the innovation, adoption, and diffusion of AI technologies as an interconnected process that moves across the technical, organizational, and institutional levels. Clarity is gained in assessing how AI technologies move within and between fields, which is interpreted through a technology's elaboration of digital- and institutional infrastructure (Hinings, et al., 2017; Hinings, et al., 2018). The notion of AI-induced legitimacy associated with digital infrastructure as elaborated through three new constructs – AI-based technological maturity, data sensitivity, and AI autonomy – contributes to information systems theory (Henfridsson & Bygstad, 2013; Tilson, et al., 2010). The notion of AI-induced legitimacy associated with institutional infrastructure, elaborated through a more precise identification of the many ways in which AI technologies have the ability to act on and interact with their environments, contributes to informing institutional theory building on the area (Powell, et al., 2017).

Third, an empirical contribution in this thesis advances the literature on technology-related governance and regulation. The empirical contribution informs the theoretical relationship between regulation and innovation, with specific reference to the particularities of AI technologies. A contribution is made by arguing that legislative pressure challenges present-biased managerial preferences, which causes additional consideration to be placed on developing and implementing solutions that are more ethically oriented across the technical, organizational, and institutional levels (Ambec & Barla, 2006). The thesis further argues that ethics-related domains that are harder to quantify and measure (e.g., transparency and explainability) also could be more challenging for managers and organizations to sufficiently respond to. For example, for areas of algorithmic bias, these can be linked to individual and value-based judgments that need to be configured at several distinct levels of technology and organization pre-and post-implementation. This makes it difficult for managers to devise all-encompassing ethical solutions that will have thoughtful and equitable impacts across all development processes and socio-technical levels of implementation. When regulation increases the salience of specific issues, a need for managers and engineers is created where these must ensure that the functional aspects of a model (i.e., accuracy, data, performance, etc.) are soundly established through organizational procedures and technical mechanisms such as certification, testing, and auditing, as well as through the elaboration of technological standards (Mittelstadt, et al. 2016; Nuno, Gomes, & Kontschieder 2021). Based on these considerations, this thesis contributes by stressing the need for regulators to engage in the development of legislation that clarifies new and expected areas of AI-related compliance. As managers embrace associated actionable mechanisms that ensure greater algorithmic oversight, present-biased managerial preferences may be reversed and, as a result, more ethically oriented AI solutions may be attained.

Fourth, this thesis makes theoretical and empirical contributions to the literature surrounding great power tech competition at the institutional level. Empirically, this thesis clarifies how great power tech competition between the United States and China can raise individuals' sense of nationalism, shifting their willingness to share data with companies and the government. As ideas of digital sovereignty gain in popularity, tech-induced forms of nationalism could have implications for AI governance. The theoretical implications are that tech companies increasingly are becoming politically loaded enterprises, which to varying degrees have the power to influence digital innovation and digital infrastructures in ways that enhance or diminish individual and collective discourses while affecting socio-political preferences. Likewise, large technology enterprises can choose how they interact with local conditions on global markets, e.g., on the spectrum between democratic and authoritarian institutions. This thesis clarifies some of the budding relationships between nationalism, tech competition, surveillance, and data privacy, which have implications for structuring disparate AI governance regimes. Tech-induced forms of nationalism may, for example, be used to favor continued government centralization of data, which is an important driver for AI innovation as well as an essential element in AI governance. These findings consequently underscore the importance of ensuring that democratic forms of oversight are built into all processes surrounding AI governance.

Table 10. Scientific contributions

Type	Contribution	Article
Theoretical/conceptual	i. Extending theory on technology-related regulation by clarifying that tradeoffs between regulation and innovation could be offset by more ethically motivated forms of technological development.	I
	ii. Proposing a novel conceptual framework for analyzing AI-induced field-level change, as well as processes of AI legitimacy and institutionalization	II
	iii. Extending existing theory on platform governance of boundary resources through the addition of several government	III

		mechanisms that can be used to affect platforms resourcing tools and securing rules	
	iv.	Clarification of the conceptual links between great power tech competition, nationalism, and data privacy, and how they inform certain aspects of disparate AI governance regimes	IV
Methodological	i.	Adopting online large-scale survey experiments (AB testing) to measure and inform policy-related aspects of AI governance – based on managerial and individual perceptions and preferences	I, IV
Empirical	i.	Providing empirical clarity on some of the tradeoffs involved between AI regulation and innovation	I
	ii.	Providing empirical insight on the mechanisms that governments can use to impact and affect platform governance and innovation	III
	iii.	Providing empirical evidence on how tech competition potentially affects nationalistic sentiment and shifts data privacy preferences	IV

6.3. Policy and managerial implications

The findings of this thesis offer several potential implications for policymakers and managers. For policymakers, implications relate to the design and analysis of AI-related policies and new forms of regulation and how these impact digital and AI-related innovation. For instance, in terms of platform governance, it is vital that policymakers understand the full range of tools at their disposal and how these interact to shape AI and other forms of digital innovation. Policymakers are encouraged to deploy mechanisms that target data availability, software accessibility, and interoperability of digital ecosystems. Mechanisms that target anti-competitive behavior are also encouraged, without relying on overly discriminatory measures to enhance digital sovereignty at the cost of international forms of digital integration and cooperation.

In terms of AI regulation, four separate recommendations are extended. First, although AI regulation conceivably could slow innovation or reduce competition by lowering AI adoption, instituting regulation at the early stages of AI diffusion could improve overall consumer welfare through increased safety and better addressing bias and discrimination issues. For policymakers, it is, therefore, necessary to distinguish between innovation at the level of the firm consuming AI technology and at the level of the firm producing such technology. Even if regulation slows innovation in the former, it can still spur innovation in the latter. Second, policymakers are encouraged to take a meticulous approach to AI regulation to sufficiently account for diverse technology and industry-specific use cases. This includes taking sector-specific considerations into account when devising novel regulatory solutions. Third, policymakers should consider the full range of regulatory tools, including existing legal requirements, soft-law governance of AI, and the costs and benefits of relying on industry standards. The interplay between new and existing forms of legislation and regulation must be considered at a high level of complementarity and possible interactions when seeking to devise the most optimal policy environments, i.e., environments that minimize externalities and maximize innovation. Fourth, a continued lack of transparency in markets for data as well as during data-collection and data-processing, arguably, leaves large segments of the population unaware of where and how their data and information is being used, stored, and traded, as well as for what purposes (Mittelstadt, et al., 2016). Therefore, policymakers are encouraged to continue developing data-related policies that enable greater transparency and enhanced forms of user-based interactivity that, over time, may create a heightened sense of individual ownership and control. These developments would contribute to smoothening existing information asymmetries between data users (companies) and data producers (individuals) (Tene & Polonetsky, 2013). In terms of AI, empowering users to better understand how AI agents use varying data points to structure their queries and make predictions would similarly benefit users by flattening information- and power asymmetries.

Based on the collective findings of this thesis, policymakers are encouraged to experiment with new forms of governance that are more efficient in addressing the emergent characteristics of a GPT, such as AI. This includes experimentation with new institutional infrastructures and designs that, over time, can result in more adaptive forms of organization and regulation (Taeihagh, et al., 2021; Wang, et al., 2018). Proposed measures of institutional adaptation to mitigate AI-induced externalities include enhanced measures of algorithmic auditing carried out by companies (Zarsky, 2016), third-party auditors (Clark & Hadfield, 2019), or external regulators (Tutt, 2016). New forms of auditing can create procedural records of complex algorithmic decisions that contribute to tracking inaccurate predictions while detecting flawed or discriminatory algorithms and biases and harmful practices (Mittelstadt, et al., 2016). Pilot studies of AI applications in different sectors or regulatory sandboxes (Kop, 2021) that target areas such as autonomous driving, drug discovery processes, and online advertising, are suggested as essential intermediary steps for understanding the implications related to more widespread use of AI technologies. Regulatory sandboxes or pilot studies could involve novel public-private partnerships to examine how liability can be shared among developers, insurers, and the government, as well as consumers (Kalra & Paddock 2016).

For managers, three specific recommendations emerge from this thesis. First, managers of international platforms ought to pay considerable attention to new and incoming policy mechanisms that can be used to enable or constrain existing resourcing tools and securing rules. Given the rise of interest in reinforcing varying forms of digital sovereignty, managers ought to pay special attention to local or regional, i.e., geographical platform requirements, e.g., data use, access, openness, interoperability, portability, control, and so on. The kind of services offered on international innovation platforms and how these stay compliant with legal requirements that vary across countries and constituencies is a rising case in point.

Second, managers are encouraged to ensure that the functional aspects of an AI model, i.e., accuracy, data, performance, etc., are soundly established through mechanisms such as certification, testing, auditing, as well as through the elaboration of technological standards (Mittelstadt, et al., 2016). Recommendations include documenting the lineage of AI products or services and their behaviors during operation (Madzou & Firth-Butterfield, 2020). Documentation could include information about the purpose of the product, the datasets used for training and while running the application, and ethics-oriented results on safety and fairness. The use of documentary models is encouraged as these contribute to limiting externalities that otherwise could have costly consequences for individuals and firms (e.g., in terms of social or reputational damage). Documentary models can also help managers prepare for new and incoming regulations and may help engineers better evaluate AI systems and data across training, testing, and post-implementation scenarios. Several workable documentary models such as Google's model cards and End-to-End Framework for Internal Algorithmic Auditing, IBM's AI Factsheets, Microsoft's datasheets for datasets (Gebru, et al., 2020), Meta's System Cards, as well as "data statements" (Bender & Friedman, 2018) and "nutrition labels for data sets" (Stoyanovich & Howe, 2019) already exists, while managers and engineers are encouraged to adopt new procedural practices that document all stages of the AI lifecycle.[16]

Third, managers are encouraged to work towards establishing cross-functional teams consisting of risk and compliance officers, product managers, and data scientists who are enabled to perform

[16] The AI life cycle includes all stages from data collection, data analysis, feature engineering, selection of algorithm, model building, tuning, testing, deployment, management, monitoring and feedback loops for continuous improvement.

internal audits to assess ongoing compliance with existing and emerging regulatory demands. For businesses that develop or deploy AI products or services, a new set of managerial standards and practices that details AI liability under varying circumstances and ethical dimensions must be embraced, even before these are regulatory prescribed. As many of these practices are yet to emerge, more robust internal audits, as well as third-party examinations, would provide more information for managers, which could reduce managerial uncertainty and aid the development of AI products and services that are subject to higher ethical as well as legal and policy standards. As policymakers continue to grapple with the best way forward in terms of regulation, managers, and businesses that have developed standardized forms of internal algorithmic assessment are expected to be better equipped to handle any incoming regulations.

6.4. Concluding remarks and future research

The underlying motivation of this dissertation was to investigate the United States and China's respective approaches to AI governance while outlining some of the implications for the future of the field. In answering the main research question, this thesis has contributed to the literature on platform- and technology-related governance and regulation, as embedded in information systems, institutional theory, and political economy. The combined findings have revealed that disparate approaches to AI governance are likely to have consequences for the international alignment of best practices in the years to come.

By drawing on the individual cases of AI governance in the United States and China, broader and more profound characteristics have emerged. At present, the US and China's national differences and industrial idiosyncrasies point towards the emergence of incongruent long-term approaches to AI governance. The current standpoints on AI innovation and AI regulation by the United States and China are informed by value-based socio-economic structures that construe path-departing conceptualizations of what constitutes appropriate use of AI technologies. When held together with recent developments in digital sovereignty and technological decoupling, the findings of this thesis point to a latent infliction point of contrasting approaches to innovation, adoption, and regulation of AI systems and technologies. Over time, these approaches could give rise to different AI-powered socio-economic forms of organization and visions of national AI-powered orchestration of the civil sphere. While this extrapolated scenario is speculative at best, it is equally plausible that mitigation of externalities and alignment of best practices can be secured in new and AI-specific fora's at the international level.[17]

The combined findings of this thesis open several avenues for future research. First, in terms of AI innovation, the relationship between data and centralization of compute needs to be understood at a more granular level in terms of associated impacts and long-term consequences for innovation. At present, large hyperscalers (e.g., Google, Baidu, Amazon, Alibaba, Microsoft, Huawei) operate at a scale of centralization of data and compute that enables these to engage in varieties of AI innovation and model development that may be unfeasible or out of reach for many SMEs due to resource constraints. The emergence of national science clouds could be one solution that levels the field of AI innovation and democratizes access to strategic digital resources.

Second, the concentration of AI-related capabilities also entails a geographical dimension. Countries or regions such as the United States, China, and Europe have an outsized gravitational pull that potentially sets these regions apart from national technological capabilities developed elsewhere. The lowest value-added processes of the AI value chain, such as data labeling, are already being outsourced to developing countries such as India, Vietnam, and the Philippines, where salaries are comparatively lower. These developments underscore the need to understand dependencies associated with the AI value chain at greater depths internationally. This includes a more sensitive approach to interpreting how varying cultures, values, and ideologies influence and accentuate different ethical and philosophical concerns related to thoughtful and equitable development and implementation of AI systems and products. Research is encouraged to move in this direction.

Third, as new forms of AI governance continue to emerge from varying countries around the world, it is important to understand how these interact at the international level. Therefore, more comparative research that studies the varying approaches, positions and interactions of the EU, the US, China, and other countries is encouraged. This includes a focus on the emergence of AI-specific governance forums at the international level, and an assessment of their possible effects and mechanisms towards harmonizing competing frameworks, standards and approaches.

[17] The author of this thesis is sympathetic towards achieving this latter scenario. Establishing international forms of AI-specific arbitration and multistakeholder engagement, where negative externalities can be mitigated and promising forms of AI governance can be formulated and embraced, is deemed a viable path forward. AI-specific international forums are considered as the best approach to mitigate national differences while assuring that AI alignment is accomplished at the international level.

Fourth, while research on AI regulation is honing in on a set of governing mechanisms and procedures, such as audits and standards as leading tools for conformity assessment, the study of more dynamic and flexible institutional arrangements is needed. This thesis encourages new research to develop tangible solutions for what dynamic institutions and forms of AI regulation could look like in practice. Research aimed at flexible interactions between regulatory structures and AI systems, and forms of organization is therefore encouraged.

Finally, in terms of the governance of digital institutional infrastructures, there is a need to understand how AI empowers new organizational forms and how these give rise to new socio-economic dependencies. Ultimately, what emerges from varying considerations and constellations of AI governance is an expression of a new type of digital institution. The tradeoffs between algorithmic accuracy, transparency, use of data and rights to privacy, explanation, and right of redress remain subject to ongoing forms of mediation concerning concomitant organizational practices that emerge at the intersection of human and machine-based forms of interaction. While these tradeoffs have wide-ranging implications for the kind of digital institutions that are likely to emerge, devising inclusive and reflexive institutional infrastructures that can encompass a wide variety of AI-associated risks remains a crucial area to focus on for years to come. A nascent research agenda is currently forming around studying what a (good) AI-powered society could look like, e.g., in terms of novel, inclusive, equitable, and reflexive digital infrastructures and governing arrangements. This agenda includes further research into the structure of hybrid platform arrangements, the ongoing informatization of human behavior, human-robotic coexistence (e.g., mixed autonomy vehicles), AI-powered regulation of social behavior, and so on.

One of the core tenets of this thesis is that AI-powered systems are not easily detached from the values that inform their architectures. In some sense, this means that all AI systems essentially are political and value-based constructions, which have the potential to limit or amplify existing structures and biases in society. This thesis has sought to shape and encourage a more nuanced understanding of AI governance through lessons from the United States and China. While AI governance remains in its infancy, the conceptual frameworks that inform the field's nascent contours are slowly coming into focus. This thesis has stressed that it is essential to consider various national, industrial, technical, and value-based scenarios and experiences in this process, as well as how these inform novel governing arrangements.

In order to understand the field of AI governance more holistically, it has become clear that it is of great importance to understand the interactions among the technical, organizational, and institutional levels across processes associated with AI innovation, adoption, diffusion, and regulation. While this thesis has touched on some of the interactive processes and causal mechanisms between the levels, it has by no means been able to provide exhaustive evidence, empirical insight, and theoretical and conceptual clarification of the entirety of the field. Instead, this thesis has contributed to establishing the foundation for an evolving research agenda on AI governance that will continue to grow as AI technologies mature. As mentioned in the introduction, we remain at the very beginning of this process, while artificial intelligence will continue to evolve in ways that are yet to be imagined.

References

Acquisti, A. (2014). *From the Economics of Privacy to the Economics of Big Data*. http://www.heinz.cmu.edu/~acquisti/papers/economics-big-data-acquisti-lane-book.pdf

Acquisti, A., Taylor, C., & Wagman, L. (2016). The economics of privacy. *Journal of Economic Literature*, *54*(2), 442–492. https://doi.org/10.1257/jel.54.2.442

Aghion, P., Jones, B., & Jones, C. (2017). *Artificial Intelligence and Economic Growth*. https://doi.org/10.3386/w23928

Agrawal, A., Gans, J., & Goldfarb, A. (2019). Economic policy for artificial intelligence. *Innovation Policy and the Economy*, *19*(1), 139–159. https://doi.org/10.1086/699935

AI Ethics Impact Group. (2020). From Principles to Practice - An interdisciplinary framework to operationalise AI ethics. *VDE Association for Electrical Electronic & Information Technologies e.V., Bertelsmann Stiftung*, 1–56. https://doi.org/10.11586/2020013

AIOSS. (2018). *AIOSS*. http://www.aioss.cn/list-10.html

Aldrich, H. E., & Fiol, C. M. (1994). Fools Rush in? The Institutional Context of Industry Creation. *Academy of Management Review*, *19*(4), 645–670.

Ambec, S., & Barla, P. (2006). Can Environmental Regulations be Good for Business? An Assessment of the Porter Hypothesis. *Energy Studies Review*, *14*(2), 42–62. https://doi.org/10.15173/esr.v14i2.493

Ambec, S., Cohen, M. A., Elgie, S., & Lanoie, P. (2013). The porter hypothesis at 20: Can environmental regulation enhance innovation and competitiveness? *Review of Environmental Economics and Policy*, *7*(1), 2–22. https://doi.org/10.1093/reep/res016

Anderson, P., & Tushman, M. L. (1990). Technological Discontinuities and Dominant Designs: A Cyclical Model of Technological Change. *Administrative Science Quarterly*. https://doi.org/10.2307/2393511

Aragón-Correa, J. A., Marcus, A. A., & Vogel, D. (2020). The effects of mandatory and voluntary regulatory pressures on firms' environmental strategies: A review and recommendations for future research. *Academy of Management Annals*, *14*(1), 339–365. https://doi.org/10.5465/annals.2018.0014

Assaf, D. (2008). Models of critical information infrastructure protection. *International Journal of Critical Infrastructure Protection*, *1*(C), 6–14. https://doi.org/10.1016/j.ijcip.2008.08.004

Bagozzi, R. P., & Dholakia, U. M. (2006). Open source software user communities: A study of participation in Linux user groups. *Management Science*, *52*(7), 1099–1115. https://doi.org/10.1287/mnsc.1060.0545

Barfield, W., & Pagallo, U. (2018). *Research Handbook on the Law of Artificial Intelligence*. Edward Elgar Publishing.

Bauer, M., Ferracane, M. F., & Marel, E. Van Der. (2016). Tracing the Economic Impact of

Regulations on the Free Flow of Data and Data Localization. *Cigi*, *30*.

Baumol, W. J., & Blackman, S. A. B. (1991). Perfect markets and easy virtue : business ethics and the invisible hand. In *Mitsui lectures in economics*.

Bender, E. M., & Friedman, B. (2018). Data Statements for Natural Language Processing: Toward Mitigating System Bias and Enabling Better Science. *Transactions of the Association for Computational Linguistics*, *6*, 587–604. https://doi.org/10.1162/tacl_a_00041

Beraja, M., Yang, D. Y., & Yuchtman, N. (2021). Data-intensive Innovation and the State : Evidence from AI Firms in China. *NBER Working Paper*. https://doi.org/10.3386/w27723

Berengut, D. (2006). Statistics for Experimenters: Design, Innovation, and Discovery. *The American Statistician*, *60*(4), 341–342. https://doi.org/10.1198/000313006x152991

Berg, B. (2007). *Qualitative Research Methods for the Social Sciences* ((6th ed.)). Pearson Education.

Berry, J. M. (2002). Validity and Reliability Issues In Elite Interviewing. *PS: Political Science and Politics*, 679–682.

Bessen, J. (2018). AI AND JOBS: THE ROLE OF DEMAND. *NBER Working Paper Series*. https://doi.org/10.1590/s1809-98232013000400007

Bhaskar, R. (2008). A realist theory of science. In *A Realist Theory of Science*. Verso (originally published by Harvester Press 1978). https://doi.org/10.4324/9780203090732

Birkinshaw, J., Brannen, M. Y., & Tung, R. L. (2011). From a distance and generalizable to up close and grounded : Reclaiming a place for qualitative methods in international business research. *Journal of International Business Studies*, *42*(5), 573–581. https://doi.org/10.1057/jibs.2011.19

Bommert, B. (2010). The international public management review IPMR : the e-journal of the IPMN. *International Public Management Review*, *11*(1), 15–33.

Bonina, C., & Eaton, B. (2020). Cultivating open government data platform ecosystems through governance: Lessons from Buenos Aires, Mexico City and Montevideo. *Government Information Quarterly*, *37*(3), 101479. https://doi.org/10.1016/j.giq.2020.101479

Bonina, C., Koskinen, K., Eaton, B., & Gawer, A. (2021). Digital platforms for development: Foundations and research agenda. *Information Systems Journal*, *October 2019*, 1–34. https://doi.org/10.1111/isj.12326

Boudreau, K. J., & Hagiu, A. (2009). Platform rules: Multi-sided platforms as regulators. *Platforms, Markets and Innovation*, *November 2008*, 163–191. https://doi.org/10.4337/9781849803311.00014

Bradshaw, B., Celli, R., & Dyer, R. (2020). *China Publishes "Unreliable Entities" Rules Targeting Foreign Enterprises*. *September*. https://www.omm.com/resources/alerts-and-publications/alerts/china-launches-unreliable-entities-list-targeting-foreign-enterprises/#:~:text=The new MOFCOM regulations indicate,normal transactions with%2C or taking

Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies: “Engines of growth?” *Journal of Econometrics*.

Bryman, A. (2016). *Social Research Methods*. Oxford University Press.

Brynjolfsson, E., Collis, A., & Eggers, F. (2019). Using massive online choice experiments to measure changes in well-being. *Proceedings of the National Academy of Sciences of the United States of America*, *116*(15), 7250–7255. https://doi.org/10.1073/pnas.1815663116

Brynjolfsson, E., Rock, D., Syverson, C., Abrams, E., Agrawal, A., Autor, D., Benzell, S., Gans, J., Goldfarb, A., Goolsbee, A., Saint-Jacques, G., Meyer, A., & Tratjenberg, M. (2017). Chapter 2 - Artificial Intelligence and the Modern Productivity Paradox: a Clash of Expectations and Statistics. In *Nber Working Paper Series*. http://www.nber.org/papers/w24001

Buiten, M. C. (2019). Towards intelligent regulation of artificial intelligence. *European Journal of Risk Regulation*, *10*(1), 41–59. https://doi.org/10.1017/err.2019.8

Buolamwini, J., & Gebru, T. (2018). Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classificatio. *Proceedings of Machine Learning Research*, *81*, 1–15. https://doi.org/10.2147/OTT.S126905

Burns, E., & Burke, J. (2021). *What is a neural network? Explanation and examples*. TechTarget. https://searchenterpriseai.techtarget.com/definition/neural-network

CAAI. (2020). *Chinese Association for Artificial Intelligence*. http://www.caai.cn/index.php?s=/home/article/index/id/2.html

CAC. (2021). *Provisions on the Administration of Algorithm Recommendations for Internet Information Services*. *November*. http://www.cac.gov.cn/2022-01/04/c_1642894606364259.htm

CAICT. (2021). *White Paper on Trustworthy Artificial Intelligence*. *July*.

California State Senate. (2018). *ACR-215 23 Asilomar AI Principles*. *215*. http://leginfo.legislature.ca.gov/faces/billPdf.xhtml?bill_id=201720180ACR215&version=20170ACR21597CHP

Campbell, L. (2021). Editorial: Regulating the digital economy. *Journal of Telecommunications and the Digital Economy*, *9*(2), 117–127. https://doi.org/10.18080/JTDE.V9N2.422

Cao, X., Kostka, G., & Xu, X. (2021). Information Asymmetry and Public Support for Social Credit Systems in China ∗. *Journal of Politics*.

Capri, A. (2020). *Techno-nationalism : The US-China tech innovation race New challenges for markets , business and academia*. *August*.

Castro, D., McLaughlin, M., & Chivot, E. (2019). Who Is Winning the AI Race: China The EU Or The United States? *Center for Data Innovation*, *August*. www.technologyreview.com/s/608112/who-is-winning-the-ai-race/

Cath, C., Wachter, S., Mittelstadt, B., Taddeo, M., & Floridi, L. (2018). Artificial Intelligence and the ‘Good Society’: the US, EU, and UK approach. *Science and Engineering Ethics*, *24*(2), 505–528. https://doi.org/10.1007/s11948-017-9901-7

Cave, S., & ÓhÉigeartaigh, S. S. (2018). An AI Race for Strategic Advantage: Rhetoric and Risks. *AIES - AI Ethics and Society*, 36–40.

Ceccagnoli, Forman, Huang, & Wu. (2012). Cocreation of Value in a Platform Ecosystem! The Case of Enterprise Software. *MIS Quarterly*, *36*(1), 263. https://doi.org/10.2307/41410417

Cennamo, C., & Santalo, J. (2013). PLATFORM COMPETITION: STRATEGIC TRADE-OFFS IN PLATFORM MARKETS. *Strategic Management Journal*, *34*, 1331–1350.

Chen, J., & Xu, Y. (2017). Information Manipulation and Reform in Authoritarian Regimes. *Political Science Research and Methods*, *5*(1), 163–178. https://doi.org/10.1017/psrm.2015.21

Chesbrough, H. (2006). *Open Innovation: The New Imperative for Creating and Profiting From Technology*. Harvard Business Press.

Chomanski, B. (2021). The Missing Ingredient in the Case for Regulating Big Tech. *Minds and Machines*, *31*(2), 257–275. https://doi.org/10.1007/s11023-021-09562-x

Chui, M., Kamalnath, V., & McCarthy, B. (2020). *An Executives Guide to AI*. McKinsey.

Citron, D. K., & Wittes, B. (2018). The Problem Isn’t Just Backpage: Revising Section 230 Immunity. *Georgetown Law Technology Review*, *22*, 247–259.

Clark, J., & Hadfield, G. K. (2019). REGULATORY MARKETS FOR AI SAFETY. *Conference Paper at ICLR 2019*.

Coase, R. H. (1960). The Problem of Social Cost. *The Journal of Law and Economics*, *56*(4), 837–877. https://doi.org/10.1002/9780470752135.ch1

H.R. 6395, (2020).

Constantinides, P., Henfridsson, O., & Parker, G. G. (2018). Platforms and infrastructures in the digital age. *Information Systems Research*, *29*(2), 381–400. https://doi.org/10.1287/isre.2018.0794

Cordella, A., & Contini, F. (2012). Socio technical regimes and e-government deployment: The case of the Italian judiciary. *ECIS 2012 - Proceedings of the 20th European Conference on Information Systems*.

Cordella, A., & Paletti, A. (2019). Government as a platform, orchestration, and public value creation: The Italian case. *Government Information Quarterly*, *36*(4), 101409. https://doi.org/10.1016/j.giq.2019.101409

Cowgill, B., & Tucker, C. E. (2019). Economics, Fairness and Algorithmic Bias. *SSRN Electronic Journal*, 1–65. https://doi.org/10.2139/ssrn.3361280

Creswell, J. W. (2003). *Research Design: Qualitative, Quantitative, and Mixed methods*. SAGE.

Creswell, J. W., & Plano Clark, V. L. (2018). *Designing and Conducting Mixed Methods Research*.

SAGE.

Crotty M. (1998). *The foundations of social research: meaning and perspectives in the research process*. SAGE.

Cuéllar, M.-F. (2019). A COMMON LAW FOR THE AGE OF ARTIFICIAL INTELLIGENCE. *Columbia Law Review*.

Curchod, C., Patriotta, G., Cohen, L., & Neysen, N. (2020). Working for an Algorithm: Power Asymmetries and Agency in Online Work Settings. *Administrative Science Quarterly*, *65*(3), 644–676. https://doi.org/10.1177/0001839219867024

Cusumano, M. A., Gawer, A., & Yoffie, D. B. (2019). *The Business of Platforms: Strategy in the Age of Digital Competition, Innovation, and Power*. Harper Business.

Dacin, M. T., Ventresca, M. J., & Beal, B. D. (1999). The embeddedness of organizations: Dialogue & directions. *Journal of Management*, *25*(3), 317–356. https://doi.org/10.1177/014920639902500304

Davenport, T., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. *Future Healthcare Journal*, *6*(2), 94–98.

De Quidt, J., Haushofer, J., & Roth, C. (2018). Measuring and Bounding Experimenter Demand †. *American Economic Review*, *108*(11), 3266–3302.

De Reuver, M., Sørensen, C., & Basole, R. C. (2018). The digital platform: A research agenda. *Journal of Information Technology*, *33*(2), 124–135. https://doi.org/10.1057/s41265-016-0033-3

Deighton, J. A., & Blattberg, R. (1991). Interactive Marketing: Exploiting the age of Addressability. *Sloan Management Review*, *33*(1), 5–14.

Denzin, N. K. (2012). Triangulation 2.0*. *Journal of Mixed Methods Research*, *6*(2), 80–88. https://doi.org/10.1177/1558689812437186

Di Tella, R., & Rodrik, D. (2019). *Labor Market Shocks and the Demand for Trade Protection: Evidence from Online Surveys*.

DiMaggio, P. J., & Powell, W. W. (1983). The Iron Cage Revisited : Institutional Isomorphism and Collective Rationality in Organizational Fields. *American Sociological Review*, *48*(2), 147–160.

Dixon, P. (2013). What Information Do Data Brokers Have on Consumers, and How Do They Use It? *World Privacy Forum*. https://doi.org/10.1142/9789812796165_0001

Dupont, B. Y. A. (2020). New Cold War: De-risking US-China conflict. *Foundation, Hinrich*, *June*.

Eaton, B., Elaluf-Calderwood, S., Sørensen, C., & Yoo, Y. (2015). Distributed tuning of boundary resources: The case of Apple's iOS service system. *MIS Quarterly*, *39*(1), 217–243. https://doi.org/10.25300/MISQ/2015/39.1.10

Economic Information Daily. (2019). *A new generation of artificial intelligence innovation pilot area will be expanded soon* (p. October).

http://www.clii.com.cn/jingjiyunxing/201910/t20191009_3936632.html

Eisenhardt, K. M. (1989). *Building Theories from Case Study Research*. *14*(4), 532–550.

esteramorperez. (2020). How to manage complexity and realize the value of big data. *IBM Blog*. https://www.ibm.com/blogs/services/2020/05/28/how-to-manage-complexity-and-realize-the-value-of-big-data/

FDA. (2021). *Artificial Intelligence/Machine Learning (AI/ML)-Based Software as a Medical Device (SaMD) Action Plan: Vol. January*. https://doi.org/10.22270/ijdra.v4i2.181

Federal Register. (2019). Federal Register. *Federal Register*, *84*(196). https://doi.org/10.1016/0196-335x(80)90058-8

FLI. (2017). *Asilomar AI Principles*. https://futureoflife.org/ai-principles/

Floridi, L. (2014). *The Fourth Revolution: How the infosphere is reshaping human reality*. Oxford University Press.

Floridi, L. (2020). The Fight for Digital Sovereignty: What It Is, and Why It Matters, Especially for the EU. *Philosophy and Technology*, *33*(3), 369–378. https://doi.org/10.1007/s13347-020-00423-6

Floridi, L., & Sanders, J. W. (2004). On the morality of artificial agents Luciano. *Minds and Machines*. https://doi.org/10.1023/B

Fountaine, T., McCarthy, B., & Saleh, T. (2019). Building the AI-Powered Organization. *Harvard Business Review*, *July-August*.

Frank, M. R., Autor, D., Bessen, J. E., Brynjolfsson, E., Cebrian, M., Deming, D. J., Feldman, M., Groh, M., Lobo, J., Moro, E., Wang, D., Youn, H., & Rahwan, I. (2019). Toward understanding the impact of artificial intelligence on labor. *Proceedings of the National Academy of Sciences*, *116*(14), 6531–6539. https://doi.org/10.1073/pnas.1900949116

Friedman, B., & Nissenbaum, H. (1996). Bias in computer systems. *ACM Transactions on Information Systems*, 330–347. https://doi.org/10.4324/9781315259697-23

Fuller, D. B. (2020). Cutting off our nose to spite our face. *Johns Hopkins Applied Physics Laboratory*.

Furman, J., & Seamans, R. (2019). AI and the economy. *Innovation Policy and the Economy*, *19*(1), 161–191. https://doi.org/10.1086/699936

Galasso, A., & Luo, H. (2021). Risk-mitigating technologies: The case of radiation diagnostic devices. *Management Science*, *67*(5), 3022–3040. https://doi.org/10.1287/mnsc.2020.3634

Garud, R., & Karnøe, P. (2003). Bricolage versus breakthrough: distributed and embedded agency in technology entrepreneurship. *Research Policy*, *32*, 277–300.

Gawer, A. (2009). *Platforms, Markets and Innovation* (Issue January). https://doi.org/10.4337/9781849803311.00006

Gawer, A. (2014). Bridging differing perspectives on technological platforms : Toward an integrative framework. *Research Policy*, *43*(7), 1239–1249. https://doi.org/10.1016/j.respol.2014.03.006

Gawer, A., & Cusumano, M. A. (2013). Industry platforms and ecosystem innovation. *Journal of Product Innovation Management*, *31*(3), 417–433. https://doi.org/10.1111/jpim.12105

Gebru, T., Morgenstern, J., Vecchione, B., Vaughan, J. W., Wallanch, H., Daume, H., & Crawford, K. (2020). Datasheets for Datasets. *Arxiv*.

Geels, F. W. (2002). Technological transitions as evolutionary reconfiguration processes: A multi-level perspective and a case-study. *Research Policy*, *31*(8–9), 1257–1274. https://doi.org/10.1016/S0048-7333(02)00062-8

Geels, F. W., & Schot, J. (2007). Typology of sociotechnical transition pathways. *Research Policy*, *36*(3), 399–417. https://doi.org/10.1016/j.respol.2007.01.003

Ghauri, P., & Gronhaug, K. (2005). *Research Methods in Business Studies*. FT/Prentice Hall.

Ghazawneh, A., & Henfridsson, O. (2010a). Governing third-party development through platform boundary resources. *ICIS 2010 Proceedings - Thirty First International Conference on Information Systems*.

Ghazawneh, A., & Henfridsson, O. (2010b). Governing Third-Party Development through Platform boundary Resources. *Proceedings of the International Conference on Information Systems, ICIS 2010*.

Ghazawneh, A., & Henfridsson, O. (2012). Balancing platform control and external contribution in third-party development: the boundary resources model. *Information Systems Journal*. https://doi.org/10.1111/j.1365-2575.2012.00406.x

Ghazawneh, A., & Henfridsson, O. (2013). Balancing platform control and external contribution in third-party development: The boundary resources model. *Information Systems Journal*, *23*(2), 173–192. https://doi.org/10.1111/j.1365-2575.2012.00406.x

Goldfarb, A., & Tucker, C. E. (2011). Privacy Regulation and Online Advertising. *Management Science*, *57*(1), 57–71. https://doi.org/10.1287/mnsc.1100.1246

Gorwa, R. (2019). What is platform governance. *Information Communication and Society*.

GOV.UK. (2019). AI Sector Deal. *Policy Paper*, 1–16. https://www.gov.uk/government/publications/artificial-intelligence-sector-deal/ai-sector-deal

Greene, J. (2007). *Mixed Methods in Social Inquiry*. Wiley.

Gutierrez, C. I., Marchant, G. E., & Michael, K. (2021). Effective and Trustworthy Implementation of AI Soft Law Governance. *IEEE Transactions on Technology and Society*, *2*(4), 168–170. https://doi.org/10.1109/tts.2021.3121959

Haas, R., & Davies, J. (2020). What's powering artificial intelligence. *Technical Report, ARM (White Paper)*.

Hagemann, R., Huddleston, J., & Thierer, A. D. (2018). Soft Law for Hard Problems: The Governance of Emerging Technologies in an Uncertain Future. In *Colorado Technology Law*

Journal (Vol. 17, Issue 1). https://heinonline.org/HOL/Page?handle=hein.journals/jtelhtel17&id=52&div=8&collection=journals%0Ahttps://ssrn.com/abstract=3118539

Hagiu, A., & Wright, J. (2015). Multi-sided platforms. *International Journal of Industrial Organization*, *43*, 162–174. https://doi.org/10.1016/j.ijindorg.2015.03.003

Hall, J., Matos, S. V., & Martin, M. J. C. (2014). Innovation pathways at the Base of the Pyramid: Establishing technological legitimacy through social attributes. *Technovation*, *34*(5–6), 284–294. https://doi.org/10.1016/j.technovation.2013.12.003

Han, P., Jiang, W., & Mei, D. (2021). *Mapping U.S.-China Technology Decoupling, Innovation, and Firm Performance ∗*.

Hanson, M. (2020). China to ditch all Windows PCs by 2022 – could this be Linux's time to shine? *TechRadar*. https://www.techradar.com/news/china-to-ditch-all-windows-pcs-by-2022-could-this-be-linuxs-time-to-shine

Hascic, I., Johnstone, N., & Kalamova, M. (2009). Environmental policy flexibility, search and innovation. *Finance a Uver - Czech Journal of Economics and Finance*, *59*(5), 426–441.

He, Y. (2017). *How China is Preparing for an Artificial Intelligence Future*. *Wilson Briefs*.

Henfridsson, O., & Bygstad, B. (2013). The generative mechanisms of digital infrastructure evolution. *MIS Quarterly: Management Information Systems*, *37*(3), 907–931. https://doi.org/10.25300/MISQ/2013/37.3.11

Henfridsson, O., Nandhakumar, J., Scarbrough, H., & Panourgias, N. (2018). Recombination in the open-ended value landscape of digital innovation. *Information and Organization*, *28*(2), 89–100. https://doi.org/10.1016/j.infoandorg.2018.03.001

Hengstler, M., Enkel, E., & Duelli, S. (2016). Applied artificial intelligence and trust-The case of autonomous vehicles and medical assistance devices. *Technological Forecasting and Social Change*, *105*, 105–120. https://doi.org/10.1016/j.techfore.2015.12.014

Hequan, W. (2000). *The Progress of Communication Technology Subject of Hi-tech Research Development Plan of China*. https://doi.org/10.1109/ICCT.2000.889157

Hine, E., & Floridi, L. (2022). Artificial Intelligence with American Values and Chinese Characteristics: A Comparative Analysis of American and Chinese Governmental AI Policies. *Ssrn*.

Hinings, B., Gegenhuber, T., & Greenwood, R. (2018). Digital innovation and transformation: An institutional perspective. *Information and Organization*, *28*(1), 52–61. https://doi.org/10.1016/j.infoandorg.2018.02.004

Hinings, B., Logue, D., & Zietsma, C. (2017). Fields, Institutional Infrastructure and Governance. In *The SAGE Handbook of Organizational Institutionalism* (pp. 163–189).

Huld, A. (2022). China's Sweeping Recommendation Algorithm Regulations in Effect from March 1. In *China Briefing* (Issue January 6). https://www.china-briefing.com/news/china-passessweeping-recommendation-algorithm-regulations-effect-march-1-2022/

Iansiti, M., & Levien, R. (2004). Strategy as Ecology. *Harvard Business Review*, *82*(3). https://doi.org/10.1108/eb025570

Ibrahim, D. (2016). An Overview of Soft Computing. *Procedia Computer Science*, *102*(August), 34–38. https://doi.org/10.1016/j.procs.2016.09.366

Ingeman, K. (2021). *STATE-OWNED ENTERPRISES*.

Jacobides, M. G., Sundararajan, A., & Alstyne, M. Van. (2019). Platforms and Ecosystems: Enabling the Digital Economy February. *World Economic Forum*, *February*. www.weforum.org

Jaffe, A. B., Peterson, S. R., Portney, P. R., & Stavins, R. N. (1995). Environmental Regulation and the Competitiveness of U.S. Manufacturing: What does the evidence tell us? *Journal of Economic Literature*, *33*(1), 132–163. http://www.ncbi.nlm.nih.gov/entrez/query.fcgi?cmd=Retrieve&db=PubMed&dopt=Citation&list_uids=11893638

Janssen, M., Brous, P., Estevez, E., Barbosa, L. S., & Janowski, T. (2020). Data governance: Organizing data for trustworthy Artificial Intelligence. *Government Information Quarterly*, *37*(3), 101493. https://doi.org/10.1016/j.giq.2020.101493

Janssen, M., & Helbig, N. (2016). Innovating and changing the policy-cycle: Policy-makers be prepared! *Government Information Quarterly*, *35*(4), S99–S105. https://doi.org/10.1016/j.giq.2015.11.009

Janssen, M., Kuk, G., & Wagenaar, R. W. (2008). A survey of Web-based business models for e-government in the Netherlands. *Government Information Quarterly*, *25*(2), 202–220. https://doi.org/10.1016/j.giq.2007.06.005

Jing, M., & Dai, S. (2017). China recruits Baidu, Alibaba and Tencent to AI 'national team.' *South China Morning Post*. https://www.scmp.com/tech/china-tech/article/2120913/china-recruits-baidu-alibaba-and-tencent-ai-national-team

Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence*, *1*(9), 389–399. https://doi.org/10.1038/s42256-019-0088-2

Ju, J., Liu, L., & Feng, Y. (2019). Public and private value in citizen participation in E-governance: Evidence from a government-sponsored green commuting platform. *Government Information Quarterly*, *36*(4), 101400. https://doi.org/10.1016/j.giq.2019.101400

Kaelbling, L., Littman, M., & Moore, A. (1996). Reinforcement Learning: A Survey. *Journal of Artificial Intelligence Research*, *4*, 237–285. https://doi.org/10.1007/s11431-012-4938-y

Kallinikos, J., & Tempini, N. (2014). Patient data as medical facts: Social media practices as a foundation for medical knowledge creation. *Information Systems Research*, *25*(4), 817–833. https://doi.org/10.1287/isre.2014.0544

Kenderdine, T. (2017). China's Industrial Policy, Strategic Emerging Industries and Space Law. *Asia & the Pacific Policy Studies*, *4*(2), 325–342. https://doi.org/10.1002/app5.177

Ketokivi, M., & Mantere, S. (2010). Two strategies for inductive reasoning in organizational research. *Academy of Management*, *35*(2), 315–333.

Khan, A. A. (2014). Qualitative Research: A Case for a Multi-Angle View to Enhance 'Validity.' *International Journal of Business and Management*, *9*(9). https://doi.org/10.5539/ijbm.v9n9p29

Kharpal, A. (2021). First 100 days: Biden keeps Trump-era sanctions in tech battle with China, looks to friends for help. *CNBC*, *April 29*. https://www.cnbc.com/2021/04/29/biden-100-days- china-tech-battle-sees- sanctions-remain-alliances-made.html

King, G., Pan, J., & Roberts, M. E. (2017). How the Chinese government fabricates social media posts for strategic distraction, not engaged argument. *American Political Science Review*, *111*(3), 484–501. https://doi.org/10.1017/S0003055417000144

Klievink, B., Bharosa, N., & Tan, Y. H. (2016). The collaborative realization of public values and business goals: Governance and infrastructure of public-private information platforms. *Government Information Quarterly*, *33*(1), 67–79. https://doi.org/10.1016/j.giq.2015.12.002

Klievink, B., Romijn, B. J., Cunningham, S., & de Bruijn, H. (2017). Big data in the public sector: Uncertainties and readiness. *Information Systems Frontiers*, *19*(2), 267–283. https://doi.org/10.1007/s10796-016-9686-2

Kohavi, R., Longbotham, R., Sommerfield, D., & Henne, R. M. (2009). Controlled experiments on the web: Survey and practical guide. *Data Mining and Knowledge Discovery*, *18*(1), 140–181. https://doi.org/10.1007/s10618-008-0114-1

Kop, M. (2021). EU Artificial Intelligence Act: The European Approach to AI. *Stanford - Vienna Transatlantic Technology Law Forum*, *2*, 1–11. https://law.stanford.edu/publications/eu-

Koty, A. C. (2021). More Regulatory Clarity After China Bans For-Profit Tutoring in Core Education. *China Briefing*, 2021. https://www.china-briefing.com/news/china-bans-for-profit-tutoring-in-core-education-releases-guidelines-online-businesses/

Krishna, A. (2020). *IBM CEO's Letter to Congress on Racial Justice Reform*. https://www.ibm.com/blogs/policy/facial-recognition-sunset-racial-justice-reforms/

Kshetri, N. (2021). Data labeling for the artificial intelligence industry: Economic impacts in developing countries. *IEEE IT Professional*, *23*(2), 96–99.

Kulshreshtha, P. (2005). Business Ethics versus Economic Incentives: "Contemporary Issues and Dilemmas." *Journal of Business Ethics*, *60*(4), 393–410. https://doi.org/10.1007/sl0551-005-1896-3

Kwan, C. H. (2020). The China–US Trade War: Deep-Rooted Causes, Shifting Focus and Uncertain Prospects. *Asian Economic Policy Review*, *15*(1), 55–72. https://doi.org/10.1111/aepr.12284

Lambrecht, A., & Tucker, C. (2019). Algorithmic bias? An empirical study of apparent gender-based discrimination in the display of stem career ads. *Management Science*, *65*(7), 2966–2981. https://doi.org/10.1287/mnsc.2018.3093

Lamo, M., & Calo, R. (2019). Regulating bot speech. *UCLA Law Review*, *66*(4), 989–1028.

https://doi.org/10.2139/ssrn.3214572

Lash, S. (2007). Power after Hegemony: Cultural Studies in Mutation? *Theory, Culture & Society*, *24*(3), 55–78. https://doi.org/10.1177/0263276407075956

Lawrence, T. B., & Suddaby, R. (2006). Institutions and institutional work. In *The SAGE Handbook of Organization Studies* (Issue March, pp. 215–254). https://doi.org/10.4135/9781848608030.n7

Lenard, T. M., & Rubin, P. H. (2009). In Defense of Data: Information and the Costs of Privacy. *Policy & Internet*, *2*(1), 143–177. https://doi.org/10.2202/1944-2866.1035

Leusin, M. E., Günther, J., Jindra, B., & Moehrle, M. G. (2020). Patenting patterns in Artificial Intelligence: Identifying national and international breeding grounds. *World Patent Information*, *62*(July 2019). https://doi.org/10.1016/j.wpi.2020.101988

Levav, J., & Fitzsimons, G. (2006). When Questions Change Behavior The Role of Ease of Representation. *Psychological Science*, *17*(3), 207–213.

Lewis, A. (1949). *The Principles of Economic Planning*. George Allen and Unwin.

Li, H., & Zhou, L. A. (2005). Political turnover and economic performance: The incentive role of personnel control in China. *Journal of Public Economics*, *89*(9–10), 1743–1762. https://doi.org/10.1016/j.jpubeco.2004.06.009

Linders, D. (2012). From e-government to we-government: Defining a typology for citizen coproduction in the age of social media. *Government Information Quarterly*, *29*(4), 446–454. https://doi.org/10.1016/j.giq.2012.06.003

Mackenzie, A. (2006). *Cutting Code: Software and Sociality*. Peter Lang Publishing.

Madzou, L., & Firth-Butterfield, K. (2020). Regulation could transform the AI industry. Here's how companies can prepare. *World Economic Forum*, *23 October*.

Majumdar, S. K. ., & Marcus, A. A. . (2001). Rules versus Discretion: The Productivity Consequences of Flexible Regulation. *The Academy of Management Journal*, *44*(1), 170–179.

Mansour, E., Sambra, A. V., Hawke, S., Zereba, M., Capadisli, S., Ghanem, A., Aboulnaga, A., & Berners-Lee, T. (2016). *A Demonstration of the Solid Platform for Social Web Applications*. 223–226. https://doi.org/10.1145/2872518.2890529

Marcus, G., & Davis, E. (2019). *Rebooting AI: Building artificial intelligence we can trust*. Vintage.

Markus, M. L. (2017). Datification, Organizational Strategy, and IS Research: What's the Score? *Journal of Strategic Information Systems*, *26*(3), 233–241. https://doi.org/10.1016/j.jsis.2017.08.003

Marshall, C., & Rossman, G. B. (2016). *Designing Qualitative Research*. SAGE.

Mason, R. L., Gunst, R. F., & Hess, J. L. (2003). *Statistical design and analysis of experiments: with applications to engineering and science*. John Wiley & Sons.

McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (1955). *A proposal for the Dartmouth* *summer research project on artificial intelligence*. *August 31*.

Mckay, C. (2020). Predicting risk in criminal procedure: actuarial tools, algorithms, AI and judicial decision-making. *Current Issues in Criminal Justice*, *32*(1), 22–39. https://doi.org/10.1080/10345329.2019.1658694

Mckinsey. (2019). *Global AI Survey : AI proves its worth , but few scale impact*. *November*.

Meade, J. E. (1949). *Planning and the Price Mechanism: The Liberal Socialist Solution*. George Allen and Unwin.

Meijer, P. C., Verloop, N., & Beijaard, D. (2002). Multi-method triangulation in a qualitative study on teachers' practical knowledge: An attempt to increase internal validity. *Quality and Quantity*, *36*(2), 145–167. https://doi.org/10.1023/A:1014984232147

Mergel, I. (2018). Open innovation in the public sector: drivers and barriers for the adoption of Challenge.gov. *Public Management Review*, *20*(5), 726–745. https://doi.org/10.1080/14719037.2017.1320044

MIIT. (2017). *Three-Year Action Plan for Promoting Development of a New Generation Artificial Intelligence Industry (2018–2020) December*. *December 1*. http://www.miit.gov.cn/n1146285/n1146352/n3054355/n3057497/n3057507/c6492295/content.html /

Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. *Big Data and Society*, *December*, 1–21. https://doi.org/10.1177/2053951716679679

MOE. (2018). *Artificial Intelligence Action Plan for Institutions of Higher Education* . *April*. https://cset.georgetown.edu/wp-content/uploads/Notice-of-the-Ministry-of-Education-on-Issuing-the-Artificial-Intelligence-Innovation-Action-Plan-for-Institutes-of-Higher-Education.pdf

MOFCOM. (2020). *MOFCOM Order No. 4 of 2020 on Provisions on the Unreliable Entity List -*. *September*.

Mökander, J., Axente, M., Casolari, F., & Floridi, L. (2021). Conformity Assessments and Post-market Monitoring: A Guide to the Role of Auditing in the Proposed European AI Regulation. *Minds and Machines*, *0123456789*. https://doi.org/10.1007/s11023-021-09577-4

Morwitz, V. G., Johnson, E., & Schmittlein, D. (1993). Does Measuring Intent Change Behavior ? *Journal of Consumer Research*, *20*(1), 46–61.

MOST. (2020a). *China Creates National New Generation Artificial Intelligence Innovation and Development Pilot Zones: Vol*. *March*. http://invest.beijing.gov.cn/english/Choose/Under/201912/t20191207_965750.html

MOST. (2020b). *National High-tech R&D Program (863 Program)*. http://en.most.gov.cn/programmes1/

MOST. (2021a). *"A new generation of artificial intelligence ethics code" released*. *September*.

http://www.most.gov.cn/kjbgz/202109/t20210926_177063.html

MOST. (2021b). *Announcement on the public solicitation of opinions on the "Guiding Opinions on Strengthening the Ethical Governance of Science and Technology (Draft for Comment)." July*. http://www.most.gov.cn/tztg/202107/t20210728_176136.html

MOST. (2021c). *Ethical Norms for New Generation Artificial Intelligence Released*. *September*. http://www.most.gov.cn/kjbgz/202109/t20210926_177063.html

Murray, P., Schatz, B., Sasse, B., Hassan, M., Carper, T., & Portman, R. (2017). *Open, Public, Electronic and Necessary (OPEN) Government Data Act*. 1–3. ai.gov

NAIIO. (2022). *The national artificial intelligence initiative office*. ai.gov

Nellis, S. (2021). U.S. panel recommends export 'choke points' to prevent Chinese dominance in semiconductors. *Reuters*, March 1. https://www.reuters.com/article/us-usa-china-semiconductors-idUSKCN2AT39H

Nelson, R., & Winter, S. (1982). *An Evolutionary Theory of Economic Change*. Harvard University Press.

Newman, J. C. (2020). AI Principles in Context. In *Asia Society*.

Nilsson, N. (1983). Artificial Intelligence Prepares for 2001. *AI Magazine*.

Nilsson, N. (1998). *Artificial Intelligence: A New Synthesis*. Morgan Kaufmann.

NIST. (2019). *U.S. LEADERSHIP IN AI: A Plan for Federal Engagement in Developing Technical Standards and Related Tools*. https://www.nist.gov/system/files/documents/2019/08/10/ai_standards_fedengagement_plan_9aug2019.pdf

NSCAI. (2021). *Final report: National Security Commission on Artificial Intelligence*. https://www.nscai.gov/wp-content/uploads/2021/03/Full-Report-Digital-1.pdf

Nuno, N., Gomes, A. de, & Kontschieder, V. (2021). *AI Impact Assessment: A Policy Prototyping Experiment*. *January*.

Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science*, *366*(6464), 447–453. https://doi.org/10.1126/science.aax2342

OECD. (2021). *OECD.AI database of national AI policies*. https://oecd.ai/en/dashboards

Oluwatayo, J. A. (2012). Validity and Reliability Issues in Educational Research. *Journal of Educational and Social Research*, *2*(May), 391–400. https://doi.org/10.5901/jesr.2012.v2n2.391

Pan, J., & Xu, Y. (2018). China's ideological spectrum. *Journal of Politics*, *80*(1), 254–273. https://doi.org/10.1086/694255

Panagiotopoulos, P., Klievink, B., & Cordella, A. (2019). Public value creation in digital government. *Government Information Quarterly*, *36*(4). https://doi.org/10.1016/j.giq.2019.101421

Parasuraman, R., & Manzey, D. H. (2010). Complacency and bias in human use of automation: An attentional integration. *Human Factors*, *52*(3), 381–410. https://doi.org/10.1177/0018720810376055

Pardau, S. L. (2018). the California Consumer Privacy Act: Towards a European-Style Privacy Regime in the United States? *Journal of Technology Law & Policy*, *23*(1), 68–114. https://www.journaloftechlaw.org/issues/23-1-pardau/

Patton, M. (2015). *Qualitative Research & Evaluation Methods* (4th ed.). SAGE.

Pei, J., Deng, L., Song, S., Zhao, M., Zhang, Y., Wu, S., Wang, G., Zou, Z., Wu, Z., He, W., Chen, F., Deng, N., Wu, S., Wang, Y., Wu, Y., Yang, Z., Ma, C., Li, G., Han, W., … Shi, L. (2019). Towards artificial general intelligence with hybrid Tianjic chip architecture. *Nature*, *572*(7767), 106–111. https://doi.org/10.1038/s41586-019-1424-8

Pisano, G. P., & Teece, D. J. (2007). How to Capture Value from Innovation: Shaping Intellectual Property and Industry Architecture. *California Management Review*.

Pohle, J., & Thiel, T. (2020). Digital sovereignty. *Internet Policy Review*, *9*(4), 1–19. https://doi.org/10.14763/2020.4.1532

Porter, M. E., & Van Der Linde, C. (1995). Toward a new conception of the environment-competitiveness relationship. *Journal of Economic Perspectives*, *9*(4), 97–118. https://doi.org/10.1257/jep.9.4.97

Powell, W. W., Oberg, A., Korff, V., Oelberger, C., & Kloos, K. (2017). Institutional analysis in a digital era: Mechanisms and methods to understand emerging fields. In *New Themes in Institutional Analysis: Topics and Issues from European Research* (pp. 305–344). https://doi.org/10.4337/9781784716875.00016

Rai, A., Constantinides, P., & Sarker, S. (2019). Editor's comments: Next-Generation Digital Platforms: Toward Human–AI Hybrids. *MIS Quarterly*, *43*(1).

Ram, A., & Murgia, M. (2019). Data Brokers: Regulators Try to Rein in the "Privacy Deathstars." *Financial Times*, 1590694. https://www.ft.com/content/f1590694-fe68-11e8-aebf-99e208d3e521

Raunio, M., Nordling, N., Kautonen, M., & Räsänen, P. (2018). Open innovation platforms as a knowledge triangle policy tool – Evidence from Finland. *Foresight and STI Governance*, *12*(2), 62–76. https://doi.org/10.17323/2500-2597.2018.2.62.76

Reay, T., & Hinings, C. R. (2009). Managing the rivalry of competing institutional logics. *Organization Studies*, *30*(6), 629–652. https://doi.org/10.1177/0170840609104803

Reed, M. (2005). Reflections on the "realist turn" in organization and management studies. *Journal of Management Studies*, *42*(8), 1621–1644. https://doi.org/10.1111/j.1467-6486.2005.00559.x

Roberts, H., Cowls, J., Hine, E., Mazzi, F., Tsamados, A., Taddeo, M., & Floridi, L. (2021). Achieving a 'Good AI Society': Comparing the Aims and Progress of the EU and the US. *Science and Engineering Ethics*, *27*(6), 1–25. https://doi.org/10.1007/s11948-021-00340-7

Roberts, H., Cowls, J., Morley, J., Taddeo, M., Wang, V., & Floridi, L. (2020). The Chinese approach to artificial intelligence: an analysis of policy, ethics, and regulation. *AI and Society*, *0123456789*. https://doi.org/10.1007/s00146-020-00992-2

Roy, R. K. (2001). *Design of experiments using the Taguchi approach: 16 steps to product and process improvement*. John Wiley & Sons.

Russell, S. J., & Norvig, P. (2010). Artificial Intelligence: A Modern Approach. In *Artificial Intelligence*. Prentice-Hall. https://doi.org/10.1017/S0269888900007724

Salz Trautman, P. (1994). A Computer Pioneer Rediscovered, 50 Years On. *New York Times*, *April 20*.

Sanchez, A., Mcdermott, K., & Cintora, A. (2019). *A Policy Memorandum to the Partnership on AI : Accreditation and Educational Programs to Ensure Fairness in AI*. *15*(1).

Saunders, M., & Lewis, P. (2017). *Doing research in business and management*. Pearson.

Saunders, M., Lewis, P., & Thornhill, A. (2012). *Research Methods for Business Students*. Pearson.

Saunders, M., Lewis, P., & Thornhill, A. (2019). "Research Methods for Business Students" Chapter 4: Understanding research philosophy and approaches to theory development. In *Researchgate.Net* (Issue January). www.pearson.com/uk

Scharre, P. (2019). Killer Apps: The Real Dangers of an AI Arms Race. *Foreign Affairs*, *98*(3).

Schneider, J., Abraham, R., & Meske, C. (2020). *AI Governance for Businesses*. 1–19. http://arxiv.org/abs/2011.10672

Scott, R. W. (2014). *Institutions and Organizations, 4th ed*.

Sculley, D., Holt, G., Golovin, D., Davydov, E., Phillips, T., Ebner, D., Chaudhary, V., Young, M., Crespo, J. F., & Dennison, D. (2015). Hidden technical debt in machine learning systems. *Advances in Neural Information Processing Systems*, *2015-Janua*, 2503–2511.

Sheehan, M. (2022). China ' s New AI Governance Initiatives Shouldn ' t Be Ignored. *Carnegie Endowment for International Peace*, 22–25.

Shih, W. (2020). Is it time to rethink globalized supply chains? *MIT Sloan Management Review*, *61*(4).

Shleifer, A. (2005). Understanding Regulation. *European Financial Management*, *11*(4), 439–451 Understanding. https://doi.org/10.1080/09528822.2014.970769

Shoham, Y., Perrault, R., Brynjolfsson, E., & Clark, J. (2017). artificial intelligence index 2017 stanford annual report. *AI Index .Org*, *1*(November), 1–101.

Sørensen, E., & Torfing, J. (2011). Enhancing collaborative innovation in the public sector. *Administration and Society*, *43*(8), 842–868. https://doi.org/10.1177/0095399711418768

Sousa, W. G. de, Melo, E. R. P. de, Bermejo, P. H. D. S., Farias, R. A. S., & Gomes, A. O. (2019). How and where is artificial intelligence in the public sector going? A literature review and research agenda. *Government Information Quarterly*, *36*(4), 101392. https://doi.org/10.1016/j.giq.2019.07.004

Spivack, J., & Garvie, C. (2020). A Taxonomy of Legislative Approaches to Face Recognition in the United States. *Regulating Biometrics: Global Approaches and Urgent Questions*, *1166*, 86–95.

State Council. (2014). *Guideline for the Promotion of the Development of the National Integrated Circuit Industry*. https://members.wto.org/CRNAttachments/2014/SCMQ2/law47.pdf

State Council. (2015). *Notice of the State Council on Printing and Distributing the Action Outline for Promoting the Development of Big Data*. *September*. http://www.gov.cn/zhengce/content/2015-09/05/content_10137.htm

State Council. (2017). *Full Translation: China's 'New Generation Artificial Intelligence Development Plan.'* http://newamerica.org/cybersecurity-initiative/digichina/blog/full-translation- chinas-new-generation- artificial-intelligence-development-plan-2017/

State Council. (2019). *The General Office of the State Council on Promoting the Platform Economy Guiding Opinions on Standardizing Healthy Development*. *August*. http://www.gov.cn/zhengce/content/2019-08/08/content_5419761.htm

Statista. (2022). Amount of data created, consumed, and stored 2010-2025. *Statista Research Department*, 22–23. https://www.statista.com/statistics/871513/worldwide-data-created/

Stigler, G. J. (1971). The Theory of Economic Regulation. *The Bell Journal of Economics and Management Science*, *2*(1), 3–21.

Stoyanovich, J., & Howe, B. (2019). Nutritional Labels for Data and Models. *Data Engineering*, *1926250*, 13.

Stoyanovich, J., Van Bavel, J. J., & West, T. V. (2020). The imperative of interpretable machines. *Nature Machine Intelligence*, *2*(4), 197–199. https://doi.org/10.1038/s42256-020-0171-8

Straub, D., & Gefen, D. (2004). Validation Guidelines for IS Positivist Research. *Communications of the Association for Information Systems*, *13*(June 2014). https://doi.org/10.17705/1cais.01324

Strauss, A., & Corbin, J. (1998). Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory. In *Management Learning* (Vol. 31, Issue 4). Sage Publications, Inc. https://doi.org/10.1177/1350507600314007

Sun, Y., & Cao, C. (2021). Planning for science: China's "grand experiment" and global implications. In *Humanities and Social Sciences Communications* (Vol. 8, Issue 1). https://doi.org/10.1057/s41599-021-00895-7

Taeihagh, A., Tan, S. Y., & Taiehagh, A. (2021). Adaptive governance of autonomous vehicles: accelerating the adoption of disruptive technologies in Singapore. *Government Information Quarterly*, *November 2019*, 101546. https://doi.org/10.1016/j.giq.2020.101546

Taherdoost, H. (2016). Validity and Reliability of the Research Instrument; How to Test the Validation of a Questionnaire / Survey in a Research. *International Journal of Academic Research in Management*, *5*(3), 28–36.

Tashakkori, A., & Creswell, J. W. (2007). Editorial: The New Era of Mixed Methods. *Journal of Mixed Methods Research*, *1*(1), 3–7. https://doi.org/10.1177/2345678906293042

Teece, D., & Leih, S. (2016). Uncertainty, innovation, and dynamic capabilities: An introduction. In *California Management Review* (Vol. 58, Issue 4, pp. 5–12). https://doi.org/10.1525/cmr.2016.58.4.5

Tencent Research Institute. (2020). *"ARCC": An Ethical Framework for Artificial Intelligence. April*. https://www.tisi.org/13747

Tene, O., & Polonetsky, J. (2013). Big Data for All : Privacy and User Control in the Age of Analytics Big Data for All : Privacy and User Control in the. *Northwestern Journal of Technology and Intellectual Property*, *11*(5).

The White House. (2018). *Summary of the 2018 White House Summit on Artificial Intelligence for American Industry*. https://www.nitrd.gov/nitrdgroups/images/2/23/Summary-Report-of-White-House- AI-Summit.pdf

Tiange, L. (2019). Machine Learning-based Inverse Solution for Predictions of Impact Conditions during Car Collisions. *Dissertation*.

Tie, Y., Birks, M., & Francis, K. (2019). Grounded theory research: A design framework for novice researchers. *SAGE Open Medicine*, *7*, 205031211882292. https://doi.org/10.1177/2050312118822927

Tilson, D., Lyytinen, K., & Sørensen, C. (2010). Digital infrastructures: The missing IS research agenda. *Information Systems Research*, *21*(4), 748–759. https://doi.org/10.1287/isre.1100.0318

TTC. (2021). *U.S.-EU Trade and Technology Council Inaugural Joint Statement* (pp. 1–17).

Tucker, C. (2017). Privacy , Algorithms and Artificial Intelligence. *Economics of AI*, 1–20.

Turing, A. (1950). COMPUTING MACHINERY AND INTELLIGENCE. *Mind*, *49*, 433–460.

Tutt, A. (2016). AN FDA FOR ALGORITHMS. *Administrative Law Review*, *69*(1).

US Department of State. (2021). *The Clean Network*. https://2017-2021.state.gov/the-clean-network/index.html

Varian, H. (2010). Computer mediated transactions. *American Economic Review*, *100*(2), 1–10. https://doi.org/10.1257/aer.100.2.1

Veale, M., & Binns, R. (2017). Fairer machine learning in the real world: Mitigating discrimination without collecting sensitive data. *Big Data and Society*, *4*(2), 1–17. https://doi.org/10.1177/2053951717743530

Visser, P., Krosnick, J., & Lavrakas, P. (2000). Survey research. In *Handbook of research methods in social and personality psychology* (pp. 223–252). Cambridge University Press. https://doi.org/10.4018/ijavet.2015100106

Vought, R. (2020). *Guidance for Regulation of Artificial Intelligence Applications Introduction*. *3967*(13), 15. https://www.whitehouse.gov/wp-content/uploads/2020/11/M-21-06.pdf

Waddock, S. (2008). Building a new institutional infrastructure for corporate responsibility. *Academy of Management Perspectives*, *22*(3), 87–108. https://doi.org/10.5465/AMP.2008.34587997

Wallach, W., & Marchant, G. (2018). An Agile Ethical/Legal Model for the International and National Governance of AI and Robotics. *Proceedings of the AIES*, *107*(3), 7. https://doi.org/10.1109/JPROC.2019.2899422

Wang, C., Medaglia, R., & Zheng, L. (2018). Towards a typology of adaptive governance in the digital government context: The role of decision-making and accountability. *Government Information Quarterly*, *35*(2), 306–322. https://doi.org/10.1016/j.giq.2017.08.003

Wang, E. (2020). China's Kunlun says U.S approves sale of Grindr to investor group. *Reuters*, *May*.

Weiss, C. (1997). *Evaluation: methods for studying programs and policies* (2nd edn). Prentice Hall.

White House. (2021a). Executive Order 14032: Addressing the Threat From Securities Investments That Finance Certain Companies of the People's Republic of China. *Federal Register - Presidential Documents*, *86*(107), 30,145-30,149. https://www.whitehouse.gov/briefing-room/presidential-actions/2021/06/03/executive-order-on-addressing-the-threat-from-securities-investments-that-finance-certain-companies-of-the-peoples-republic-of-china/

White House. (2021b). *National Artificial Intelligence Initiative*. 2021. https://trumpwhitehouse.archives.gov/ai/ai-american-values/

Whittaker, M., Crawford, K., Dobbe, R., Fried, G., Kaziunas, E., Mathur, V., Myers West, S., Richardson, R., Schultz, J., & Schwartz, O. (2018). AI Now 2018 Report. *AI Now*, *December*, 1–62. https://ainowinstitute.org/AI_Now_2018_Report.pdf

Wilson, K., & Brownstein, J. S. (2009). Early detection of disease outbreaks using the Internet. *Cmaj*, *180*(8), 829–831. https://doi.org/10.1503/cmaj.1090215

Xinhua. (2019). *Shanghai building China's first pilot zone for AI application*. *May*. http://www.chinadaily.com.cn/a/201905/22/WS5ce4fb04a3104842260bd24f.html

Xinhua News Agency. (2021). *The Fourteenth Five-Year Plan for the National Economic and Social Development of the People's Republic of China*. http://www.gov.cn/xinwen/2021-03/13/content_5592681.htm

Xue, L. (2018). *China AI Development Report 2018*. *July*.

Yang, T., Lo, J., & Shiang, J. (2015). To open or not to open? Determinants of open government data. *Journal of Information Science*, *41*(5), 596–612. https://doi.org/10.1177/0165551515586715

Yang, Y., & Goh, B. (2021). Beijing took stake and board seat in key ByteDance domestic entity this year. *Reuters*, *August*. https://www.reuters.com/world/china/beijing-owns-stakes-bytedance-weibo-domestic-entities-records-show- 2021-08-17/

Yin, R. K. (2003). *Case Study Research*. SAGE.

Yin, R. K. (2009). *Case study research: Design and methods* (p. Vol. 5). SAGE.

Yoo, Y., Boland, R. J., Lyytinen, K., & Majchrzak, A. (2012). Organizing for Innovation in the

Digitized World. *Organization Science*, *23*(5), 1398–1408. https://doi.org/10.1287/orsc.1120.0771

Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). The new organizing logic of digital innovation: An agenda for information systems research. *Information Systems Research*, *21*(4), 724–735. https://doi.org/10.1287/isre.1100.0322

Yoon-Hendricks, A. (2018). Congress Strengthens Reviews of Chinese and Other Foreign Investments The New York Times. *The New York Times*, 2018. https://www.nytimes.com/2018/08/01/business/foreign-investment-united-states.html

Zarsky, T. (2016). The Trouble with Algorithmic Decisions: An Analytic Road Map to Examine Efficiency and Fairness in Automated and Opaque Decision Making. *Science, Technology, & Human Values*, *41*(1), 118–132. https://doi.org/10.1177/0162243915605575

Zhang, D., Mishra, S., Brynjolfsson, E., Etchemendy, J., Ganguli, D., Grosz, B., Lyons, T., Manyika, J., Niebles, J. C., Sellitto, M., Shoham, Y., Clark, J., & Perrault, R. (2021). *2021 AI Index Report*. 1–222. https://aiindex.stanford.edu/report/

Zhao, Y., & Fan, B. (2018). Exploring open government data capacity of government agency: Based on the resource-based theory. *Government Information Quarterly*, *35*(1), 1–12. https://doi.org/10.1016/j.giq.2018.01.002

Zhu, J., Huang, T., Chen, W., & Gao, W. (2018). The future of artificial intelligence in China. *Communications of the ACM*, *61*(11), 44–45. https://doi.org/10.1145/3239540

Zietsma, C., Groenewegen, P., Logue, D., & Hinings, C. R. (Bob). (2017). FIELD OR FIELDS? BUILDING THE SCAFFOLDING FOR CUMULATION OF RESEARCH ON INSTITUTIONAL FIELDS. *Academy of Management Annals*, *11*(1). https://doi.org/10.1017/CBO9781107415324.004

Zittrain, J. (2006). THE GENERATIVE INTERNET Jonathan. *Harvard Law Review*.

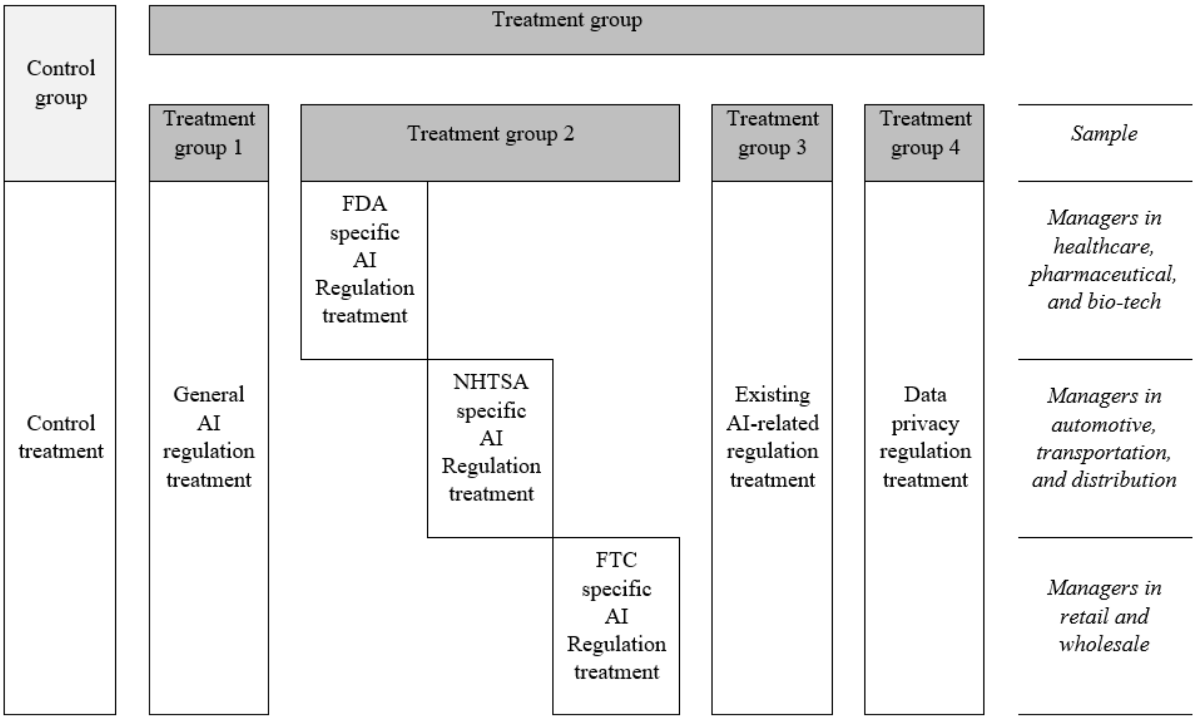
Zizzo, D. J. (2010). Experimenter demand effects in economic experiments. *Experimental Economics*, *13*(1), 75–98. https://doi.org/10.1007/s10683-009-9230-z

Zolas, N., McElheran, K., Goldschlag, N., Foster, L., Dinlersoz, E., Buffington, C., Brynjolfsson, E., & Beede, D. (2020). Measuring Technology Adoption in Enterprise-level Surveys: The Annual Business Survey. *American Economic Association Presentation*, *January 3r*(San Diego).

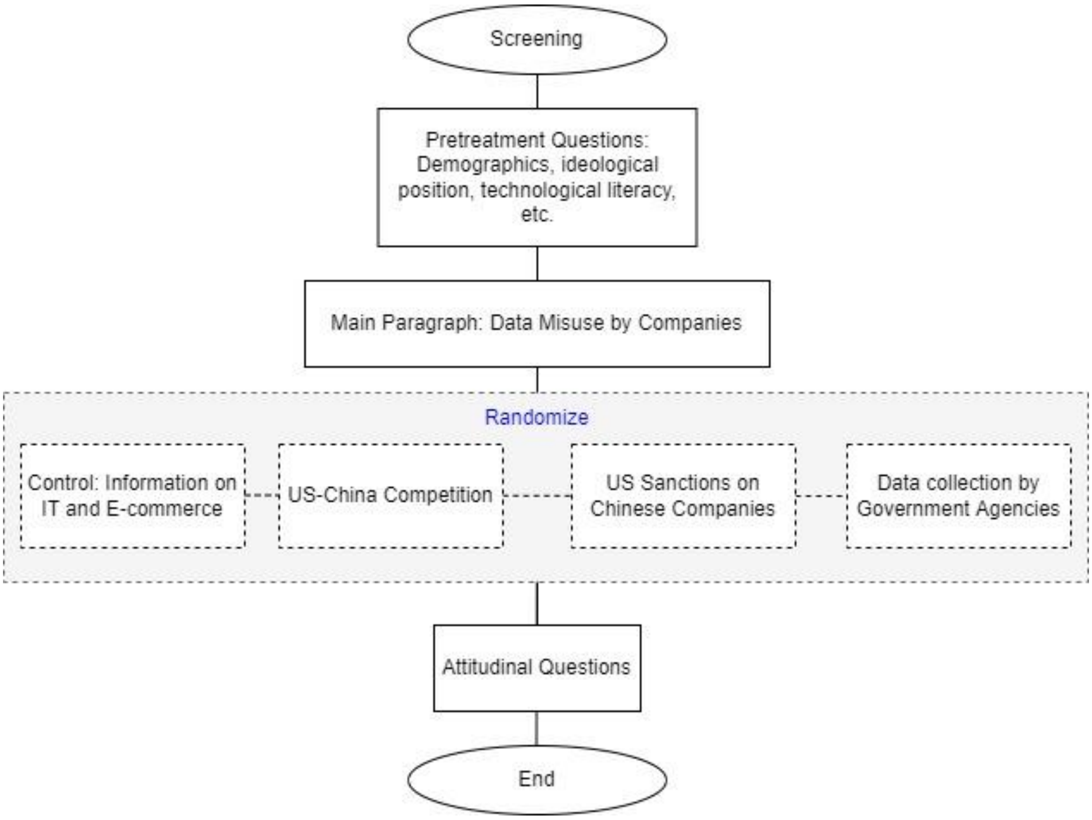
Zuiderwijk, A., & Janssen, M. (2014). Open data policies, their implementation and impact: A framework for comparison. *Government Information Quarterly*, *31*(1), 17–29. https://doi.org/10.1016/j.giq.2013.04.003

Appendix

A 1. Experimental design of survey - Article I



A 2. Experimental design of survey - Article IV



A 3. Overview of interview data sources - Article III

	Organization	Position	Informant Code	Interview mins	Interview N
NOIPAI	1 - Baidu	Manager	1NOIP1	24	1
	2 - Alibaba	Developer	1NOIP2	82	2
	3 - Tencent	Developer	1NOIP3	51	1
	4 - SenseTime	Director	1NOIP4	33	1
	5 - JD	Manager	1NOIP5	126	2
Domestic Tech-Firms	6 - DiDi	Director	2DTF1	97	1
	7 - VIPSHOP	Director	2DTF2	25	1
	8 - Gridsum	Director	2DTF3	65	1
	9 - Xiaoai	President	2DTF4	44	1
Domestic AI start-ups	10 - Trio.ai	CEO	3AIST1	75	1
	11 - Meezao	Founder	3AIST2	97	1
International Tech-Firms	12 - Microsoft	Director	4ITF1	55	1
	13 - Oracle	Manager	4ITF2	89	1
	14 - AI Technology Center	Co-founder	4ITF3	123	1
TOTAL				986	16

Research Articles

Article I:	Cuellar, M. Larsen, B. Lee, Y. Webb, M. (2021) Does Information About AI Regulation Change Manager Evaluation of Ethical Concerns and Intent to Adopt AI? *Journal of Law, Economics, & Organization.* 2022.
Article II:	Larsen, B. (2021) A Framework for Understanding AI-Induced Field Change: How AI Technologies are Legitimized and Institutionalized. Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society. 2021.
Article III:	Larsen, B. (2021) Government Mechanisms for Platform Boundary Resource Tuning: The case of China's National Open Innovation Platforms for AI
Article IV:	Larsen, B. Lee, Y. Wu, M. (2022) US-China Tech Competition and the Willingness to Share Personal Data in China

Article I

Does Information About AI Regulation Change Manager Evaluation of Ethical Concerns and Intent to Adopt AI?

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Abstract:

We examine the impacts of potential AI regulations on managers' perceptions of ethical issues related to AI and their intentions to adopt AI technologies. We conduct a randomized online survey experiment on more than a thousand managers in the US. We randomly present managers with different proposed AI regulations, and ask about ethical issues related to AI and their intentions related to AI adoption. We find that information about AI regulation increases manager perception of the importance of safety, privacy, bias/discrimination, and transparency issues related to AI. However, there is a trade-off; regulation information reduces manager intent to adopt AI technologies. Moreover, information about regulation increases manager intent to invest in developing AI strategy including ethical issues at the cost of investing in AI adoption, such as providing AI training to current employees or purchasing AI software packages. Variations in the concreteness of the ethical issues at hand and manager perceptions of regulation enforcement likely drive heterogeneous responses to regulation.

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Keywords: AI, Regulation, Innovation

JEL codes: K24 (Cyber Law), L21 (Business Objectives of the Firm), L51 (Economics of Regulation), O33 (Technological Change: Choices and Consequences • Diffusion Processes), O38 (Government Policy)

1. Introduction

Artificial intelligence (AI) technologies have become increasingly widespread over the last decade. In particular, the fields of image recognition, speech recognition, data analytics, and machine translation have advanced rapidly, spurred by important breakthroughs in deep neural networks (Varian 2018). But as the use of artificial intelligence has become more common, and the performance of AI systems has improved, policymakers, scholars, and advocates have also raised concerns. Policy and ethical issues such as algorithmic bias, data privacy, and transparency have gained increasing attention, raising renewed calls for policy and regulatory changes to address the potential consequences of AI (Frank et al. 2019). As AI continues to improve and diffuse, it will likely have important long-term consequences for jobs, inequality, organizations, and competition. AI technologies may likely create or exacerbate negative externalities when firms develop or deploy AI products and systems prematurely, which could aggravate existing biases and discrimination or violate data privacy and data protection practices. Because AI technologies tend to have a wide-ranging impact, stakeholders are increasingly interested in whether firms are likely to embrace measures of self-regulation based on ethical or policy considerations, and how decisions of policymakers or courts affect the use of AI systems. Where policymakers or courts step in, and regulatory changes affect the use of AI systems, how are managers likely to respond to new or proposed regulations across different industries, and how might those responses affect the use of different AI systems across various industries?

Currently, AI technologies are implicitly regulated through common law doctrines such as tort and contract law, which affect liability risks and the nature of agreements among private parties, as well as by statutory and regulatory obligations on organizations, such as emerging standards governing autonomous vehicles (Cuéllar 2019). As AI technologies are diffusing rapidly and have wide-ranging social and economic consequences, both policymakers and federal and state agencies, are contemplating new ways of regulating AI. These include broad proposals of general AI regulation, such as the Algorithmic Accountability Act introduced in the House of Representatives on April 10, 2019. State regulations include the California Consumer Privacy Act, which went into effect in January 2020 and was significantly updated through an initiative enacted by California voters in November 2020. Domain-specific regulations are currently being developed by federal regulators such as the Food and Drug Administration (FDA), the National Highway Traffic and Safety Administration (NHTSA), and the Federal Trade Commission (FTC). While many potential impacts of AI technologies are increasingly being examined and understood (Agrawal et al. 2019; Frank et al. 2019), we know less about the consequences of public-sector responses designed to regulate firm behavior– and even less about how managers might respond to these changes. Both policies and firm practices associated with AI development and adoption hold important ethical concerns and considerations that are likely to affect human behavior.

In this paper, we seek to address how different kinds of AI-related regulation – or even the prospect of regulation – might affect firm behavior, including firm responses to ethical concerns. We examine the impact of information on actual and potential AI-related regulations on business managers. In particular, we examine the degree to which managers change perceptions on the importance of ethical issues related to AI (privacy, transparency, safety, bias/discrimination, labor issues) and their intent to adopt AI technologies and alter their AI-related business strategies. We conduct a randomized online survey experiment where the treatment group is informed of the core features of different regulatory treatments. Specifically, we randomly expose managers to one of the following treatments: (1) a general AI regulation treatment that invokes the prospect of statutory changes imposing legislation like the Algorithmic Accountability Act, (2) industry-specific regulatory treatments that involve the relevant agencies, i.e., the FDA (for healthcare, pharmaceutical, and biotech), NHTSA (for automobile, transportation,` and distribution), and the FTC (for retail and wholesale), (3) a treatment that reminds managers that AI adoption in businesses is subject to existing common law and statutory requirements including tort law, labor law, and civil rights law, and (4) a data privacy regulation treatment that invokes legislation like the California Consumer Privacy Act.

Our results indicate that exposure to information about AI regulation increases the importance managers assign to various ethical issues when adopting AI. All four regulation treatments increase the importance managers put on safety and accidents related to AI technologies. However, there is a trade-off. Increases in manager awareness of ethical issues are offset by a decrease in manager intent to adopt AI technologies. All four regulation treatments decrease manager intent to adopt AI. Exposure to information about AI regulation significantly increases expenditure intent for developing AI strategy, which includes a budget for assessing ethical impact and internal strategy development. We also find that information about AI regulation increases manager intent to hire more managers, which is consistent with the intent to invest more in firm strategies that include assessments of ethical impact. The trade-off between AI ethics and adoption is more pronounced in smaller firms, which are generally more resource-constrained than larger firms. When comparing the healthcare, automotive, and retail industries, we find heterogeneity in our results, which indicates that regulation information also is likely to have a range of effects on industries and their varying compositions in terms of ethical concerns, customer relations, business models, data usage, and applied strategic components differently due to industry-specific characteristics.

The heterogeneous responses across ethical issues and firm characteristics suggest that the concreteness of the ethical issue and manager perception of enforcement of regulation likely drive the heterogeneous responses to regulation. Overall, our findings imply that AI regulation may slow innovation or reduce competition through lower adoption, but improve consumer welfare through increased safety and heightened attention in terms of addressing bias and discrimination issues.

To the best of our knowledge, our paper is the first to examine the potential impact of new and intended AI regulation on AI adoption and the ethical and legal concerns related to AI. Our paper is related to the literature that examines the broader effects of technology-related regulations, such as privacy regulation or tort law, on social and economic activity. Goldfarb and Tucker (2012) have found that in data-driven industries, privacy regulation impacts the rate and direction of innovation. Too little privacy protection means that consumers may be reluctant to participate in market transactions where their data are vulnerable. Privacy regulation can affect firms' use of data to innovate. Some scholars find that privacy regulation or tort law can affect technology adoption and might slow down innovation (Goldfarb & Tucker 2011; Miller & Tucker 2011; Miller & Tucker 2014; Kim & Wagman 2015; Galasso & Luo 2017; Galasso & Luo 2019). Research on environmental regulation has, however, found that regulation also can play a supporting role in terms of encouraging innovation, for example, by raising emission requirements, which forces firms to implement new solutions (Hascic et al. 2009). Legislation such as the California Consumer Privacy Act requires firms to develop new practices, which could result in a demand for more privacy-related innovation.

We also contribute to the literature on business ethics and regulation in relation to organizational decision making. Ethical guidelines have been observed to significantly influence decision-making in certain fields (e.g., healthcare, environment), comparable to the influence of legislative norms (Campbell & Glass 2001). At the same time, the implementation and adoption of biased or discriminatory algorithms have been revealed to cause substantial systemic harm when immature systems have been prematurely adopted and implemented (Kim 2017; Turner & Lee 2018). When the economic value associated with a new market opportunity is uncertain in the early stages of new technology adoption, it can be difficult for managers to know which resources should be assembled and coordinated (Alvarez & Barney 2005). New regulation challenges present biased managerial preferences (Ambec & Barla 2006), which in turn cause new considerations to be placed on developing or implementing ethical AI solutions. Our paper contributes an empirical understanding of some of the potential trade-offs that managers face when striking a balance between ethics and AI adoption preferences. Our findings hold implications for firm strategy as well as for AI-related public policymaking.

The outline of the paper is as follows. In the next section, we elaborate on the notions of AI ethics and regulation and develop our hypotheses. Section 3 discusses the empirical strategy, and Section 4 the data and sample. In section 5, we report our main results and offer some concluding discussions in Section 6.

2. Ethical Issues of AI and AI Regulation

AI describes a broad set of computing techniques and associated technologies with widespread applications in a variety of workplace, commercial, and governmental settings. We define artificial intelligence (AI) as the capacity of a technology to perform functions that, if performed by a human, would ordinarily be understood to require intelligence (Russell and Norvig, 2009). This tends to include functions associated with applications such as natural language processing (NLP), computer vision (CV), and machine learning (ML) technologies. Our definition of AI aims to cover the most widespread uses, including, but not limited to, chatbots (NLP), object and facial recognition (CV), and recommendation engines (ML).

The increasing reliance on algorithms as instruments for the regulation of social relationships, paired with the invisibility of algorithmic evaluation processes (Curchod, Patriotta, Cohen, & Neysen, 2020), creates new opportunities for algorithms to affect human interaction, behavior, and decision making. For businesses that develop and deploy AI algorithms, this means that the characteristics of the system are likely to affect varying socio-economic structures, which may create or potentially exacerbate ethical issues. For example, in terms of hiring, algorithms have been shown to aggravate racial and gender bias and discrimination (Raub, 2018). In terms of autonomous vehicles, issues pertain to areas of safety and accountability (Koopman & Wagner, 2017). For many kinds of AI systems that are deployed in online settings, such as social media or retail, ethical issues that relate to data privacy and transparency are essential strategic areas for firms' to take into account (Goldfarb & Tucker, 2011). In terms of algorithmic solutions deployed in the criminal justice system, ethical issues are often linked to principles of transparency and fairness, while algorithms deployed in the healthcare system are subject to stringent requirements over patient data privacy. Relatedly, Jobin, Ienca, & Vayena (2019) find that the literature on AI ethics has converged around five ethical principles of transparency, justice and fairness, non-maleficence, responsibility, and privacy.[18]

2.1 AI Related Regulation

As interest in AI has grown, companies and governments have sought to translate general principles of AI ethics into concrete practices (see e.g.: AI Ethics Impact Group, 2020). This implies that two different but interrelated sets of actionable mechanisms are currently emerging. One is soft law governance, which functions as self-regulation based on non-legislative policy instruments. Private sector firms issuing their own guidelines for ethical AI, or stakeholder organizations such as The Partnership on AI, or standard-setting bodies such as The Institute of Electrical and Electronics Engineers (IEEE) are all examples of soft-law guidance, which play an important role in setting the default for how AI is governed (Wallach & Marchant 2018). Actionable mechanisms by private sector participants often focus on the development of concrete technical solutions, including the development of standards or explicit normative encoding. Legally binding regulations, or so-called hard law measures, are passed by the legislatures to define permitted or prohibited conduct.

[18] The increasing literature on ethical AI (Boddington 2017; Bostrom & Yudkowsky 2014; Etzioni & Etzioni 2017; Yuste & Goering 2017), focus on diverse areas from societal considerations (Cath, Wachter, Mittelstadt, Taddeo, & Floridi 2018; Greene, Hoffmann, & Stark 2019) to systemic risks (Altman, Wood, & Vayena 2018; Crawford & Calo 2016) and legal and policy issues that may affect firms such as those arising from algorithmic bias or discrimination (Lambrecht & Tucker 2019; Veale & Binns 2017).

Regulatory approaches generally refer to legal compliance, the issuing of certificates, or the creation or adaptation of laws and regulations to accommodate the specificities of an AI system (Jobin et al., 2019).

In the United States, the use of AI is implicitly governed by a variety of common law doctrines and statutory provisions, such as tort law, contract law, and employment discrimination law (Cuéllar 2019). This implies that judges' rulings on common law-type claims already plays an important role in how society governs AI. While common law often involves decision making that builds on precedent, federal agencies also engage in important governance and regulatory tasks that may affect AI across a variety of sectors of the economy (Barfield & Pagollo 2018). Federal autonomous vehicle legislation, for instance, carves out a robust domain for states to make common law decisions about autonomous vehicles through the court system. Through tort, property, contract, and related legal domains, society shapes how people utilize AI, while gradually defining what it means to misuse AI technologies (Cuéllar 2019). Existing law (e.g., tort law) may, for instance, require that a company avoid any negligent use of AI to make decisions or provide information that could result in harm to the public (Gallaso & Luo 2019). Likewise, current employment, labor, and civil rights laws imply that a company using AI to make hiring or termination decisions could face liability for its decisions involving human resources.

Policymakers and the public nonetheless often consider new legal and regulatory approaches when faced with potentially transformative technologies because these technologies may pose challenges for and ultimately fail to fit the purpose or reach of some existing laws and regulations (Barfield & Pagollo 2018). The Algorithmic Accountability Act is one proposal to deal with such perceived gaps. Co-sponsored by several federal legislators, the Act would regulate large firms with gross annual receipts of $50 million or more over the last three consecutive years, or which possess or control personal information on more than 1 million consumers (Congress 2019). If passed, The Algorithmic Accountability Act would regulate large firms through mandatory self-assessments of their AI systems, including disclosure of firm usage of AI systems, their development process, and system design and training, as well as the data gathered and its use.

While statutes imposing new regulatory requirements such as the Algorithmic Accountability Act are still under debate, regulation of data privacy is already being implemented. The state of California introduced the California Consumer Privacy Act (CCPA), which went into effect in January 2020.

The CCPA affects all businesses buying, selling, or otherwise trading the "personal information" of California residents, including companies using online-generated data from California residents in their products. The CCPA thus adds another layer of oversight to the area of data handling and privacy, on which many AI applications are contingent.

Although the common law, existing statutes, and forthcoming privacy regulations already govern many terms of usage related to AI application and data handling, domain-specific regulators are also devising their own approaches to regulate AI. In this study, we have chosen to focus on the current regulatory approaches to healthcare, automotive, and retail, and so focus on the current initiatives applied by the Food and Drug Administration (FDA), the National Highway Traffic and Safety Administration (NHTSA), and the Federal Trade Commission (FTC).[19]

In short, AI regulation is emerging and is likely to materialize more intensely across several directions simultaneously: from existing laws, new general regulations, and evolving domain-specific regulations. The main goal of regulators is to ensure opportunity in the application and innovation of AI-based tools, products, and services while limiting negative externalities in the areas of competition, privacy, safety, and accountability. It remains little known, however, how the proposed Algorithmic Accountability Act and the incoming CCPA, as well as the regulatory approaches taken by the FDA, NHTSA, and the FTC, will affect managerial preferences and therefore the likely rate of AI adoption and innovation across different firms and industries.

2.2 Firm Response to AI Regulation

Society's legal and policy decisions to implement regulatory changes are often driven not just by concerns about national competitiveness or political economy, but also by ethical considerations that become more salient to the public as new technologies, such as AI, become more pervasive. These ethical concerns also matter to business leaders, even if firms are not forced to internalize the cost of complying with ethical norms by outright regulations.

The primary aim of ethics in business is to lay down rules of "good conduct" for firms, which take account of the ethical implications of managers' strategic decisions (Wilson, 1997). Making ethical decisions and setting policies in a firm often involves choosing between competing purposes,

[19] Each of the domain-specific regulatory approaches are elaborated in greater detail in Section 3.1.

which has to be based on a clear listing of priorities or values (Hosmer, 1994). Business managers are usually the ones with the capabilities to set new directions and guidelines, as well as the underlying ethics and values for the firm and for its employees to follow and use as leadership and direction for the organization (Kulshreshtha, 2005). Although ethical violations and moral improprieties within business organizations often are the focus of policy debates, little attention has been placed on the ethical dilemmas that firm managers face in the utilization of AI technologies. When governments impose new regulations, which can cause markets to take unexpected turns, uncertainty is a major challenge to managers (Teece & Leih, 2016).

Managers have to make day-to-day decisions, as well as longer-term decisions, with highly incomplete information – including decisions about exploiting new and untested technological and market opportunities (Teece & Leih, 2016). This forces some managers to exhibit present-biased preferences and, as a result, managers may choose to put off AI investment in profitable but otherwise costly opportunities, as the cost of (e.g. ethics-related) innovation occurs "now," but the benefits only occur "later" (Ambec & Barla, 2006). In the absence of any clear legislation or regulation, firm managers could be faced with a predicament in terms of how fast and how far managers should push new products or systems, which in the case of AI, have proved to hold the possibility of exacerbating social biases and varying forms of discrimination or abuse of data and privacy.

The difficulty with many AI products or systems is that ethical or responsible behavior could be costly to adopt, e.g., in relation to the use of data, or increased time associated with developing and marketing an ethically-tested product, while the returns to the additional investments are not guaranteed, which could reinforce present-biased preferences. Therefore, by requiring ethics-related consideration, regulations could help the manager overcome this self-control problem, which could lead to increased awareness of ethical issues (Ambec, Cohen, Elgie, & Lanoie, 2013). In relation, mandatory regulations may demand new investments that are aimed specifically at addressing ethical concerns, which could impose added costs on firms and therefore delay adoption and innovation in the short term. (Jaffe et al., 1995; Majumdar & Marcus, 2001). Over the longer term, however, firms may reorient certain aspects of innovation in order to meet both regulatory and consumer demands for (e.g., more transparent, trustworthy, or safe) AI systems, that in turn pose fewer legal, regulatory, or ethical risks.

The so-called Porter's hypothesis argues that regulation can also enhance firms' competitiveness and bolster their innovative behaviors (Porter & Van der Linde, 1995). Aragón-Correa, Marcus, & Vogel (2020) argue that the existence of strong regulation, or even the uncertain anticipation of future regulation, has encouraged firms' to invest in otherwise neglected fields (e.g., environmental protection), while attracting additional investment in affiliated areas. Regulatory mechanisms would require firms to allocate some inputs (labor, capital) to the development and deployment of ethical AI systems. If the production of unsafe products is made sufficiently expensive, firms would be encouraged to innovate and produce safer products (Baumol & Blackman, 1991). This approach could cause a reduction in the divergence between business ethics and economic incentives while encouraging and enhancing the socially responsible behavior of businesses (Kulshreshtha, 2005) in the long term. However, when the economic value associated with a new market opportunity is particularly uncertain in the early stages of new technology adoption, it is difficult for managers to know which resources should be assembled and coordinated (Alvarez & Barney, 2005), and consequentially managers may invest in strategy and human resources that reduce such uncertainty from new regulation.

New forms of regulation can be viewed as an uncertain shock to a firm or an industry (Teece & Leih, 2016). This implies that firm managers have to engage in a variety of actions to try to increase the certainty of the outcomes associated with making decisions. For example, data on consumer preferences can be collected, the successes and failures of other firms can be analyzed, and a variety of strategic and financial tools can be applied in an effort to increase the level of certainty associated with decision-making (Alvarez & Barney, 2005). These considerations are connected with industry- and sector-specific characteristics that are further linked to a firm's organization and structure. As firms operating in different industries tend to deploy varying kinds of AI, it is plausible to assume that firms operating in diverse industries are likely to respond differently to regulation. Furthermore, achieving legitimacy associated with new AI systems or products requires substantial firm strategies, while these are expected to differ across industries.

In terms of firm size, managers of smaller firms generally hold fewer resources, which could make it more costly for them to produce the initial investments required to develop responsible strategies (Pava & Krausz, 1996). Bowen (2002) suggests that it is not size per se that promotes responsible firm behavior, but the elements of an organization's visibility and the resources available to it, which could result from its size. Correspondingly, larger firms are more likely to find their reputation suffering if they do not perform well on social measures, and act accordingly (Moore & Manring, 2009). Such developments have, for example, been seen in relation to large technology companies' development of facial recognition technologies, which has faced severe public backlash due to exacerbating racial biases and discrimination.

3. The Online Survey Experiment and Empirical Framework

3.1 The Survey Design

We conduct a randomized online survey experiment to study the effects of different regulatory treatments. Managers are randomly assigned to 'treatment' and 'control" groups, and the differences in the survey responses between the groups can be attributed to the treatments (Visser, Krosnick, & Lavrakas, 2000). For our control group, we present some of the same concerns that our treatment group is subjected to, although without specifically mentioning regulation or any form of regulatory compliance. For our treatment groups, managers are exposed to one of the following treatments: a general AI regulation treatment that invokes the proposed Algorithmic Accountability Act (T1); industry-specific regulation treatments that invoke the relevant agencies, i.e., the FDA (for managers in healthcare, pharmaceutical, and biotech), NHTSA (for managers in automotive, transportation, and distribution), and the FTC (for managers in retail and wholesale) (T2); a treatment that reminds that AI adoption in businesses are subject to existing common law and statutory requirements such as tort law, labor law, and civil rights law (T3); and a data privacy regulation treatment based on the California Consumer Privacy Act (T4). Figure 1 summarizes the structure of the online experiment. Other than for the agency-specific AI regulation treatment, managers in different industries are exposed to the same general AI regulation, existing AI-related regulation, and data privacy regulation statements.

We present both the treatment and the control groups with an introductory paragraph that contains details about the current and forecasted adoption of AI technologies:[20] For our control group, we do not mention regulation or compliance. For the treatment groups, we rephrase the next paragraph

[20] The contents of the introductory paragraph are based on a McKinsey Global Survey of AI adoption (McKinsey 2019). We define AI technologies to include NLP, CV, and ML and give examples of each in the earlier part of the survey.

(depending on the treatment group) to contain details about the relevant laws or agencies that could affect the use and adoption of AI.

For T1 (General Regulation), the paragraph stresses that the Algorithmic Accountability Act requires firms to disclose their usage of AI systems, including their development process or contractor of origin, AI system design, model training, as well as data gathered and in use. For T2a (Healthcare Regulation), the paragraph notes that the FDA aims to examine and pre-approve, consistent with its legal authority, the underlying performance of a firm's AI products before they are marketed, and post-approve any algorithmic modifications.

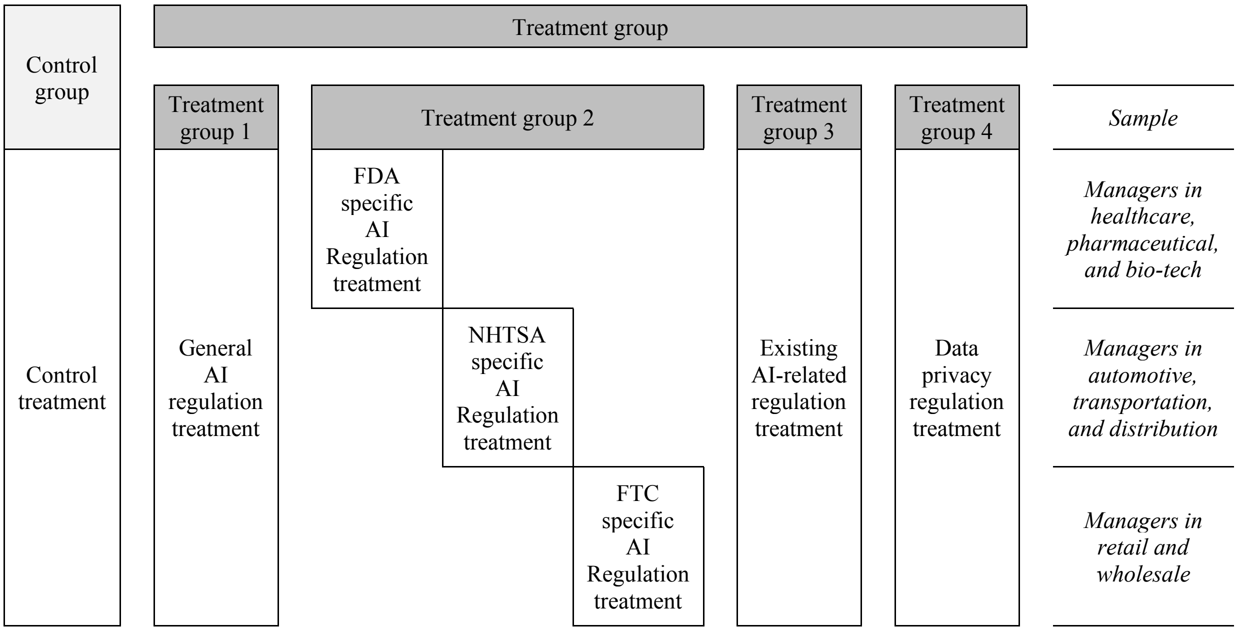

Figure 1. Research design

For T2b (Automotive Regulation), it specifies that NHTSA emphasizes the importance of removing unnecessary barriers while issuing voluntary guidance rather than regulations that could stifle innovation. For T2c (Retail Regulation), it conveys that the FTC has engaged in hearings to safeguard consumers from unfair and deceptive practices surrounding potential issues across algorithmic discrimination and bias (e.g. in online adds / micro-targeting of consumer groups), transparency (e.g. product recommendation engines) and security (e.g. use and protection of consumers private information). For T3 (Common Law and Existing Statutes), the paragraph stresses that firms using AI technology in the United States are already subject to some common law and statutory requirements relevant to AI. It notes that existing laws (e.g., tort law) may require that a company avoid any negligent use of AI to make decisions or provide information that could result in harm to the public. For T4 (Data Privacy Regulation), it stresses that the California Consumer Privacy Act of 2018 (CCPA) will affect all businesses buying, selling or otherwise trading the "personal information" of California residents – including companies using online-generated data from California residents across their products.

For most treatments, except T2b (Automotive Regulation) and T3 (Common Law and Existing Statutes), we identify 2020 as the year when the new regulation will take effect, in order to minimize variation based on different manager assumptions about the effective date of new regulations. The full texts of the treatments can be found in Appendix Table A1.

The treatments render AI-related regulation salient and underscore the different types and approaches to regulation. The differences in the responses by each treatment group and the control group can be considered as the effect of making each AI-related regulation salient to the managers. Following the treatment/control scenario, participants are asked five sets of questions related to managers' inclination towards 1) adoption of AI technologies; 2) budget allocation; 3) AI-related innovation; 4) ethical issues; and (5) labor.[21]

Our survey design examines manager intent, but the literature finds that the act of stating one's intent to engage in a behavior often is associated with an increased likelihood of subsequently engaging in the behavior (Levav & Fitzsimons, 2006). Though a substantial social psychology literature notes that survey responses often don't match behavior (see e.g.: Tourangeau, Roger & Rips 2000), Dellavigna (2009) notes that a key difference between consumers and firms and these top managers, however, is captured by experience. This implies that unlike individual consumers, who often display nonstandard preferences and beliefs that may deviate from economic models, firms obtain experience through specialization, market analysis, and competition, and managers are expected to maximize profits and are therefore less likely to be influenced by biases (Dellavigna, 2009). Hence, we expect the interest of the majority of subjects in our sample to be economically

[21] The survey questionnaire is in the Online Appendix, which features the FDA treatment for the healthcare sector. The survey questions for the automotive and retail sectors are the same as above, except for the industry-specific regulation treatment texts, which are presented in Appendix Table A1.

aligned with the interests of the firms that we survey.[22] Of course, the short-term changes in intent captured by exposing managers to the different regulatory contexts may not result in the same changes in the long term. However, given the nascent status of AI regulation and the dearth of data related to real-world AI adoption, we believe examining manager intent can offer meaningful insights for AI regulation.

3.2 Sample and Data

We recruit managers in the US using SurveyMonkey Audience. We focus on managers in businesses with at least 50 employees, since they are likely to be well-aware of the types of technologies being used at their businesses and be involved in the decisions surrounding adoption. The managers we recruited include owners and partners of businesses, C-level executives, and senior and middle managers in the three broad industries discussed above. We launched the survey in August 2019.[23]

We collected 2,610 responses. Of these, about 20.9% were from non-managers and about 33.8% were from businesses with less than 50 employees. We exclude those as well as those who indicated that they did not devote full attention to answering the questions (about 9.9%). We also dropped responses from those who finished the survey in an unreasonably short time, i.e., the first percentile of response time. Applying these restrictions, we end up with 1,245 managers. The average response time in this sample was about 7.3 minutes.[24]

[22] Literatures on how surveys affect behaviors also point to mere measurement and self-prophecy effects, where the act of measuring itself can induce subsequent changes in respondents' behavior. (Morwitz, Johnson, & Schmittlein, 1993). The literature also discusses "experimenter demand effects," which is the possibility that respondents change their behavior since they know they are subjects in an experiment (Zizzo, 2010; Di Tella & Rodrik, 2019). Zwane et al., (2011) find that surveys can affect behavior and parameter estimates, but conclude that infrequent survey visits on large samples is preferable to smaller samples with higher-frequency data collection, which is more likely to confound estimates of parameters. Given the above literatures, we have restricted our sample to a relatively large population of managers in firms with more than 50 employees.

[23] A growing literature in economics has relied on online survey companies, such as SurveyMonkey and Amazon Mechanical Turk, to conduct online surveys and experiments. Though the respondents identified and recruited by these companies are not necessarily representative samples of the population, they do comprise a sample that is not too different from the general population, and, as in our case, the possibility to target a specific subset of the population.

[24] In Appendix Tables A2 and A3 we compare some basic characteristics of our sample relative to the samples in recent papers (Kuziemko et al. 2015, Di Tella and Rodrik 2019) that have used Amazon Mechanical Turk, as well as the American Community Survey (ACS). While our sample is a subset of managers of businesses with 50 or more employees, and employed in the three broad industry sectors, the other samples in Appendix Tables A2 and A3 do not have any explicit restrictions. Appendix Table A2 presents the distribution across states in the US and shows that the geographical

Table 1. Summary statistics of key variables

Variable	Mean	Std. Dev.	Min	Max	Obs
Control group	0.194	0.395	0	1	1,245
General AI regulation	0.196	0.397	0	1	1,245
Agency-specific AI regulation	0.214	0.411	0	1	1,245
Existing AI-related regulation	0.204	0.403	0	1	1,245
Data privacy regulation	0.192	0.394	0	1	1,245
Healthcare/pharmaceutical/bio-tech	0.425	0.495	0	1	1,245
Auto/transportation/distribution	0.186	0.390	0	1	1,245
Retail and wholesale	0.389	0.488	0	1	1,245
Number of business processes to adopt AI	3.405	2.777	0	10	1,245
Ln(AI budget)	9.456	4.511	0	23	1,245
Budget share- AI-related research and development	22.393	20.270	0	100	1,245
Budget share-hiring workforce to manage, operate, maintain AI	18.776	14.199	0	100	1,245
Budget share-AI training for existing employees	16.382	12.737	0	100	1,245
Budget share- purchase AI packages from external vendors	14.989	12.260	0	100	1,245
Budget share-computing and data related costs	12.881	11.097	0	100	1,245
Budget share-developing company's AI strategy	14.579	14.948	0	100	1,245
AI innovation activities – co-operation with other institutions	3.714	1.133	1	6	1,245
AI innovation activities – filing patents	3.742	1.170	1	6	1,245
AI innovation activities – produce or process innovation	3.806	1.064	1	6	1,245
Ethical concerns related to AI-layoffs or labor related issues	3.437	1.117	1	5	1,245
Ethical concerns related to AI-racial and gender bias/discrimination	3.461	1.203	1	5	1,245
Ethical concerns related to AI-safety and accidents	3.740	1.103	1	5	1,245
Ethical concerns related to AI-privacy and data security	3.933	1.082	1	5	1,245
Ethical concerns related to AI-transparency and explainability	3.645	1.073	1	5	1,245
Labor adjust from AI adoption-managers	3.370	0.995	1	5	1,201
Labor adjust from AI adoption-technical workers	3.638	0.991	1	5	1,195
Labor adjust from AI adoption-office workers	3.360	1.010	1	5	1,201
Labor adjust from AI adoption-sales workers	3.453	1.037	1	5	1,172
Labor adjust from AI adoption-service workers	3.434	1.041	1	5	1,185
Labor adjust from AI adoption-production workers	3.405	1.013	1	5	1,152

distribution of managers in our sample is not very different from that of the other papers, or the ACS. Appendix Table A3 presents the gender, education, racial distribution. The managers in our sample tend to include a higher representation of females than in the overall population. Only a third of our respondents are male. However, the female share is considerably higher in Kuziemko et al. 2015 and Di Tella and Rodrik 2019 as well. Given our focus on managers, the educational attainment of our respondents tends to be higher than in the other samples. In terms of race, our sample of managers have a relatively higher share of blacks and a lower share of whites compared to the other samples.

While our sample is not representative of all businesses and all industries operating in the United States, we note that comparable surveys reflect similar results in terms of firms' rate of AI adoption. For example, a McKinsey global AI survey from 2019 finds that from a sample of 2360 firms across 12 industries, "fifty-eight percent of respondents report that their organizations have embedded at least one AI capability into a process or product in at least one function or business unit, up from 47 percent in 2018" (Mckinsey, 2019 p.4). When the sample is widened to include the majority of firms operating in the U.S, such as reflected in the 2017 Annual Business Survey, which encompasses 800,000 firms, the rate of adoption of AI technologies is reported to be much lower and skewed towards adoption in larger enterprises (Zolas et. al. 2019).

In Table 1 we present the summary statistics of the main variables in our survey. The first five variables indicate the share in the control group and each of the four treatment groups. When we launched the survey, we designated each treatment to be randomized evenly across each group, and the resulting distribution reflects this well, with each group consisting of approximately 20% of the total sample. In terms of industry, about 42.5% are in healthcare, 38.9% in retail and wholesale, and 18.6% in automotive.

Next is a set of key outcome variables. In terms of adoption, we ask in how many business processes they would adopt any of the AI technologies (i.e., machine learning, computer vision, and natural language processing) in the following year. To clarify what business processes are, we spell out several examples of business processes when we introduce each technology in the survey. Respondents were allowed to choose from 0 to 10 or more (i.e., top-coded at 10). On average, managers in our sample said that they would adopt AI in about 3.4 business processes.

We ask managers how they would allocate budgets across six expense categories. By forcing the allocation to sum to 100 percent, we can examine the trade-offs managers choose in response to the perceived impact of AI regulation. We measure budget allocation by having managers fill out six different categories with costs related to: 1) developing AI strategy that is compatible with the company's overall business strategy; 2) hiring managers, technicians, and programmers, excluding R&D workers, to operate and maintain AI systems; 3) AI training for current employees; 4) purchasing AI packages from external vendors; 5) computers and data centers, including purchasing or gathering data; and 6) R&D related to creating new AI products or processes. We randomize how the six categories are presented to each respondent, so that the order of the categories does not affect how the percentages are allocated. The average log AI budget in dollars was 9.45. On average, managers allocated 14.6% to developing AI strategy, 18.8% to hiring, 16.3% to training, 15% to purchasing AI packages, 12.9% to computing and data resources, and 22.4% to R&D.[25] In addition to the R&D budget allocation, we directly ask how they would adjust their workplaces' AI-related innovation activities in terms of patenting, co-operation, and product or process innovation on a 5-point Likert scale (decrease greatly=1, decrease slightly, the same, increase slightly, increase greatly=5).

Manager perceptions of ethical and policy concerns are assessed by asking the degree of importance that managers attach to: 1) layoffs or labor-related issues due to AI adoption; 2) racial and gender bias/discrimination from AI algorithms; 3) safety and accidents related to AI technologies; 4) privacy and data security issues related to AI adoption, and; 5) transparency and explainability of AI algorithms. We measure managerial values on a standard Likert scale ranging from not important to very important. On average managers considered each ethical issue more than moderately important, and considered privacy and data security issues the most important. In a subsequent question, we ask managers whom they consider to be primarily responsible for AI-related ethical issues in their business: 1) managers; 2) engineers; 3) AI package vendors; 4) the government, i.e., regulatory agencies; 5) the courts; and 6) other.

Finally, we ask managers to use a 5-point Likert scale (decrease greatly=1, decrease slightly, the same, increase slightly, increase greatly=5) to describe the likelihood that they would adjust the number of the different types of workers (managers, technical workers, office workers, sales workers, service workers, and production workers) because of AI adoption. On average, managers responded that they would slightly increase all types of workers, but the technical workers somewhat more.

3.3 Treatment and Control Group Balance

Before turning to the regression results, we examine whether individual and firm characteristics are balanced across the control and treatment groups. Table 2 presents the mean and standard errors of the variables across each group. All variables are dummy variables related to the described

[25] Some of the respondents allocated 100% of the budget to one category. We tried dropping these individuals in the empirical analysis, but the results remain the same.

character. Table 2 shows that the data is well balanced across the different treatment groups, other than a higher share of black respondents and a lower share of white respondents for the general AI treatment group. In the regression analysis, we control for all the variables in Table 2. The key assumption in identifying the impact of the treatment is that there are no unobservable differences between the control group and treatment groups. For example, if the control and treatment groups differ systematically in terms of manager familiarity to AI regulation, the estimated treatment effects could be biased. A well-randomized experiment would address this by balancing out such unobserved characteristics between treatment and control. Since randomization may not be perfect in real-world settings, we include control variables to increase the precision of the treatment effect. Table 2 does provide reassurance that randomization was

Table 2. Summary statistics of individual and business characteristics by treatment

	Control group		Treatment group								Total	
			General AI regulation		Agency-specific AI regulation		Existing AI-related regulation		Data privacy regulation			
Panel A. Individual characteristics												
Owner or partner	0.166	(0.024)	0.172	(0.024)	0.187	(0.024)	0.118	(0.020)	0.134	(0.022)	0.156	(0.010)
CEO or C-level executive	0.145	(0.023)	0.143	(0.022)	0.135	(0.021)	0.169	(0.024)	0.155	(0.023)	0.149	(0.010)
Managers	0.689	(0.030)	0.684	(0.030)	0.678	(0.029)	0.713	(0.028)	0.711	(0.029)	0.695	(0.013)
Bachelor's degree or above	0.593	(0.032)	0.566	(0.032)	0.547	(0.031)	0.591	(0.031)	0.573	(0.032)	0.573	(0.014)
White	0.664	(0.030)	0.574	(0.032)**	0.622	(0.030)	0.626	(0.030)	0.640	(0.031)	0.625	(0.014)
Black	0.149	(0.023)	0.221	(0.027)**	0.191	(0.024)	0.197	(0.025)	0.163	(0.024)	0.185	(0.011)
Asian	0.054	(0.015)	0.041	(0.013)	0.064	(0.015)	0.043	(0.013)	0.050	(0.014)	0.051	(0.006)
Hispanic	0.075	(0.017)	0.078	(0.017)	0.096	(0.019)	0.098	(0.019)	0.075	(0.016)	0.084	(0.008)
Other	0.021	(0.009)	0.016	(0.008)	0.007	(0.005)	0.008	(0.006)	0.025	(0.010)	0.015	(0.003)
Female	0.656	(0.031)	0.689	(0.030)	0.629	(0.030)	0.650	(0.030)	0.715	(0.029)	0.667	(0.013)
Age less than 30	0.349	(0.031)	0.381	(0.031)	0.348	(0.029)	0.315	(0.029)	0.364	(0.031)	0.351	(0.014)
Age 30 to 45	0.402	(0.032)	0.365	(0.031)	0.419	(0.030)	0.417	(0.031)	0.377	(0.031)	0.397	(0.014)
Age above 45	0.249	(0.028)	0.254	(0.028)	0.232	(0.026)	0.268	(0.028)	0.259	(0.028)	0.252	(0.012)

Continued

Table 2. Continued

	Control group		Treatment group								Total	
			General AI regulation		Agency-specific AI regulation		Existing AI-related regulation		Data privacy regulation			
Panel B. Workplace characteristics												
Small business (less than 500 emp.)	0.456	(0.032)	0.467	(0.032)	0.509	(0.031)	0.433	(0.031)	0.435	(0.032)	0.461	(0.014)
Large business (500 or more emp.)	0.544	(0.032)	0.533	(0.032)	0.491	(0.031)	0.567	(0.031)	0.565	(0.032)	0.539	(0.014)
Revenue less than 1M	0.203	(0.026)	0.262	(0.028)	0.228	(0.026)	0.224	(0.026)	0.201	(0.026)	0.224	(0.012)
Revenue 1M to 9.9M	0.253	(0.028)	0.275	(0.029)	0.281	(0.028)	0.240	(0.027)	0.318	(0.030)	0.273	(0.013)
Revenue 10M to 99M	0.253	(0.028)	0.189	(0.025)*	0.199	(0.024)	0.244	(0.027)	0.234	(0.027)	0.223	(0.012)
Revenue 100M or more	0.290	(0.029)	0.275	(0.029)	0.292	(0.028)	0.291	(0.029)	0.247	(0.028)	0.280	(0.013)
Low management practices	0.481	(0.032)	0.426	(0.032)	0.442	(0.030)	0.437	(0.031)	0.444	(0.032)	0.446	(0.014)
High management practices	0.519	(0.032)	0.574	(0.032)	0.558	(0.030)	0.563	(0.031)	0.556	(0.032)	0.554	(0.014)
Previous budget less than 100K	0.257	(0.028)	0.287	(0.029)	0.262	(0.027)	0.252	(0.027)	0.276	(0.029)	0.267	(0.013)
Previous budget 100K to 999K	0.539	(0.032)	0.500	(0.032)	0.472	(0.031)	0.465	(0.031)	0.464	(0.032)	0.488	(0.014)
Previous budget 1M or more	0.614	(0.031)	0.570	(0.032)	0.607	(0.030)	0.614	(0.031)	0.598	(0.032)	0.601	(0.014)
Natural language processing in use	0.739	(0.028)	0.738	(0.028)	0.734	(0.027)	0.752	(0.027)	0.736	(0.029)	0.740	(0.012)
Computer vision processing in use	0.693	(0.030)	0.717	(0.029)	0.719	(0.028)	0.709	(0.029)	0.745	(0.028)	0.716	(0.013)
Machine learning processing in use	0.763	(0.027)	0.758	(0.027)	0.775	(0.026)	0.752	(0.027)	0.791	(0.026)	0.768	(0.012)
No. of observations	241		244		239		254		267		1245	

Notes: ***, **, and * denote statistical significant at 1%, 5%, and 10% level.

relatively well done, especially in the use of different AI applications across groups. The use of AI applications would likely be related to awareness of AI regulation.

To further address any concern that manager awareness of regulatory issues between the control group and treatment group could differ by industry, we compare the control and treatment groups on variables that could be related to manager awareness of regulatory issues. Specifically, we use a regression framework to examine treatment vs control variations in whether the manager had previously managed an annual budget of \$1M, whether the respondent was an owner/partner or C-level executive, whether the respondent had a BA or above, was age 45 or above, or worked at a firm with revenue \$100M or above. Appendix Table A6 presents the results. Panel A presents results for all industries combined and Panels B, C, and D show results when we separately examine healthcare, automotive, and retail and wholesale. There is no significant difference between the control and treatment, even when we examine each industry separately. Also, the R-squared values are extremely low, and in many cases very close to zero, which suggests that treatment status does very little to explain each outcome. Overall, these checks suggest that randomization was well achieved in the survey experiment and help alleviate the concern that there might be unobserved differences between the treatment and control groups.[26]

3.4 Empirical framework

The most basic model we examine in the empirical analysis is the following equation

$$y_i = \alpha + \beta T_i + \mathrm{X_i}\pi + \varepsilon_i \qquad (1)$$

where y_i represents individual i's intent to adopt AI, perception of ethical issues, hypothetical budget allocation plan, or labor adjustment intent. T_i is equal to 1 if individual i was in any treatment group and 0 otherwise. $\mathrm{X_i}$ is the vector of control variables that include firm-level controls (state, industry, firm size, and firm revenue fixed effects), individual controls (gender, race, education, and age fixed effects), management controls (management practice variables related to promotion and firing, and organizational role fixed effects), dummy variables that control for the largest budget previously

[26] We also reran the key analyses related to AI ethics and adoption by each industry and present the results in Appendix Table A7. When we compare the results in this table to that of Table 5 we can see that the estimates are quite similar. Based on the balance in manager and firm characteristics by industry in Appendix Table A6, and the consistency of industry specific treatment effects in Appendix Table A7, we believe the randomized design well accounts for any potential differences in perception between treatment and control.

managed, and dummy variables indicating whether the business currently uses natural language processing, computer vision, or machine learning. The coefficient β estimates the impact of any AI-related regulation information on the outcome variables.

We separately examine the impacts of the different AI-related regulations with the following equation:

$$y_i = \alpha + \beta_1 T1_i + \beta_2 T2_i + \beta_3 T3_\mathrm{i} + \beta_4 T4_i + \mathrm{X_i}\pi + \varepsilon_i \quad (2)$$

where $T1_i$ is a dummy variable indicating the general AI regulation treatment group, $T2_i$ is a dummy variable indicating the agency-specific AI regulation treatment group, $T3_i$ is a dummy variable indicating the existing AI-related regulation treatment group, and $T4_i$ is a dummy variable indicating the data privacy regulation treatment group.

We then examine the treatment effects by industry by interacting the treatment dummy variable(s) with the industry dummy variables. That is, we examine the following variant of equation (1)

$$y_i = \beta_A T_i * IndA_i + \beta_B T_i * IndB_i + \beta_C T_i * IndC_i + \mathrm{X_i}\pi + \varepsilon_i, \quad (3)$$

where $IndA_i$ is a dummy variable for healthcare, $IndB_i$ is a dummy variable for automotive, and $IndC_i$ is a dummy variable for retail and wholesale. Now the coefficient estimates represent the treatment effect of any AI-related regulation information in each of the three different industries. Similarly, we examine the following variant of equation (2) which interacts all treatment groups with the three industry dummy variables.

$$y_i = \sum_{\substack{j=1,2,3,4 \\ K=A,B,C}} \beta_{j,k} Tj_i * IndK_i + \mathrm{X_i}\pi + \varepsilon_i. \qquad (4)$$

The coefficient estimate $\beta_{j,k}$ captures the treatment effect of AI-related regulation information Tj in industry K. In additional heterogeneity and robustness analyses, we run similar regressions to equation (4) but use firm size dummy variables instead of the industry dummy variables.

4. Results

4.1 Impact of AI Regulation on Ethical Issues Related to the Adoption of AI Technologies

We find that AI regulation information increases how managers consider various ethical and policy issues when weighing the possibility of adopting AI technology (Table 3). In Panel A, we examine results when we combine all treatment groups together. Overall, the coefficient estimates are all positive in Panel A, suggesting a general positive effect of AI-related regulation

Table 3. Perception of ethical issues related to AI and adoption of AI technologies

	Perception of ethical issues related to AI					Adoption of AI	
	Labor issues	Bias and discrimina tion	Safety and accidents	Privacy and data security	Transparency and explainability	Number of business processes to adopt AI	
	Ordered Pobit	Ordered Pobit	Ordered Pobit	Ordered Pobit	Ordered Pobit	OLS	Censored Poisson
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. All Treatments Combined							
Any AI related regulation	0.0836	0.0863	0.246***	0.135*	0.146*	-0.497**	-0.135***
	(0.0824)	(0.0757)	(0.0759)	(0.0773)	(0.0763)	(0.193)	(0.0512)
R-squared						0.231	
Panel B. Treatment Specific Effects							
General AI regulation	0.0697	0.0411	0.237***	0.00648	0.0426	-0.553**	-0.157**
	(0.0870)	(0.0848)	(0.0877)	(0.0834)	(0.0842)	(0.260)	(0.0716)
Agency specific AI regulation	0.0382	0.154*	0.300***	0.0896	0.215**	-0.385	-0.0975
	(0.0937)	(0.0914)	(0.0962)	(0.103)	(0.0978)	(0.245)	(0.0659)
Existing AI related regulation	0.0843	0.0112	0.248**	0.217**	0.157*	-0.622**	-0.171**
	(0.111)	(0.106)	(0.102)	(0.0869)	(0.0948)	(0.246)	(0.0687)
Data privacy regulation	0.146	0.131	0.194**	0.229**	0.157	-0.443**	-0.120**
	(0.101)	(0.105)	(0.0964)	(0.109)	(0.104)	(0.196)	(0.0536)
Observations	1,245	1,245	1,245	1,245	1,245	1,245	1,245
R-squared						0.232	
Firm level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Management controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Budget experience	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Current AI adoption	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Firm level controls include state, industry, firm size, and firm revenue fixed effects. Individual controls include gender, race, education, and age fixed effects. Management controls include management practice variables related to promotion and firing, and organizational role fixed effects. Budget experience includes dummy variables that control for the largest budget previously managed. Current AI adoption includes dummy variables indicating whether the business currently uses natural language processing, computer vision, or machine learning. Standard errors clustered at the state-industry level are presented in parentheses. ***, **, and * denote statistical significant at 1%, 5%, and 10% level.

on manager perceptions of the ethical issues related to AI technology, but the estimate is statistically most significant for safety and accident issues. When we separate out the treatment groups in Panel B, we find that each regulation treatment increases the importance managers put on safety and accident concerns related to AI-technologies, and the existing AI regulation (T3) and data privacy regulation (T4) treatments significantly increase manager perceptions of the importance of privacy and data security. The agency-specific regulation (T2) also increases manager perceptions of the importance of bias and discrimination, and transparency and explainability. We also asked managers who they think are primarily responsible for AI-related ethical issues at their firm. Firm managers consider themselves to be primarily responsible for ethical issues related to AI (38.6%).[27]

However, when we examine the effect of AI regulation information on manager intention to adopt AI technologies, we find a negative effect. Since respondents' choices are top-coded, we present both OLS regression results (Table 3 column 6) and Censored Poisson regression results (Table 3 column 7). The general AI regulation treatment (T1) significantly reduces managers' intent to adopt AI technologies in their business processes. Focusing on the OLS results, the general AI regulation treatment reduces the number of business processes that adopt AI by 0.55, which is about 16% of the mean value (3.405). The Censored Poisson regression result also indicates that the general AI regulation treatment reduces AI adoption by 15.7%. The coefficient estimates on the industry-specific AI regulation treatments (T2abc) are negative but not significant and the magnitudes are smaller compared to that of the general AI regulation treatment. Reminding managers that using AI technology in their businesses will be subject to existing regulations and potential lawsuits (T3) or data privacy regulations (T4) deters them from adopting AI technology. Figure 2 plots the coefficient estimates in Table 3 and visually illustrates the trade-off between the increased perception of ethical issues related to AI and the decreased intent to adopt AI technologies. Information on AI regulation makes managers focus more on increasing the safety and accountability of their firms' AI products and systems, which however comes at the cost of slowing down the general rate of AI adoption.

[27] Managers are followed by: AI package vendors (20.9%), engineers (17.2%), the government i.e., regulatory agencies (16.9%), and the courts (3.9%). The regulation treatments in general do not significantly affect managers' belief on who should primarily be responsible for AI-related ethical issues. However, we find that the agency-specific AI regulation treatment increases managers' beliefs that the court should be primarily responsible for ethical issues (Appendix Table A4).

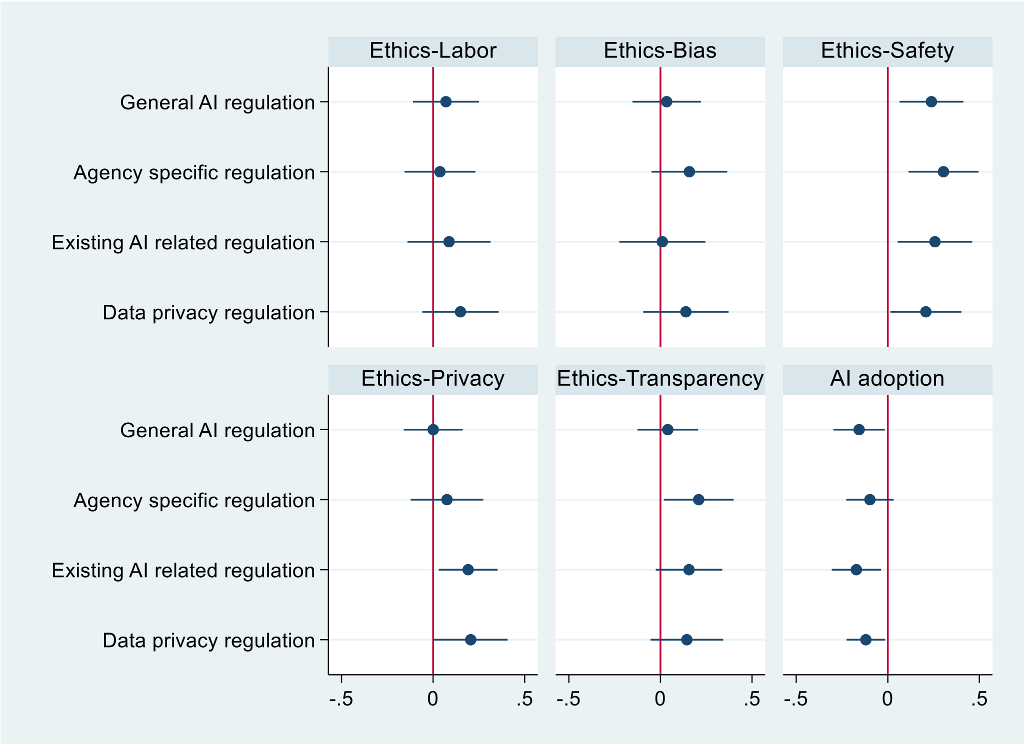

Figure 2. Coefficient plot of the treatment effects of AI regulation on ethical issues and AI adoption
Notes: The dots represent the coefficient estimates from the regression and the bar represents the 95% confidence interval. Each coefficient estimate represents the difference between each treatment group and the control group.

Based on our findings, we see that when managers are informed of potential AI regulations, they tend to respond differently to varying ethical issues. Our findings indicate that managers are more likely to respond to concrete ethical guidelines, especially when these can be quantified or measured. Ethical areas such as safety and accidents, for example, are concrete and measureable instances that may be easier for managers to relate to, should an AI system cause harm. Elaborated, managers across treatments are considered to display greater awareness of safety-related issues, which could be an expression of managers having a more concrete sense of what constitutes either an improvement or a deterioration of safety-related concerns. Ethical issues related to bias and discrimination or transparency and explainability, on the other hand, can be thornier for managers to find broad solutions for, which shows in our sample where managers across treatments respond less favorably to such issues.

Brundage et al. (2020) have argued that ethics principles in many cases are non-binding, and that their translation into actions often is unclear. While the publication of AI principles has gained traction, the introduction of actionable mechanisms that managers and policymakers can engage with are lacking (Zhang et al. 2021). Avelar et al. (2021: 1) suggests that AI systems must be endowed with “clear metrics based on datadriven approaches that improve the quality, fairness, explainability, and accountability of AI systems and technologies”. For managers, however, it is a general problem that such metrics are little developed and not readily available. We conjecture that ethics-related domains that are harder to quantify and measure (e.g. transparency and explainability), or that may be further removed from a mangers daily tasks (e.g. bias and discrimination in instances where these are not entirely clear or obvious) may be harder for managers to soundly respond to and react on. Areas such as algorithmic bias tend to be linked to individual and value-based judgments that need to be configured at several distinct layers of technology and organization pre- and post-implementation. For example, an algorithm’s social impact post-implementation could prove to have unintended effects on certain groups or users, which means that software engineers and product owners as well as managers need to devise new solutions in greater unison across teams. At the same time, managers may not always understand the technical aspects that are needed to make sure that an algorithm or a system is tested sufficiently (Davenport 2013) e.g., in order to avoid any potential negative effects.

Coming up with novel ways to embed ethical principles into AI systems (Rossi and Mattei 2019) portray hard questions for managers and engineers to devise thoughtful solutions for. Recent research such as Stanford’s AI Index Report (Zhang et al. 2021) tries to do that by way of developing more appropriate metrics for AI ethics and policies, which managers, policy-makers, and researchers can use to better inform themselves (Avelar et al. 2021).

On labor issues, managers in our sample do not display any significant concerns. In a recent survey of 5700 Harvard Business School Alumni, 52% of this elite group believe that companies will employ fewer workers three years from now (Fleming 2020), which is a sentiment that is not visibly shared by managers in our sample. The reason for this could be that we sample a broad range of managers that do not yet experience any significant AI-induced labor displacement effects, while we acknowledge that such effects already are present in companies that implement large-scale AI solutions e.g., in order to create greater efficiency or to reduce labor induced costs.

Table 4. Impact of AI regulation on budget allocation and labor adjustment

	Log(AI budget)		Budget allocation						Labor adjustment due to AI adoption					
			Developing AI strategy	AI related R&D	Hiring workers related to business' AI system	AI training for existing employees	Purchase AI package from vendors	Computing resource and data for AI system	Managers	Technical workers	Office workers	Sales workers	Service workers	Production workers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Panel A. All Treatments Combined														
Any AI related regulation	0.120	0.164	2.076**	0.173	0.802	-1.854*	-1.678	0.480	0.147**	-0.0159	0.0259	-0.00675	0.0112	0.00428
	(0.334)	(0.200)	(0.979)	(1.721)	(0.961)	(0.989)	(1.060)	(0.748)	(0.0720)	(0.0634)	(0.0675)	(0.0661)	(0.0818)	(0.0784)
R-squared	0.259	0.343	0.091	0.094	0.081	0.073	0.101	0.074						
Panel B. Treatment Specific Effects														
General AI regulation	-0.0139	0.190	2.966**	0.102	2.237*	-2.349*	-1.749	-1.208	0.134	-0.125	0.0875	-0.0671	0.0342	0.0180
	(0.421)	(0.294)	(1.229)	(2.076)	(1.333)	(1.333)	(1.360)	(0.893)	(0.102)	(0.0948)	(0.109)	(0.120)	(0.112)	(0.115)
Agency specific AI regulation	0.506	0.383*	2.221*	-0.307	0.466	-1.493	-1.880*	0.993	0.0982	-0.0474	-0.0487	0.0223	-0.0470	-0.0532
	(0.391)	(0.197)	(1.206)	(1.754)	(1.126)	(1.168)	(1.098)	(1.049)	(0.0925)	(0.0907)	(0.0946)	(0.0875)	(0.111)	(0.101)
Existing AI related regulation	-0.254	-0.00226	2.735*	0.307	-0.221	-1.956	-1.977	1.113	0.238**	0.0791	0.0646	0.0577	0.0270	0.101
	(0.384)	(0.223)	(1.395)	(2.279)	(1.148)	(1.328)	(1.214)	(0.986)	(0.103)	(0.0927)	(0.100)	(0.0896)	(0.0956)	(0.114)
Data privacy regulation	0.198	0.0580	0.410	0.636	0.871	-1.684	-1.083	0.850	0.209**	-0.00362	0.0153	-0.0569	0.0315	-0.0455
	(0.419)	(0.224)	(1.207)	(1.899)	(1.350)	(1.025)	(1.212)	(0.971)	(0.104)	(0.0923)	(0.103)	(0.0862)	(0.105)	(0.114)
R-squared	0.262	0.347	0.094	0.094	0.084	0.074	0.102	0.080						
Observations	1,245	813	1,245	1,245	1,245	1,245	1,245	1,245	1,201	1,195	1,201	1,172	1,185	1,152
Firm level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Management controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Budget experience	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Current AI adoption	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Firm level controls include state, industry, firm size, and firm revenue fixed effects. Individual controls include gender, race, education, and age fixed effects. Management controls include management practice variables related to promotion and firing, and organizational role fixed effects. Budget experience includes dummy variables that control for the largest budget previously managed. Current AI adoption includes dummy variables indicating whether the business currently uses natural language processing, computer vision, or machine learning. Columns (1) to (8) are OLS regressions and columns (9) to (14) are Ordered Probit regressions. Standard errors clustered at the state-industry level are presented in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% level.

Overall, the increased focus on AI ethics across our sample does signal that managers and organizations are paying greater attention to the governance of AI systems, which means that an increasing number of measurable and standardized solutions also are likely to be devised in the years to come (Zhang et al. 2021).

4.2 Impact of AI Regulation on AI Budget and Personnel Allocation

Next, we examine how regulation information affects how managers plan to allocate to AI-related activities at the firm, and the allocation of that budget across six different expense categories. Table 4 presents the results. Column 1 indicates that none of the regulation treatments significantly change next year's AI budget allocation intent. There are clusters of responses at multiples of tens and hundreds. Despite asking respondents to write in the dollar amount, some may have responded in thousands of dollars. In column 2, we restrict the sample to those who answered "$10,000" or more. The impact of the agency-specific AI regulation treatment (T2) is positive and the magnitude is quite large indicating a treatment effect of about 38%. The coefficient estimate on the general AI regulation treatment (T1) is positive at 0.19 as well, though standard errors are larger. AI regulation seems to increase manager intent to allocate more to future AI budgets.

Columns 3 to 8 examine how managers would allocate that budget across six expense categories in terms of the percentage of the total AI budget. By enforcing the allocation to add to 100 percent, we examine the trade-offs managers choose due to AI regulation. We find that AI regulation significantly increases expenditure intent for developing an AI strategy that is compatible with the company's business strategy, including ethical issues (Column 3). The impact is strongest for the general AI regulation treatment (T1), which increases allocation to AI strategy purposes by 3 percentage points. The agency-specific AI regulation (T2) and existing AI-related regulation (T3) treatments also increase expenditure intent for developing AI strategy by 2.2 and 2.7 percentage points. However, the increase for developing AI business strategy is mostly offset by a decrease for training current employees on how to code and use AI technology, as well as purchasing AI packages from external vendors. Figure 3 visually illustrates the trade-off by plotting the coefficient estimates of each regulation treatment. The main takeaway from Table 4 and Figure 3 is that AI regulation induces manager intent to expend more on strategizing, including

Figure 3. Coefficient plots of the treatment effects of AI regulation on budget allocation
Notes: The dots represent the coefficient estimates from the regression and the bar represents the 95% confidence interval. Each coefficient estimate represents the difference between each treatment group and the control group.

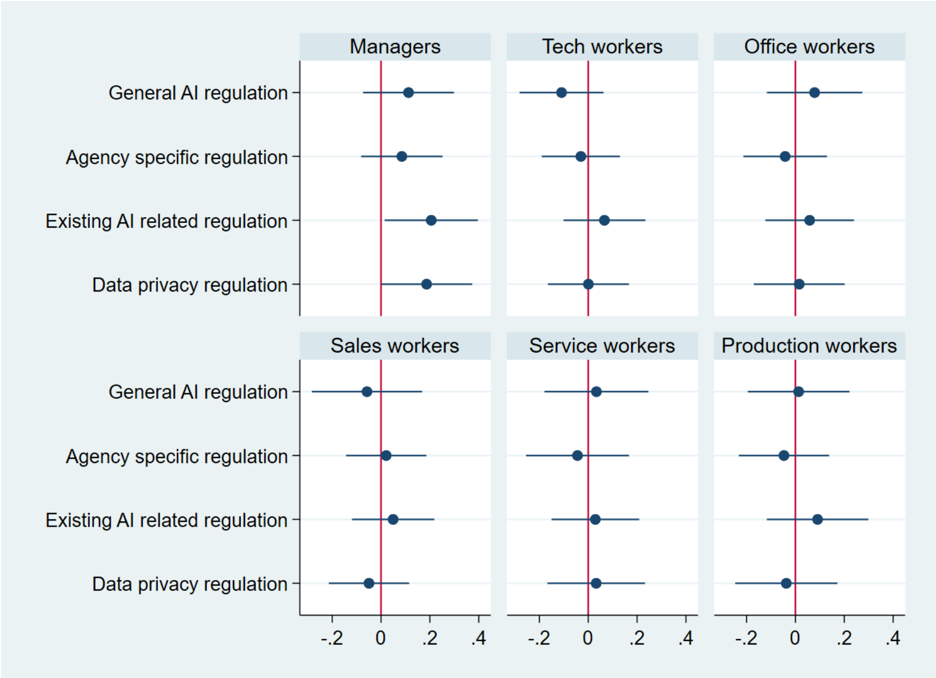

Figure 4. Coefficient plots of the treatment effects of AI regulation on adjustment to labor
Notes: The dots represent the coefficient estimates from the regression and the bar represents the 95% confidence interval. Each coefficient estimate represents the difference between each treatment group and the control group.

issues related to AI ethics, but reduces intent to spend on aspects related to AI adoption, including AI training for existing employees and purchasing AI packages.

In columns 9 to 15 we examine how AI regulation information affect staffing intentions by occupation. Specifically, we ask how managers would adjust the total number of managers, technical workers, office workers, service workers, sales workers, and production workers because of AI adoption. Figure 4 illustrates these results. Exposure to AI-related regulation, in particular, existing AI-related regulation (T3) and data privacy regulation (T4), induces firms to increase the number of managers. The positive impact of AI regulation on the number of managers is consistent with the previous finding that AI regulation induces managers to be more aware of ethical issues and allocating more budget to AI strategy, given that most managers believe that they themselves are primarily responsible for ethical issues related to AI. We find no consistent nor significant impact of regulation on other types of workers.[28]

Table 4 results show that when managers are prompted with information regarding new AI regulations, they respond by restructuring their resource allocation intentions towards strategy development (Alvarez & Barney, 2005), and increasing the number of managers – the occupation that would be directly involved in strategy development. Such reallocation comes at the cost of, temporarily, slowing down AI adoption, until organizational practices are altered.

4.3 Heterogeneous Impact of AI Regulation

4.3.1 Impact by industry

In Table 5 we examine industry-specific effects. We find a trade-off between perception of ethical issues and adoption intent in the healthcare and retail and wholesale, but not in the automotive sector. Column (1) indicates that the negative impact of regulation on AI adoption is especially pronounced in retail and wholesale. All four treatments have a negative impact on the rate of AI adoption, and the

[28] We also examined whether exposure to AI regulation information affected managers' intent to adjust AI-related innovation activities in the following year (Lee et al. 2019). In particular, we ask how they would adjust the following activities: co-operation on AI-related R&D activities with other institutions, such as, universities, research institutes, other businesses; filing AI-related patents; introduction of an AI-related good, service, or production/delivery method that is new or significantly improved. None of the AI-related regulation treatments significantly affected any of the innovation-related intents.

magnitudes of the impacts are large and consistent at about a 23% to 28% reduction compared to the control group. In retail, the use of online ads, consumer profiling, digital marketing, and so on, may at present embody greater uncertainty for how revised regulations are likely to impact existing AI practices and use cases. Similarly, the impact of regulation on AI adoption intent is negative for all four regulation treatments for healthcare. However, we find no significant impact of regulation on AI adoption across all treatments for automotive. Firms operating in the automotive, transportation, and distribution industries generally seem to factor in a positive outlook on the future of their operations, despite existing laws as well as the mentioning of new and incoming regulations. This positive sentiment is symptomatic of NHTSA's current regulatory approach of removing unintended barriers to AI adoption and innovation.

On ethical and policy considerations, we also see some variation across industries. For automotive, existing AI-related regulation (T3), has a consistently positive impact on ethical issues across safety and accidents, privacy and data security, as well as transparency and explainability. The healthcare industry is more prone to respond positively when faced with general AI regulation (T1) as well as agency-specific regulation (T2a), which increases attention devoted to safety and accidents. For retail, focus on transparency and explainability is positively affected under agency-specific regulation (T2c).[29]

Our results show that when faced with AI-related regulations, managers in the automotive industry and retail and wholesale sectors are inclined to focus more on increasing their budgets for strategizing, while the healthcare industry devotes more budget to computing resources and data for AI systems. The corresponding budgetary offsets are seen in decreasing AI training for existing workers, as well as in purchasing AI packages, respectively.

In terms of staffing, the coefficient estimates of all the treatment effects for managers are positive across industries. Whether it be for AI strategizing or concerns over ethical issues, regulation induces firms to increase the number of managers. Another pattern that we see is that the existing AI-related regulation treatment (T3) tends to increase the number of office workers in the automotive sector,

[29] We do, however, find one negative effect, namely that general AI regulation (T1) decreases privacy and data security concerns in the retail and wholesale industries. The finding suggests that when uncertainties in existing laws and regulations are exchanged for a broad regulatory framework, managers in retail reduce their concerns over privacy and data security, as the rules for staying compliant become clearer and can more easily be followed.

Table 5. Impact of AI regulation on adoption, budget allocation, and innovation activity by industry

	A. Adoption	B. Importance of ethical issues					C. Budget allocation						D. Adjustment to labor					
	No. of business processes to adopt AI	Labor issues	Bias and discrimination	Safety and accidents	Privacy and data security	Transparency and explainability	Developing AI strategy	AI related R&D	Hiring related to business' AI system	AI training for existing employees	Purchase AI package from vendors	Computing resource and data	Managers	Technical workers	Office workers	Sales workers	Service workers	Production workers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
								Panel A. All treatments combined										
Any AI related regulation																		
x Healthcare	-0.115	0.0644	0.125	0.247**	0.175	0.0824	0.00134	-0.308	1.440	-1.377	-1.899	2.143**	0.168	-0.0414	-0.0129	-0.132	0.0127	-0.137
	(0.0759)	(0.114)	(0.125)	(0.0987)	(0.118)	(0.134)	(1.397)	(2.599)	(1.422)	(1.283)	(1.305)	(0.953)	(0.120)	(0.100)	(0.104)	(0.101)	(0.115)	(0.122)
x Automotive	0.0743	0.140	0.142	0.402**	0.250	0.240	7.145***	-0.474	0.232	-4.071	-1.142	-1.690	0.266	-0.00994	0.235*	0.0810	0.193	0.221
	(0.114)	(0.201)	(0.185)	(0.192)	(0.196)	(0.163)	(2.620)	(2.631)	(2.324)	(2.792)	(2.995)	(1.509)	(0.205)	(0.138)	(0.135)	(0.167)	(0.165)	(0.149)
x Retail and	-0.255***	0.0773	0.00359	0.157	0.0168	0.177*	1.990	1.177	0.274	-1.242	-1.685	-0.514	0.116	-0.00294	-0.0344	0.101	-0.0935	0.0673
wholesale	(0.0894)	(0.137)	(0.1000)	(0.137)	(0.114)	(0.0968)	(1.203)	(3.231)	(1.516)	(1.343)	(1.771)	(1.239)	(0.114)	(0.139)	(0.133)	(0.119)	(0.168)	(0.154)
R-squared							0.096	0.094	0.081	0.074	0.101	0.077						
								Panel B. Treatment specific effects										
General AI regulation																		
x Healthcare	-0.178*	0.0956	0.183	0.326***	0.226	0.0690	1.785	-1.003	3.102	-1.470	-1.570	-0.844	0.191	-0.0701	0.0990	-0.228	0.0705	-0.130
	(0.107)	(0.105)	(0.127)	(0.115)	(0.146)	(0.137)	(1.857)	(3.295)	(2.016)	(1.943)	(2.177)	(1.401)	(0.155)	(0.150)	(0.160)	(0.191)	(0.136)	(0.164)
x Automotive	0.0631	0.208	-0.00237	0.343	-0.0222	0.146	7.739***	2.883	1.904	-6.873**	-1.716	-3.937**	0.0799	-0.0718	0.185	-0.123	0.206	0.407
	(0.141)	(0.235)	(0.241)	(0.255)	(0.210)	(0.182)	(2.437)	(3.737)	(3.108)	(3.091)	(3.087)	(1.756)	(0.213)	(0.213)	(0.172)	(0.229)	(0.305)	(0.253)
x Retail and	-0.233*	-0.0199	-0.114	0.0756	-0.246**	-0.0250	2.042	0.564	1.354	-1.339	-2.046	-0.575	0.0767	-0.205	0.0159	0.143	-0.0966	0.0286
wholesale	(0.122)	(0.161)	(0.127)	(0.165)	(0.122)	(0.145)	(2.016)	(3.268)	(2.189)	(1.680)	(1.845)	(1.449)	(0.161)	(0.165)	(0.198)	(0.191)	(0.210)	(0.192)
Agency specific AI regulation																		
x Healthcare	-0.0336	0.0917	0.249*	0.307***	0.154	0.175	-1.051	-0.453	1.762	-2.157	-2.106	4.005**	0.109	-0.0576	-0.0772	-0.0531	-0.0265	-0.152
	(0.0947)	(0.145)	(0.138)	(0.111)	(0.160)	(0.167)	(1.758)	(2.647)	(2.003)	(1.516)	(1.346)	(1.666)	(0.139)	(0.136)	(0.139)	(0.126)	(0.155)	(0.154)
x Automotive	0.0508	0.114	0.245	0.568**	0.189	0.228	6.838***	0.650	-0.571	-2.472	-2.409	-2.036	0.185	-0.251*	0.117	0.0776	0.0801	0.161
	(0.155)	(0.186)	(0.222)	(0.221)	(0.238)	(0.202)	(2.501)	(2.512)	(2.290)	(3.059)	(3.147)	(1.834)	(0.257)	(0.145)	(0.219)	(0.233)	(0.218)	(0.210)
x Retail and	-0.240**	-0.0533	-0.00882	0.141	-0.0471	0.270**	3.648**	-0.408	-0.433	-0.464	-1.282	-1.061	0.0323	0.0939	-0.106	0.0923	-0.140	-0.0288
wholesale	(0.119)	(0.160)	(0.130)	(0.187)	(0.155)	(0.118)	(1.735)	(3.321)	(1.660)	(1.704)	(1.761)	(1.642)	(0.126)	(0.171)	(0.142)	(0.127)	(0.223)	(0.173)
Existing AI related regulation																		
x Healthcare	-0.163	-0.0797	0.0156	0.158	0.178	0.0134	1.054	0.284	0.559	-1.990	-2.526*	2.618*	0.266*	-0.0115	0.0307	-0.101	0.0352	-0.0512
	(0.102)	(0.175)	(0.172)	(0.156)	(0.127)	(0.156)	(2.045)	(3.598)	(1.612)	(2.226)	(1.522)	(1.495)	(0.154)	(0.127)	(0.132)	(0.137)	(0.124)	(0.192)
x Automotive	0.0494	0.124	0.0860	0.450*	0.455*	0.351*	7.360*	-2.642	-1.483	-2.237	-1.061	0.0643	0.360	0.263	0.382**	0.235	0.332*	0.348*
	(0.184)	(0.258)	(0.253)	(0.252)	(0.240)	(0.207)	(3.838)	(4.219)	(2.491)	(3.292)	(3.207)	(2.618)	(0.277)	(0.207)	(0.188)	(0.263)	(0.184)	(0.208)
x Retail and	-0.282**	0.221	-0.0475	0.224	0.121	0.221	2.441	1.975	-0.539	-1.807	-1.872	-0.198	0.139	0.0926	-0.0558	0.151	-0.131	0.167
wholesale	(0.111)	(0.164)	(0.152)	(0.155)	(0.121)	(0.135)	(1.930)	(3.958)	(2.070)	(1.690)	(2.128)	(1.250)	(0.166)	(0.175)	(0.202)	(0.144)	(0.190)	(0.185)
Data privacy regulation																		
x Healthcare	-0.0941	0.151	0.0348	0.188	0.155	0.0705	-1.738	0.158	0.245	0.00918	-1.394	2.719*	0.112	-0.00270	-0.101	-0.164	-0.0189	-0.200
	(0.0826)	(0.148)	(0.173)	(0.138)	(0.155)	(0.174)	(1.924)	(2.741)	(2.121)	(1.437)	(1.481)	(1.383)	(0.174)	(0.132)	(0.153)	(0.141)	(0.179)	(0.138)
x Automotive	0.139	0.145	0.213	0.195	0.391	0.227	6.707*	-2.284	1.806	-5.989**	0.923	-1.163	0.442*	0.0683	0.276	0.0956	0.196	0.0158
	(0.121)	(0.254)	(0.296)	(0.222)	(0.307)	(0.265)	(3.786)	(3.207)	(3.239)	(2.839)	(3.550)	(2.068)	(0.230)	(0.207)	(0.227)	(0.181)	(0.208)	(0.183)
x Retail and	-0.263***	0.144	0.164	0.178	0.199	0.222	-0.123	2.708	0.915	-1.438	-1.657	-0.405	0.185	-0.0228	0.000343	0.00298	-0.00873	0.104
wholesale	(0.0857)	(0.166)	(0.132)	(0.170)	(0.179)	(0.141)	(1.166)	(3.643)	(2.023)	(1.596)	(2.133)	(1.584)	(0.146)	(0.164)	(0.165)	(0.148)	(0.161)	(0.220)
Observations	1,245	1,245	1,245	1,245	1,245	1,245	1,245	1,245	1,245	1,245	1,245	1,245	1,201	1,195	1,201	1,172	1,185	1,152
R-squared							0.101	0.097	0.086	0.079	0.103	0.088						

Notes: All regressions include firm level, individual level, management, budget, and current AI use controls. Firm level controls include state, industry, firm size, and firm revenue fixed effects. Individual controls include gender, race, education, and age fixed effects. Management controls include management practice variables related to promotion and firing, and organizational role fixed effects. Budget experience includes dummy variables that control for the largest budget previously managed. Current AI adoption includes dummy variables indicating whether the business currently uses natural language processing, computer vision, or machine learning. Number of observations in the regressions is 1,245. Standard errors clustered at the state-industry level are presented in parentheses. ***, **, and * denote statistical significant at 1%, 5%, and 10% level.

which may be a complementary response to increasing the number of managers to deal with potential litigation issues. Heterogeneity in our results when comparing the healthcare, automotive, and retail industries indicates that regulation information is likely to affect industries and their varying compositions in terms of ethical concerns, customer relations, business models, data usage, and applied strategic components differently due to industry-specific characteristics. These findings confirm that firms across transportation, retail, and healthcare, respond differently to AI regulation. Industrial idiosyncrasies are associated with disparate forms of sector-specific regulation, such as highlighted in the approaches taken by the FTC, NHTSA, and the FDA. In the case of the automotive sector, for example, we interpret our results as managers displaying less uncertainty with the stated approach of NHTSA. We take this as managers interpreting a regulatory outcome that is less uncertain in its trajectory (e.g. in terms of expected costs due to industrial readjustments associated with possible regulatory shocks) than is the case for healthcare or retail, where greater regulatory shocks may be expected.

4.3.2 Impact by firm size

In Table 6 we examine how the impact of AI regulation information differs across small versus large firms. We use an annual revenue of $10 million as the cut-off for small and large firms. AI regulation information increases manager awareness of ethical issues in both small and large firms. AI regulation increases manager perception of the importance of bias, safety, privacy, and transparency issues in small firms. Large firms primarily increase their perception of safety and accidents, and privacy and data security issues. The negative impact of AI regulation on AI adoption intent is found for both small firms and large firms and is statistically stronger for small firms.

Our findings do provide some indication that suggests that large firms could be better situated to handle the costs of regulation. Small firms seem to be faced with hard trade-offs that consistently imply a general reduction in the number of AI processes across all treatments, and that AI regulation could be more likely to reduce AI adoption and innovative activities in small firms. Since managers of smaller firms hold fewer resources, new regulations could therefore make it more costly for them to produce the initial investments required to develop responsible strategies (Pava and Krausz, 1996).

Table 6. Impact of AI regulation on adoption, budget allocation, and innovation activity by firm size.

	A. Adoption	B. Importance of ethical issues					C. Budget allocation						D. Adjustment to labor					
	Number of business processes to adopt AI	Labor issues	Bias and discrimination	Safety and accidents	Privacy and data security	Transparency and explainability	Developing AI strategy	AI related R&D	Hiring workers related to business' AI system	AI training for existing employees	Purchase AI package from vendors	Computing resource and data for AI system	Managers	Technical workers	Office workers	Sales workers	Service workers	Production workers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
								Panel A. All treatments combined										
Any AI related regulation																		
xSmall business	-0.219***	0.145	0.118	0.282***	0.0745	0.161*	2.724	3.400	-1.613	-2.945**	-1.758	0.193	0.247*	-0.0557	0.161	0.173	0.0583	0.0680
	(0.0709)	(0.113)	(0.0973)	(0.105)	(0.113)	(0.0894)	(1.699)	(2.109)	(1.322)	(1.289)	(1.950)	(1.223)	(0.128)	(0.104)	(0.124)	(0.122)	(0.137)	(0.129)
xLarge business	-0.0684	0.0296	0.0582	0.214*	0.189*	0.133	1.516	-2.617	2.891**	-0.909	-1.609	0.729	0.100	0.00671	-0.0862	-0.162	-0.0322	-0.0512
	(0.0707)	(0.116)	(0.122)	(0.113)	(0.109)	(0.123)	(1.273)	(2.435)	(1.340)	(1.538)	(1.544)	(1.059)	(0.117)	(0.115)	(0.107)	(0.105)	(0.125)	(0.115)
R-squared							0.092	0.099	0.109	0.076	0.102	0.075						
								Panel B. Treatment specific effects										
General AI regulation																		
xSmall business	-0.207**	0.165	0.0810	0.226*	-0.0219	-0.0685	5.768***	1.144	-1.246	-4.559***	-0.807	-0.301	0.265*	-0.170	0.298**	0.164	0.166	0.108
	(0.0921)	(0.132)	(0.107)	(0.126)	(0.115)	(0.104)	(2.083)	(2.480)	(1.664)	(1.496)	(2.067)	(1.404)	(0.146)	(0.144)	(0.148)	(0.177)	(0.161)	(0.169)
xLarge business	-0.117	-0.0263	0.00239	0.255*	0.0162	0.162	-0.0249	-0.220	5.379***	-0.0123	-2.818	-2.304*	0.0214	-0.0653	-0.105	-0.266*	-0.0884	-0.0502
	(0.0971)	(0.140)	(0.153)	(0.150)	(0.146)	(0.145)	(1.701)	(3.108)	(2.050)	(2.066)	(1.862)	(1.327)	(0.136)	(0.137)	(0.144)	(0.144)	(0.155)	(0.158)
Agency specific AI regulation																		
xSmall business	-0.174**	0.158	0.229*	0.385***	-0.00596	0.223*	2.608	4.030	-2.332	-2.136	-2.600	0.431	0.252	-0.0144	0.0206	0.268*	0.0379	0.0852
	(0.0849)	(0.144)	(0.123)	(0.123)	(0.150)	(0.114)	(2.200)	(2.629)	(1.634)	(1.551)	(2.250)	(1.608)	(0.154)	(0.149)	(0.158)	(0.140)	(0.155)	(0.137)
xLarge business	-0.0329	-0.0758	0.0762	0.214	0.179	0.201	2.047	-4.247	2.735	-0.989	-1.135	1.588	-0.0409	-0.0787	-0.0796	-0.186	-0.113	-0.176
	(0.103)	(0.132)	(0.152)	(0.134)	(0.131)	(0.150)	(1.615)	(2.656)	(1.694)	(1.679)	(1.676)	(1.412)	(0.154)	(0.132)	(0.150)	(0.125)	(0.167)	(0.143)
Existing AI related regulation																		
xSmall business	-0.242**	0.0699	0.0921	0.233	0.136	0.239*	2.008	1.927	-1.265	-1.698	-1.164	0.192	0.198	-0.0209	0.180	0.233	-0.0281	0.195
	(0.0951)	(0.138)	(0.132)	(0.155)	(0.143)	(0.140)	(1.884)	(2.461)	(1.675)	(1.722)	(2.071)	(1.474)	(0.154)	(0.130)	(0.154)	(0.151)	(0.167)	(0.159)
xLarge business	-0.109	0.0982	-0.0575	0.260*	0.285**	0.0862	3.375*	-0.978	0.529	-2.116	-2.703	1.892	0.283**	0.171	-0.0195	-0.0803	0.0836	0.0358
	(0.0935)	(0.149)	(0.147)	(0.151)	(0.127)	(0.145)	(1.918)	(3.011)	(1.521)	(1.798)	(1.758)	(1.426)	(0.142)	(0.162)	(0.143)	(0.143)	(0.133)	(0.160)
Data privacy regulation																		
xSmall business	-0.237***	0.190	0.0671	0.273**	0.200	0.228	0.525	6.394**	-2.049	-3.024*	-2.259	0.413	0.320*	0.0115	0.204	0.0663	0.104	-0.0482
	(0.0785)	(0.141)	(0.141)	(0.127)	(0.147)	(0.141)	(2.018)	(2.733)	(1.698)	(1.760)	(2.012)	(1.531)	(0.170)	(0.127)	(0.143)	(0.147)	(0.152)	(0.165)
xLarge business	-0.0237	0.112	0.211	0.118	0.250	0.0751	0.391	-4.817**	3.327	-0.355	0.207	1.247	0.122	-0.0161	-0.142	-0.131	-0.0188	-0.0103
	(0.0846)	(0.144)	(0.155)	(0.142)	(0.154)	(0.151)	(1.444)	(2.257)	(2.087)	(1.682)	(1.887)	(1.431)	(0.142)	(0.152)	(0.145)	(0.130)	(0.156)	(0.150)
R-squared							0.101	0.105	0.115	0.080	0.108	0.084						
Observations	1,245	1,245	1,245	1,245	1,245	1,245	1,245	1,245	1,245	1,245	1,245	1,245	1,201	1,195	1,201	1,172	1,185	1,152

Notes: All regressions include firm level, individual level, management, budget, and current AI use controls. Firm level controls include state, industry, firm size, and firm revenue fixed effects. Individual controls include gender, race, education, and age fixed effects. Management controls include management practice variables related to promotion and firing, and organizational role fixed effects. Budget experience includes dummy variables that control for the largest budget previously managed. Current AI adoption includes dummy variables indicating whether the business currently uses natural language processing, computer vision, or machine learning. Number of observations in the regressions is 1,245. Standard errors clustered at the state-industry level are presented in parentheses. ***, **, and * denote statistical significant at 1%, 5%, and 10% level.

At the same time, larger firms are more likely to find their reputation suffering if they do not perform well on social measures (Moore and Manring, 2009), which generally makes larger firms devote more resources to the organization's visibility e.g., in terms of developing ethical AI solutions.

In terms of budget allocation, we find that for both small and large firms, AI regulation increases the expected budget allocation for developing AI strategy. The general AI regulation (T1) result is strong for small firms and the existing AI regulation (T3) for large firms. In small firms, this increase is offset by decreasing AI training for existing employees and purchasing AI packages from vendors. For large businesses, on the other hand, this means hiring more workers related to a business' AI systems, which in turn is offset by investments in computing resources and data for AI systems. In terms of staffing, AI regulation induces both small firms and large firms to hire more managers, as well as office workers for small firms. This might come with a trade-off, reducing technical workers related to AI, which again is consistent with the AI ethics versus adoption trade-off.

Younger firms may have responded differently to AI regulation compared to older firms as well. Jia et al. (2020) find that EU's General Data Protection Regulation had a larger negative impact on new ventures. Similarly, AI regulation could have more negative effects on younger firms and startups. Though we do not know firm age, younger firms generally have a smaller number of employees. In Appendix Table A8, we examine the results by employee size and find that smaller (fewer employees) firms delay adopting AI technologies more so than larger (more employee) firms.

4.3.3 Discussion of the potential mechanism

In addition to the measurement and concreteness of ethical issues discussed in Section 4.1, managers may also exhibit differential perceptions on the level of enforcement that is associated with the information provided in the treatment statements. This could be an additional factor that explains the different results by ethical issue, industry, regulation type, and firm size.[30]

In Section 4.1, we argued that manager perception of enforcement will likely be related to whether an issue is concrete and quantifiable, which could explain why we find the strongest effects on safety and accidents. In the case of autonomous vehicle safety, for example, an AI-controller is expected to hold the ability to locate persons and objects from a distance of 100 meters with an accuracy of +/- 20 cm, within a false negative rate of 1% and false-positive rate of 5% (Grigorescu et al. 2020). These

[30] We thank an anonymous referee for pointing us to this angle.

concrete and measurable specifications relate to the perceived safety of an autonomous vehicle. Manager perception on the enforcement level therefore relates directly to whether such specifications are identified and fulfilled. In other cases where outcomes are more arbitrary and where clear measurables' or guidelines have not yet been established, we argue that it will be harder for managers to devise clear and actionable mechanisms and to devise ethical solutions for a given problem.

Generally speaking, in areas that involve high-stakes decisions (e.g., autonomous driving, credit applications, judicial decisions, and medical recommendations), algorithmic accuracy alone may not be sufficient, as applications require high levels of trust in order to be implemented (Arnold et al. 2019). This creates a need for managers to ensure that the functional aspects of a model (i.e., accuracy, data, performance, etc.) are soundly established through measures such as certification, testing, auditing, as well as through the elaboration of technological standards (Mittelstadt et al. 2016; Nuno, Gomes, and Kontschieder 2021). The perceived level of regulatory enforcement and other forms of algorithmic compliance are therefore associated with context-specific legislation, regulation, and standards that exert varying forms of institutional pressure over actors to conform to best practice. Enforcement therefore is going to be context-specific, which means that managers are going to perceive varying levels of enforcement across industries (e.g. transportation, retail, and healthcare) and in association with diverse ethical issues (e.g. privacy, transparency, safety, bias/discrimination, labor issues). This makes it hard to establish an actual baseline for manager perception of the estimated enforcement levels that is associated with each of our treatment scenarios. In other words, AI systems are deployed under specific circumstances where baseline expectations of enforcement may vary considerably.

In high-stakes environments such as in healthcare or autonomous vehicles, high standards e.g. surrounding safety and privacy are likely to create high expectations for basic levels of enforcement. In other areas where practices are less clear and where levels of enforcement historically have been more arbitrary (e.g. recommender algorithms used in online shopping, or the regulation of content on social media platforms), expectations about enforcement levels are motley and harder for managers to ascertain and devise ethical actionable mechanisms for. In such cases, compliance is situated between social expectations, self-governance, and vague or missing legislation and regulation, which makes it harder for managers to develop sound forms of algorithmic governance (Ghosh 2021).

Different approaches to regulation by government agencies are going to be further associated with new and incoming technological standards that are going to be determined on an individual and sector-specific basis. Relatedly, emerging technological standards can be thought of as implicit ethical standards that seek to remove or reduce unethical technological impacts (Winfield 2019). The IEEE standard P7001 for the "Transparency of Autonomous Systems," for example, addresses the ethical principle that it should be possible to know why an autonomous system made a specific decision. In doing so, P7001 is formulating measurable, testable levels of transparency so that autonomous systems can be objectively assessed and levels of compliance determined (Winfield 2019). While these standards are still under development, their consideration contributes a foundation managers can use as they devise new sets of actionable mechanisms to ensure trustworthy and ethical AI.

Technological standards across varying AI domains are therefore going to have a large impact on the governance of AI technologies, making it more salient for managers just which specifications they need to address and fulfill when bringing a new product or service to market. As standards are context-specific, this means that managers' expectations about levels of enforcement also are going to be met through the provision of a clearer set of measurable and quantifiable mechanisms that needs to be satisfied before an AI system is released.

5. Conclusion

Our randomized online survey experiment tests how information about actual or future AI regulation affects managers' intention on ethical and policy issues, technology adoption, and resource (budget and personnel) allocation. We analyze four treatments, each presenting the respondent with different information about: (1) a general AI regulation involving a new Algorithmic Accountability Act; (2) industry-specific regulations implemented by the FDA, NHTSA, and FTC (respectively); (3) existing legal requirements having de facto regulatory effects on AI through common law doctrines such as tort law, or current statutes governing matters such as employment discrimination; and (4) data privacy regulation, including new statutes such as the California Consumer Privacy Act. Our results confirm that exposure to information about AI regulation increases how important managers consider various ethical issues when adopting AI, but increases in manager awareness of ethical issues are offset by a decrease in manager intent to adopt AI technologies. The heterogeneous responses across ethical issues and firm characteristics suggest that the concreteness of the ethical issue and manager perception of the enforcement of regulation likely drive the heterogeneous responses to regulation. The prospect of future regulation possibly encourages managers' to invest in new areas (Aragón-Correa et al., 2020). Some of these areas are expected to be associated with ethical issues, such as enhancing the importance of bias and discrimination, and transparency and explainability of specific AI solutions. Though the manager intent captured in this study may not necessarily coincide with the firm's longer-run behavioral changes, we believe our study points toward several key implications for AI regulation, especially as businesses start to and increase AI adoption across different areas.

5.1 Key Implications of AI Regulation for Policymakers and Firm Managers

Our findings indicate several potential implications for the design and analysis of AI-related regulation. First, though AI regulation may conceivably slow innovation or reduce competition through lower adoption, instituting regulation at the early stages of AI diffusion may improve consumer welfare through increased safety and by better addressing bias and discrimination issues.[31] At the same time, there is an inherent need to distinguish between innovation at the level of the firm consuming AI technology and at the level of the firm producing such technology. Even if regulation indeed slows innovation in the former, it can still spur innovation in the latter, consistent with theoretical observations such as the Porter hypothesis (Porter & Van der Linde, 1995). The approach of regulating early, however, contrasts with the common approach of relying on competitive markets, at least in the U.S., to generate the best technology so that government only needs to regulate anticompetitive behavior to maximize social welfare (Aghion et al, 2018; Shapiro, 2019).

Second, although policymakers sometimes find justifications for adopting broad-based regulatory responses to major problems such as environmental protection and occupational safety, cross-cutting AI regulations such as the proposed Algorithmic Accountability Act may have enormously complex effects and make it harder to take important sector characteristics into account. Given the impact of industry sector and firm size on responses, policymakers would do well to take a meticulous approach to AI regulation across different technological and industry-specific use cases. While the importance

[31] We acknowledge that the reduction in AI-related investment and innovation could reduce consumer access to better products and services or result in the deterioration of product and service quality. In such cases, regulation could create an overall negative impact on consumer welfare.

of certain legal requirements and policy goals – such as reducing impermissible bias in algorithms, and enhancing data privacy and security – may apply across sectors, specific features of particular sectors may nonetheless require distinctive responses. For example, the use of AI-related technologies in autonomous driving systems must be responsive to a diverse set of parameters that are likely to be different from those relevant to AI deployments across drug discovery or online advertising.

Our findings also hold several implications for managers as well as businesses that either develop or deploy AI solutions or that intend to do so. Our survey experiment suggests that managers are not always fully aware of how a given product or technology complies with regulation. Information pertaining to AI regulation needs to be factored in by managers, both when developing and adopting AI solutions. If managerial views change systematically after understanding (or being exposed to) regulation, such as in our experiment, this suggests that potential regulatory discrepancies, preferably, should be handled at a very early stage of the investment planning process. In an ideal scenario, regulatory compliance needs to be embedded into the technology and into the development process at an early stage of investment. In most actual scenarios, however, regulation evolves at a much slower pace than technology, signified as the pacing problem (Hagemann, Huddleston, & Thierer 2018), which makes it harder for managers to ensure that a technology developed today continues to stay compliant into the future. We find that when managers are presented with information on AI-related regulation, they tend to behave in a reactionary manner, which forces managers to rethink how they allocate their budget, i.e., strategize, which is consistent with reevaluating potential issues in a product or a technology's development or adoption process. Managers and businesses that have developed more standardized ways of doing this are therefore expected to be better equipped to handle any potential regulatory shocks in the future. Concrete managerial recommendations include documenting the lineage of AI products or services, as well as their behaviors during operation (Madzou & Firth-Butterfield 2020). Documentation could include information about the purpose of the product and the datasets that have been used for training and while running the application, as well as ethics-oriented results on safety and fairness, for example.[32] Managers can also work to establish cross-functional teams consisting of risk and compliance officers, product managers, and

[32] Large technology companies have already created and adopted workable documentary models, see e.g. Google's Model Cards or IBM's Factsheets.

data scientists, enabled to perform internal audits to assess ongoing compliance with existing and emerging regulatory demands (Madzou & Firth-Butterfield 2020).

While our findings confirm that conveying information about potential AI-related regulations generally entails a slower rate of reported AI adoption, we also find that even emphasizing existing laws relevant to AI can exacerbate uncertainty for managers in terms of implementing new AI-based solutions. For businesses that develop or deploy AI products or services, this implies that a new set of managerial standards and practices that details AI liability under varying circumstances needs to be embraced. As many of these practices are yet to emerge, stronger internal audits, as well as third-party examinations, would provide more information for managers, which could help some managers overcome certain present-biased preferences. This could reduce managerial uncertainty and aid the development of AI products and services that are subject to higher ethical as well as legal and policy standards.

As AI technologies remain at an early stage of adoption, the coming magnitude of AI implementation is likely to continue on an upward trending slope, as companies increasingly will be required to adopt new AI tools and technologies in order to stay competitive. As the potential costs of broad-based general AI regulation are comparable to the costs of existing laws and statutes, this implies that the adoption of clearer rules and regulations could have a net positive effect on the number of firms that are yet to adopt AI technologies. Re-engineering existing AI solutions can be both costly and time consuming, while removing regulatory and legal uncertainties potentially could enable to-be-adopters through the provision of a clearer set of rules and admitted costs of compliance from the outset of adoption. As our study takes the cost side of the equation into consideration, further studies can provide valuable insights into the actual and perceived benefits that potentially come with new forms of AI regulation.

5.2 Concluding Observations

The extent, content, and responses to AI regulation will no doubt continue to evolve in the years to come, especially in light of the pace of technological innovation and the public's growing exposure to AI. Specific issues such as auditing requirements for algorithms, constraints of sharing of data, rules of governing explainability, and so on, may be addressed in new regulatory requirements or refined interpretations of existing ones. Given the high stakes and the impact not only of substantive requirements but perceptions of those requirements, the public will benefit from a robust, iterative exchange of ideas and information between regulators and business managers. Adopters of AI technologies may not always be fully aware of how their AI algorithms function at a detailed technical level. Furthermore, an algorithm that continuously enhances itself based on the progression of data and inputs can make it difficult to determine who is liable as it evolves. Given the pace of innovation and the possibility that managers do not fully understand these issues, clear explanations and information will help managers make well-informed decisions. Pilot studies of AI applications in different sectors, such as autonomous driving, drug discovery processes, and online advertising, may be an essential intermediate step for understanding the implications related to widespread use of AI. Moreover, such pilot studies could involve public-private partnerships and examine how liability could be shared among developers, insurers, the government, and consumers (Kalra and Paddock 2016). Our results also suggest that managers may be influenced not only by the reality of regulation but how information is presented and emphasized, underscoring the need for clarity about what is and is not regulated.

The question of what kinds of regulations are appropriate and most needed by society will remain intricate. No doubt, further research that examines the potential impact of AI regulation will help regulators design appropriate AI regulatory frameworks and consider how to implement and adapt existing laws. As policymakers consider the trade-offs, our results underscore the extent to which business managers are sensitive to the risks and costs associated with the regulation of AI. Their responses can have profound effects on workers, businesses, and consumers in the years to come.

Supplementary Material

Supplementary materialis available at Journal of Law, Economics, & Organization online.

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References

Aghion, P., Bechtold, S., Cassar, L., & Herz, H. (2018). The Causal Effects of Competition on Innovation: Experimental Evidence. *Journal of Law, Economics, and Organization*, 34(2): 162-195.

Agrawal, A., Gans, J. & Goldfarb, A. (2019). *The Economics of Artificial Intelligence: An Agenda*. University of Chicago Press.

AI Ethics Impact Group. (2020). From Principles to Practice - An interdisciplinary framework to operationalise AI ethics. *VDE Association for Electrical Electronic & Information Technologies e.V., Bertelsmann Stiftung*, 1–56. https://doi.org/10.11586/2020013

Altman, M., Wood, A., & Vayena, E. (2018). A Harm-Reduction Framework for Algorithmic Fairness. *IEEE Security and Privacy*, *16*(3), 34–45. https://doi.org/10.1109/MSP.2018.2701149

Alvarez, S., & Barney, J. (2005). How do entrepreneurs organize firms under conditions of uncertainty? *Journal of Management*, *31*(5), 776–793. https://doi.org/10.1177/0149206305279486

Ambec, S., & Barla, P. (2006). Can environmental regulations be good for business? An assessment of the Porter Hypothesis. *Energy Studies Review* 14 (2): 42–62.

Ambec, S., Cohen, M., Elgie, S., & Lanoie, P. (2013). The porter hypothesis at 20: Can environmental regulation enhance innovation and competitiveness? *Review of Environmental Economics and Policy*, *7*(1), 2–22. https://doi.org/10.1093/reep/res016

Aragón-Correa, J., Marcus, A., & Vogel, D. (2020). The effects of mandatory and voluntary regulatory pressures on firms' environmental strategies: A review and recommendations for future research. *Academy of Management Annals*, *14*(1), 339–365. https://doi.org/10.5465/annals.2018.0014

Arnold, M et al. 2019. "FactSheets: Increasing Trust in AI Services through Supplier's Declarations of Conformity." *IBM Journal of Research and Development* 63(4–5): 1–13.

Avelar, Pedro H. C., Rafael B. Audibert, Anderson R. Tavares, and Luís C. Lamb. 2021. "Measuring Ethics in AI with AI: A Methodology and Dataset Construction." http://arxiv.org/abs/2107.11913.

Barfield, W., Pagallo, U. (2018) Research Handbook on the Law of Artificial Intelligence. Edward Elgar Publishing. Northampton Massachusetts.

Baumol, J., & Blackman, S. (1991). Perfect Markets and Easy Virtue Business Ethics and the Invisible Hand. Blackwell, Cambridge.

Boddington, P. (2017) Towards a Code of Ethics for Artificial Intelligence. Springer.

Bostrom, N., & Yudkowsky, E. (2014). The ethics of artificial intelligence. *The Cambridge Handbook of Artificial Intelligence*, 316–334. https://doi.org/10.1017/cbo9781139046855.020

Bowen, F. (2002) 'Does Size Matter?: Organizational Slack and Visibility as Alternative Explanations for Environmental Responsiveness', Business & Society, 41(1), pp. 118–124. doi: 10.1177/0007650302041001007.

Brundage, Miles et al. 2020. "Toward Trustworthy AI Development: Mechanisms for Supporting Verifiable Claims." http://arxiv.org/abs/2004.07213

Campbell, A., & Glass, K. (2001). The legal status of clinical and ethics policies, codes, and guidelines in medical practice and research. *McGill Law Journal. Revue de Droit de McGill*, *46*(2), 473–489.

Cath, C., Wachter, S., Mittelstadt, B., Taddeo, M., & Floridi, L. (2018). Artificial Intelligence and the 'Good Society': the US, EU, and UK approach. *Science and Engineering Ethics*, *24*(2), 505–528. https://doi.org/10.1007/s11948-017-9901-7

Congress. (2019). Algorithmic Accountability Act 2019, 1–15.

Crawford, K., & Calo, R. (2016). There is a blind spot in AI research. *Nature*, *538*(7625), 311–313. https://doi.org/10.1038/538311a

Cuéllar, M. (2019). A Common Law for the Age of Artificial Intelligence: Incremental Adjudication, Institutions, and Relational Non-Arbitrariness. Working Paper.

Curchod, C., Patriotta, G., Cohen, L., & Neysen, N. (2020). Working for an Algorithm: Power Asymmetries and Agency in Online Work Settings. *Administrative Science Quarterly*, *65*(3), 644–676. https://doi.org/10.1177/0001839219867024

Davenport, Thomas. 2013. "Keep Up with Your Quants." *Harvard Business Review*.

Dellavigna, S. (2009). Psychology and Economics : Evidence from the Field. *Journal of Economic Literature*, 315–372.

Di Tella, R., & Rodrik, D. (2020). Labor Market Shocks and the Demand for Trade Protection: Evidence from Online Surveys. *Economic Journal*, 130: 1008-1030.

Etzioni, A., & Etzioni, O. (2017). Incorporating Ethics into Artificial Intelligence. *Journal of Ethics*, *21*(4), 403–418. https://doi.org/10.1007/s10892-017-9252-2

Frank, M., David A., James B., Brynjolfsson, E., Cebrian, M., Deming, D., Feldman, M., Groh, M., Lobo, J., Moro, E., Wang, D., Youn, H., & Rahwan. I., (2019). Toward understanding the impact of artificial intelligence on labor. *Proceedings of the National Academy of Sciences*, 116 (14): 6531-6539

Galasso, A., & Luo, H. (2017). Tort Reform and Innovation. *Journal of Law and Economics*, 60:385–412.

Galasso, A. & Luo, H. (2019). Punishing Robots: Issues in the Economics of Tort Liability and Innovation in Artificial Intelligence, in *The Economics of Artificial Intelligence: An Agenda*, Ajay Agrawal, Joshua Gans and Avi Goldfarb (Eds.), University of Chicago Press.

Ghosh, Dipayan. 2021. "Are We Entering a New Phase for Social Media Regulation?" *Harvard Business Review*.

Goldfarb, A., & Tucker, C. (2012). Privacy and Innovation. In Innovation Policy and the Economy (Vol. 12, pp. 65–89).

Goldfarb, A., & Tucker, C. (2011). Privacy Regulation and Online Advertising. *Management Science*, *57*(1), 57–71. https://doi.org/10.1287/mnsc.1100.1246

Greene, D., Hoffmann, A., & Stark, L. (2019). Better, Nicer, Clearer, Fairer: A Critical Assessment of the Movement for Ethical Artificial Intelligence and Machine Learning. *Proceedings of the 52nd Hawaii International Conference on Systems Science.*

Grigorescu, Sorin, Bogdan Trasnea, Tiberiu Cocias, and Gigel Macesanu. 2020. "A Survey of Deep Learning Techniques for Autonomous Driving." *Journal of Field Robotics* 37(3): 362–86.

Hagemann, R., Huddleston, J., & Thierer, A. D. (2018). Soft Law for Hard Problems: The Governance of Emerging Technologies in an Uncertain Future. Colorado Technology Law Journal (Vol. 17).

Haščič, I., Johnstone, N., & Kalamova, M. (2009). Environmental Policy Flexibility, Search and Innovation. Czech Journal of Economics and Finance (Finance a uver). 59. 426-441.

Hosmer, L. (1994). Strategic Planning as if Ethics Mattered. *Strategic Management Journal*, *15*, 17–34.

Jaffe, A., Peterson, S., Portney, P., & Stavins, R. (1995). Environmental regulation and the competitiveness of US manufacturing: What does the evidence tell us? *Journal of Economic Literature*, 33(1): 132–163.

Jia, J., G.Z. Jin, and L. Wagman (2020). "The short-run effect of GDPR on technology venture investment" *Marketing Science*, forthcoming.

Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence*, *1*(9), 389–399. https://doi.org/10.1038/s42256-019-0088-2

Kalra, N., & Paddock, S., (2016) Driving to Safety: How Many Miles of Driving Would It Take to Demonstrate Autonomous Vehicle Reliability? Santa Monica, CA: RAND Corporation, 2016.

Kim, P. (2017). Data-Driven Discrimination at Work. *William & Mary Law Review*, *857*(58).

Kim, J., & Wagman, L. (2015), Screening incentives and privacy protection in financial markets: a theoretical and empirical analysis. *The RAND Journal of Economics*, 46: 1-22. doi:10.1111/1756-2171.12083

Koopman, P., & Wagner, M. (2017). Autonomous Vehicle Safety: An Interdisciplinary Challenge. *IEEE Intelligent Transportation Systems Magazine*, *9*(1), 90–96. https://doi.org/10.1109/MITS.2016.2583491

Kulshreshtha, P. (2005). Business Ethics versus Economic Incentives: "Contemporary Issues and Dilemmas." *Journal of Business Ethics*, *60*(4), 393–410. https://doi.org/10.1007/sl0551-005-1896-3

Kuziemko, I., Norton, M., Saez, E., & Stantcheva. S., (2015). How Elastic Are Preferences for Redistribution? Evidence from Randomized Survey Experiments. American Economic Review, 105 (4): 1478-1508.DOI: 10.1257/aer.20130360

Lambrecht, A., & Tucker, C. (2019). Algorithmic bias? An empirical study of apparent gender-based discrimination in the display of stem career ads. *Management Science*, *65*(7), 2966–2981. https://doi.org/10.1287/mnsc.2018.3093

Lee, Y.S., Larsen, B., Webb, M., Cuellar, M-F. 2019. How Would AI Regulation Change Firms' Behavior? Evidence from Thousands of Managers. SIEPR Working Paper 19-031.

Levav, J., & Fitzsimons, G. (2006). When Questions Change Behavior The Role of Ease of Representation. *Psychological Science*, *17*(3), 207–213.

Madzou, L., & Firth-Butterfield, K. (2020). Regulation could transform the AI industry. Here's how companies can prepare. World Economic Forum. 23 October, 2020.

Majumdar, S., & Marcus, A. (2001). Rules versus discretion: The productivity consequences of flexible regulation. Academy of Management Journal, 44(1): 170–179.

McKinsey (2018). Notes from the AI Frontier: AI Adoption Advances, But Foundational Barriers Remain. November 2018.

Mckinsey. (2019). Global AI Survey: AI proves its worth, but few scale impact. November 2018.

Miller, A. & Tucker, C. (2011), Encryption and the loss of patient data. *Journal of Policy Analysis and Management*, 30: 534-556. https://doi.org/10.1002/pam.20590

Miller, A. & Tucker, C. (2014). Electronic Discovery and the Adoption of Information Technology. Journal of Law, Economics, and Organization, 30(2): 217-243

Mittelstadt, Brent Daniel et al. 2016. "The Ethics of Algorithms: Mapping the Debate." *Big Data and Society* (December): 1–21.

Moore, S., & Manring, S, (2009). Strategy development in small and medium sized enterprises for sustainability and increased value creation. Journal of Cleaner Production 17, 276-282.

Morwitz, V., Johnson, E., & Schmittlein, D. (1993). Does Measuring Intent Change Behavior ?

Journal of Consumer Research, *20*(1), 46–61.
Nuno, Norberto, Andrade de Gomes, and Verena Kontschieder. 2021. "AI Impact Assessment: A Policy Prototyping Experiment." (January).
Pava, M., & Krausz, J. (1996). The Association Between Corporate Social Responsibility and Financial Performance: The Paradox of Social Cost. *Journal of Business Ethics*. 15. 321-357.
Parker, David, and Colin Kirkpatrick. 2012. "The Economic Impact of Regulatory Policy: A Literature Review of Quantitative Evidence." *OECD Framework for Regulatory Policy Evaluation* Expert Pap(3).
Porter, M., & Van der Linde. C., 1995. Toward a New Conception of the Environment-Competitiveness Relationship. *Journal of Economic Perspectives*, 9 (4): 97-118.
Raub, M. (2018). Artificial intelligence, algorithmic bias and disparate impact liability in hiring practices. *Arkansas Law Review*, *71*(2).
Rossi, Francesca, and Nicholas Mattei. 2019. "Building Ethically Bounded Ai." *33rd AAAI Conference on Artificial Intelligence, AAAI 2019, 31st Innovative Applications of Artificial Intelligence Conference, IAAI 2019 and the 9th AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2019*: 9785–89.
Russel, S., & Norvig, P. 2009. Artificial Intelligence: A Modern Approach 3rd Edition, Pearson.
Shapiro, C. (2019). Protecting Competition in the American Economy: Merger Control, Tech Titans, Labor Markets. *Journal of Economic Perspectives*, 33 (3): 69-93.
Teece, D., & Leih, S. (2016). Uncertainty, innovation, and dynamic capabilities: An introduction. *California Management Review*. https://doi.org/10.1525/cmr.2016.58.4.5
Tourangeau, R., Rips, L., & Rasinski, K. (2000). The Psychology of Survey Response. Cambridge: Cambridge University Press. doi:10.1017/CBO9780511819322
Turner Lee, N. (2018). Detecting racial bias in algorithms and machine learning. *Journal of Information, Communication and Ethics in Society*, *16*(3), 252–260. https://doi.org/10.1108/JICES-06-2018-0056
Varian, H. (2018). Artificial Intelligence, Economics, And Industrial Organization. NBER Working Paper Series. https://doi.org/10.1590/s1809-98232013000400007
Veale, M., & Binns, R. (2017). Fairer machine learning in the real world: Mitigating discrimination without collecting sensitive data. *Big Data and Society*, *4*(2), 1–17. https://doi.org/10.1177/2053951717743530
Visser, P., Krosnick, J., & Lavrakas, P. (2000). Survey research. In Handbook of research methods in social and personality psychology (pp. 223–252). Cambridge University Press. https://doi.org/10.4018/ijavet.2015100106
Wallach, W., & Marchant, G. (2018). An Agile Ethical/Legal Model for the International and National Governance of AI and Robotics. *Proceedings of the AIES*, *107*(3), 7. https://doi.org/10.1109/JPROC.2019.2899422
Wilson R. (1997) Economics and Ethics. In Economics, Ethics and Religion. Palgrave Macmillan, London. https://doi.org/10.1057/9780230374720_1
Winfield, Alan. 2019. "Ethical Standards in Robotics and AI." *Nature Electronics* 2(2): 46–48.
Yuste, R., & Goering, S. (2017). Ethical guidelines for neurotechnologies and machine intelligence. *Nature*, *551*(163).
Zhang, Daniel et al. 2021. "2021 AI Index Report." : 1–222. https://aiindex.stanford.edu/report/.
Zwane AP, Zinman J, Van Dusen E, Pariente W, Null C, Miguel E, Kremer M, Karlan DS, Hornbeck R, Giné X, Duflo E, Devoto F, Crepon B, & Banerjee A. (2011) Being surveyed can

change later behavior and related parameter estimates. *Proceedings of the National Academy of Sciences*. 108(5):1821-1826. DOI: 10.1073/pnas.1000776108.

Zizzo, D. J. (2010). Experimenter demand effects in economic experiments. *Experimental Economics*, *13*(1), 75–98. https://doi.org/10.1007/s10683-009-9230-z

Zolas, N., McElheran, K., Goldschlag, N., Foster, L., Dinlersoz, E., Buffington, C., Brynjolfsson, E., & Beede, D, (2019) Measuring Technology Adoption in Enterprise-level Surveys: The Annual Business Survey. American Economic Association Presentation. San Diego, January 3rd 2020

APPENDIX

Appendix Table A1. Treatment texts

Control group	Recent research has found that early adopters of AI have started to reap the benefits of their investments in this technology. First-movers have already deployed and marketed AI-related solutions across healthcare, autonomous driving, retail and so on. Forty-seven percent of companies say they have embedded at least one AI capability in their business processes. While the potential for AI is vast, most organizations still have a long way to go in developing the core practices that enable them to realize the potential value of AI at scale. Business executives and managers will need to think about how to incorporate AI into their business strategy, as well as the transparency and "explainability" of AI algorithms, biases in data, and concerns about safety and privacy.
Treatment 1 – General AI Regulation	Recent research has found that early adopters of AI have started to reap the benefits of their investments in this technology. First-movers have already deployed and marketed AI-related solutions across healthcare, autonomous driving, retail and so on. Forty-seven percent of companies say they have embedded at least one AI capability in their business processes. Until now, states and the federal government have enacted little oversight and regulation specific to AI. But a new Algorithmic Accountability Act is expected to change that. Under this Act, firms that are using or selling AI-related products are subject to a variety of requirements governing their use of AI systems. Requirements include disclosure of firm usage of AI systems, including their development process or contractor of origin, AI system design, model training, and data gathered and in use. The Act also requires firms to disclose to a government agency the impact of their AI systems on safety, accuracy, fairness, bias, discrimination, and privacy. The regulation is expected to go into effect in 2020.
Treatment 2A – Agency-specific AI Regulation (FDA for Healthcare)	Recent research has found that early adopters of AI have started to reap the benefits of their investments in this technology. First-movers have already deployed and marketed AI-related solutions across healthcare, autonomous driving, retail and so on. Forty-seven percent of companies say they have embedded at least one AI capability in their business processes. The healthcare and drug sectors have been actively developing AI technologies for various purposes including patient diagnosis, treatment, drug development, and patient monitoring and care. The Food and Drug Administration (FDA) currently regulates the industry and has proposed a new regulatory framework for AI/Machine Learning-based software. This framework aims to examine and pre-approve the underlying performance of the firm's AI products before they are marketed, and post-approve any algorithmic modifications. In this process, the FDA will assess the firm's ability to manage risks associated with various issues such as, transparency and explainability (e.g., diagnosis recommendation algorithms), and security (e.g., use and protection of patient private information) of the AI/Machine Learning based software. FDA's proposed framework is expected to go into effect in 2020.
Treatment 2B – Agency-specific AI Regulation (NHTSA for Transportation)	Recent research has found that early adopters of AI have started to reap the benefits of their investments in this technology. First-movers have already deployed and marketed AI-related solutions across healthcare, autonomous driving, retail and so on. Forty-seven percent of companies say they have embedded at least one AI capability in their business processes. Autonomous vehicle capabilities have developed rapidly over the last decade and several large companies are currently using cities as testing grounds for unmanned vehicles. The National Highway Traffic and Safety Administration (NHTSA) regulates the autonomous vehicle and logistics industry. NHTSA has specified that its current safety standards constitute an unintended regulatory barrier to innovation of autonomous driving vehicles. For automated driving technologies, NHTSA has emphasized the importance of removing unnecessary barriers and is issuing voluntary guidance rather than regulations that could stifle innovation. NHTSA's existing regulations and vehicle safety standards remain in effect until a revised framework for automated driving systems is established.
Treatment 2C – Agency-specific AI Regulation (FTC for Retail and Wholesale)	Recent research has found that early adopters of AI have started to reap the benefits of their investments in this technology. First-movers have already deployed and marketed AI-related solutions across healthcare, autonomous driving, retail and so on. Forty-seven percent of companies say they have embedded at least one AI capability in their business processes. The retail sector has been especially fast at deploying and monetizing a range of AI technologies on online and e-commerce platforms. As a result, the Federal Trade Commission (FTC) has engaged in hearings to safeguard consumers from unfair and deceptive practices. For retailers deploying AI technologies, revamped oversight by the FTC will likely require these firms to assess and disclose the impact of their AI systems on various issues. Potential issues include algorithmic discrimination and bias (e.g. in online adds / micro-targeting of consumer groups), transparency (e.g. product recommendation engines) and security (e.g. use and protection of consumers private information). Based on past hearings, new guidelines are expected to be released in 2020.

Treatment 3 – Existing AI-related Regulation	Recent research has found that early adopters of AI have started to reap the benefits of their investments in this technology. First-movers have already deployed and marketed AI-related solutions across healthcare, autonomous driving, retail and so on. Forty-seven percent of companies say they have embedded at least one AI capability in their business processes. Although some observers believe little oversight and regulation has been attached to the area of AI training and product deployment, firms using AI technology in the United States generally are subject to common law and statutory requirements. Existing law (e.g., tort law) may require that a company avoid any negligent use of AI to make decisions or provide information that could result in harm to the public. Current employment, labor, and civil rights laws create the risk that a company using AI to make hiring or termination decisions could face liability for its decisions involving human resources. These legal requirements apply now, and will likely continue applying to future products, services, and company practices.
Treatment 4 – Data Privacy Regulation	Recent research has found that early adopters of AI have started to reap the benefits of their investments in this technology. First-movers have already deployed and marketed AI-related solutions across healthcare, autonomous driving, retail and so on. Forty-seven percent of companies say they have embedded at least one AI capability in their business processes. As the development of AI-related products requires more data, policymakers and the public are increasingly concerned about data privacy. For example, California's recently-enacted digital privacy initiative, the California Consumer Privacy Act of 2018 (CCPA), will affect all businesses buying, selling or otherwise trading the "personal information" of California residents – including companies using online-generated data from residents across their products. In order to stay compliant with the regulation, firms must disclose how they use and store personal data, and how they conform with data privacy rules. California's regulation goes into effect in 2020. Other states are expected to enact similar data privacy regulations in the near future.

Appendix Table A2. Comparison of state of respondents

	Our sample	DR (2019)	DDL (2017)	ACS 2015
State	% of the total			
Alabama	1.69	1.18	1.29	1.51
Alaska	0	0.11	0.05	0.22
Arizona	2.01	2.27	2.46	2.10
Arkansas	1.2	0.74	0.85	0.92
California	9.24	12.07	9.91	12.12
Colorado	1.29	1.64	1.69	1.69
Connecticut	2.01	0.88	0.97	1.14
Delaware	0.48	0.25	0.39	0.30
District of Columbia	0.4	0.16	0.28	0.22
Florida	5.94	10.92	7.08	6.52
Georgia	4.9	3.38	3.41	3.11
Hawaii	0.72	0.07	0.30	0.45
Idaho	0.24	0.42	0.62	0.49
Illinois	4.58	3.75	4.35	4.00
Indiana	2.81	1.53	2.09	2.03
Iowa	0.48	0.63	0.95	0.97
Kansas	1.04	0.72	0.92	0.88
Kentucky	1.69	1.71	1.49	1.38
Louisiana	1.53	1.13	1.17	1.43
Maine	0.72	0.23	0.50	0.43
Maryland	2.25	1.74	1.84	1.88
Massachusetts	2.57	2.30	2.01	2.18
Michigan	3.86	3.03	3.47	3.11
Minnesota	1.2	1.55	1.51	1.70
Mississippi	0.96	0.83	0.70	0.91
Missouri	1.45	1.58	2.13	1.89
Montana	0.24	0.23	0.22	0.33
Nebraska	0.72	0.46	0.65	0.58
Nevada	0.88	0.83	0.89	0.90
New Hampshire	0.08	0.26	0.50	0.43
New Jersey	2.17	2.20	2.44	2.81
New Mexico	0.24	0.56	0.67	0.64
New York	7.87	6.97	5.71	6.29
North Carolina	3.45	3.43	3.92	3.13
North Dakota	0.4	0.16	0.13	0.24
Ohio	5.46	3.43	4.30	3.63
Oklahoma	1.45	0.91	0.97	1.19
Oregon	0.88	1.62	2.03	1.28
Pennsylvania	4.9	4.20	4.72	4.08
Rhode Island	0.16	0.32	0.25	0.34
South Carolina	1.29	1.57	1.39	1.54
South Dakota	0.24	0.19	0.28	0.26
Tennessee	2.89	1.57	2.08	2.06
Texas	6.91	7.76	7.01	8.18
Utah	0.48	0.72	0.82	0.84
Vermont	0.08	0.33	0.23	0.21
Virginia	1.69	2.83	2.93	2.63
Washington	1.37	2.46	2.78	2.24
West Virginia	0.24	0.53	0.54	0.59
Wisconsin	0.56	1.46	1.91	1.81
Wyoming	0.08	0.12	0.13	0.18

Appendix Table A3. Comparison of individual characteristics

	Our sample	Di Tella and Rodrik (2019)	Di Tella, et al. (2017)	Kuziemko, et al. (2015)	WVS 6th Wave	ACS 2015
Male	33.25%	46.4%	43.8%	42.8%	48.4%	48.6%
Postgraduate degree	24.18%	17.7%	13.3%	12.6%	11.5%	10.2%
Only college degree	48.43%	49.8%	47.4%	40.7%	24.8%	25.7%
No college degree	27.39%	32.6%	39.3%	46.7%	63.7%	64.1%
White	62.73%	73.1%	80.5%	77.8%	69.8%	74.8%
Black	18.47%	8.8%	9.2%	7.6%	10.4%	12.2%
Hispanic	8.35%	5%	6.6%	4.4%	13.4%	15.5%
Asian	5.14%	6.3%	6.8%	7.6%	-	6.2%
Other race	5.31%	6.6%	2.6%	2.6%	-	2.8%

Appendix Table A4. Primarily responsible for ethical issues

	Primarily responsible for ethical issues				
	Managers	Engineers	Vendors	Government	The court
	(1)	(2)	(3)	(4)	(5)
General AI regulation	-0.358	0.187	-0.0391	-0.205	0.0796
	(0.302)	(0.123)	(0.129)	(0.131)	(0.157)
Agency-specific AI regulation	-0.227	-0.0587	-0.213	0.0315	0.354**
	(0.246)	(0.125)	(0.152)	(0.110)	(0.148)
Existing AI-related regulation	0.0398	-0.0573	-0.199	-0.00874	0.213
	(0.259)	(0.124)	(0.150)	(0.115)	(0.130)
Data privacy regulation	-0.182	0.00522	0.0206	0.0502	0.0410
	(0.254)	(0.116)	(0.149)	(0.121)	(0.172)
Observations	1,245	1,245	1,245	1,245	1,245
Firm level controls	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes
Management controls	Yes	Yes	Yes	Yes	Yes
Budget experience	Yes	Yes	Yes	Yes	Yes
Current AI adoption	Yes	Yes	Yes	Yes	Yes

Notes: Firm level controls include state, industry, firm size, and firm revenue fixed effects. Individual controls include gender, race, education, and age fixed effects. Management controls include management practice variables related to promotion and firing, and organizational role fixed effects. Budget experience includes dummy variables that control for the largest budget previously managed. Current AI adoption includes dummy variables indicating whether the business currently uses natural language processing, computer vision, or machine learning. Standard errors clustered at the state-industry level are presented in parentheses. ***, **, and * denote statistical significant at 1%, 5%, and 10% level.

Appendix Table A5. Impact of AI regulation on adoption, budget allocation, and innovation activity by employee size

	A. Adoption	B. Importance of ethical issues					C. Budget allocation						D. Adjustment to labor					
	Number of business processes to adopt AI	Labor issues	Bias and discrimination	Safety and accidents	Privacy and data security	Transparency and explainability	Developing AI strategy	AI related R&D	Hiring workers related to business' AI system	AI training for existing employees	Purchase AI package from vendors	Computing resource and data for AI system	Managers	Technical workers	Office workers	Sales workers	Service workers	Production workers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
							Panel A. All treatments combined											
Any AI related regulation																		
x Emp<=500	-0.264**	-0.0676	0.0649	0.298	0.0335	0.172	2.289	4.063	-1.853	-4.866**	-2.777	3.144*	0.261	-0.0922	0.176	0.222	0.166	-0.0210
	(0.103)	(0.170)	(0.180)	(0.210)	(0.212)	(0.142)	(2.389)	(3.427)	(1.626)	(2.303)	(1.985)	(1.699)	(0.209)	(0.164)	(0.171)	(0.138)	(0.225)	(0.141)
x Emp>500	-0.104*	0.123	0.0918	0.233***	0.161**	0.139	2.022*	-0.824	1.483	-1.081	-1.396	-0.203	0.145*	-0.00453	-0.0103	-0.0657	-0.0294	0.0107
	(0.0591)	(0.0938)	(0.0864)	(0.0873)	(0.0802)	(0.0965)	(1.048)	(1.994)	(1.152)	(1.179)	(1.130)	(0.867)	(0.0850)	(0.0855)	(0.0832)	(0.0725)	(0.0909)	(0.0891)
R-squared							0.092	0.097	0.107	0.077	0.103	0.078						
							Panel B. Treatment specific effects											
General AI regulation																		
x Emp<=500	-0.178	-0.0929	-0.120	-0.0153	-0.259	-0.238	4.885	1.695	-0.486	-6.433**	-2.252	2.591	0.113	-0.281	0.189	0.129	0.132	-0.00661
	(0.134)	(0.206)	(0.208)	(0.247)	(0.218)	(0.153)	(3.044)	(4.229)	(2.423)	(2.604)	(2.459)	(1.994)	(0.278)	(0.244)	(0.236)	(0.221)	(0.269)	(0.222)
x Emp>500	-0.160**	0.116	0.0978	0.339***	0.100	0.149	2.266*	-0.0891	2.946*	-1.162	-1.654	-2.306**	0.153	-0.0754	0.0625	-0.117	0.0122	0.0192
	(0.0802)	(0.105)	(0.105)	(0.109)	(0.105)	(0.113)	(1.365)	(2.546)	(1.536)	(1.627)	(1.449)	(1.009)	(0.106)	(0.113)	(0.125)	(0.121)	(0.124)	(0.124)
Agency specific AI regulation																		
x Emp<=500	-0.328**	-0.00395	0.274	0.546**	0.237	0.350**	5.677	4.193	-3.958**	-4.435	-2.574	1.095	0.305	0.0518	0.0751	0.511**	0.237	0.0399
	(0.134)	(0.219)	(0.172)	(0.240)	(0.246)	(0.177)	(3.479)	(4.031)	(1.992)	(2.772)	(2.522)	(1.894)	(0.215)	(0.193)	(0.213)	(0.203)	(0.262)	(0.177)
x Emp>500	-0.0413	0.0459	0.116	0.231**	0.0400	0.177	1.171	-1.467	1.653	-0.751	-1.704	1.096	0.0436	-0.0798	-0.0816	-0.109	-0.125	-0.0863
	(0.0798)	(0.101)	(0.113)	(0.110)	(0.106)	(0.120)	(1.163)	(2.062)	(1.360)	(1.424)	(1.226)	(1.235)	(0.0986)	(0.104)	(0.109)	(0.0880)	(0.120)	(0.109)
Existing AI related regulation																		
x Emp<=500	-0.352***	-0.182	-0.0537	0.270	0.0229	0.322	0.517	2.435	0.336	-3.063	-4.281**	4.056*	0.220	-0.0226	0.340	0.238	0.221	0.238
	(0.107)	(0.176)	(0.238)	(0.265)	(0.230)	(0.201)	(2.528)	(3.730)	(2.496)	(2.734)	(1.986)	(2.408)	(0.269)	(0.217)	(0.213)	(0.169)	(0.229)	(0.200)
x Emp>500	-0.128	0.154	0.0266	0.241**	0.267***	0.110	3.285**	-0.135	-0.471	-1.767	-1.360	0.448	0.247**	0.103	-0.00625	0.00921	-0.0255	0.0608
	(0.0783)	(0.125)	(0.113)	(0.118)	(0.0895)	(0.112)	(1.547)	(2.733)	(1.262)	(1.540)	(1.375)	(1.189)	(0.116)	(0.117)	(0.111)	(0.101)	(0.108)	(0.118)
Data privacy regulation																		
x Emp<=500	-0.205	0.0153	0.153	0.429*	0.193	0.313	-3.648	8.964*	-3.602	-5.566**	-1.979	5.831*	0.458*	-0.113	0.108	-0.0363	0.0514	-0.405**
	(0.148)	(0.214)	(0.253)	(0.225)	(0.267)	(0.206)	(3.001)	(5.141)	(2.277)	(2.642)	(2.054)	(3.104)	(0.256)	(0.197)	(0.206)	(0.194)	(0.258)	(0.192)
x Emp>500	-0.0992	0.179	0.125	0.134	0.236**	0.116	1.439	-1.435	1.965	-0.740	-0.854	-0.374	0.148	0.0238	-0.00843	-0.0579	0.0285	0.0417
	(0.0631)	(0.117)	(0.117)	(0.108)	(0.117)	(0.122)	(1.256)	(1.934)	(1.625)	(1.235)	(1.317)	(1.019)	(0.115)	(0.104)	(0.114)	(0.0963)	(0.111)	(0.122)
R-squared							0.104	0.100	0.114	0.079	0.104	0.089						
Observations	1,245	1,245	1,245	1,245	1,245	1,245	1,245	1,245	1,245	1,245	1,245	1,245	1,201	1,195	1,201	1,172	1,185	1,152

Notes: All regressions include firm level, individual level, management, budget, and current AI use controls. Firm level controls include state, industry, firm size, and firm revenue fixed effects. Individual controls include gender, race, education, and age fixed effects. Management controls include management practice variables related to promotion and firing, and organizational role fixed effects. Budget experience includes dummy variables that control for the largest budget previously managed. Current AI adoption includes dummy variables indicating whether the business currently uses natural language processing, computer vision, or machine learning. Number of observations in the regressions is 1,245. Standard errors clustered at the state-industry level are presented in parentheses. ***, **, and * denote statistical significant at 1%, 5%, and 10% level.

Appendix Table A6. Comparing treatment and control on variables that potentially reflect manager awareness of regulatory issues by industry

	Have managed annual budget of $1M or more	Owner/partner	C-level executive	Education BA or above	Age 45 or above	Firm revenue $100M or above
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All industries						
Any AI related regulation	-0.0165	-0.0126	0.00517	-0.0246	0.00403	-0.0136
	(0.0352)	(0.0260)	(0.0256)	(0.0355)	(0.0312)	(0.0322)
Observations	1,245	1,245	1,245	1,245	1,245	1,245
R-squared	0.000	0.000	0.000	0.000	0.000	0.000
Panel B. Healthcare						
Any AI related regulation	-0.0217	0.00918	0.0242	-0.00242	-0.0101	-0.0623
	(0.0519)	(0.0382)	(0.0376)	(0.0504)	(0.0442)	(0.0449)
Observations	529	529	529	529	529	529
R-squared	0.000	0.000	0.001	0.000	0.000	0.004
Panel C. Automotive						
Any AI related regulation	0.0692	-0.00164	0.0362	-0.0921	0.0397	0.0617
	(0.0801)	(0.0592)	(0.0605)	(0.0825)	(0.0781)	(0.0764)
Observations	232	232	232	232	232	232
R-squared	0.003	0.000	0.002	0.005	0.001	0.003
Panel D. Retail and wholesale						
Any AI related regulation	-0.0584	-0.0490	-0.0364	0.00470	0.00260	-0.00309
	(0.0600)	(0.0448)	(0.0431)	(0.0612)	(0.0523)	(0.0567)
Observations	484	484	484	484	484	484
R-squared	0.002	0.002	0.001	0.000	0.000	0.000

Notes: ***, **, and * denote statistical significant at 1%, 5%, and 10% level.

Appendix Table A7. Key results by industries

	Perception of ethical issues related to AI					
	Labor issues	Bias and discrimination	Safety and accidents	Privacy and data security	Transparency and explainability	Adoption of AI
	(1)	(2)	(3)	(4)	(5)	(6)
I. Healthcare						
Panel A. All Treatments Combined						
Any AI related regulation	0.0599	0.0956	0.215**	0.137	0.0159	-0.131*
	(0.136)	(0.134)	(0.0976)	(0.114)	(0.152)	(0.0717)
Panel B. Treatment Specific Effects						
General AI regulation	0.0655	0.151	0.274**	0.153	-0.0938	-0.172
	(0.122)	(0.136)	(0.125)	(0.149)	(0.167)	(0.113)
Agency specific AI regulation	0.0379	0.211	0.290***	0.118	0.124	-0.0485
	(0.175)	(0.133)	(0.111)	(0.170)	(0.199)	(0.0877)
Existing AI related regulation	-0.0773	-0.00769	0.132	0.136	0.0107	-0.203**
	(0.192)	(0.178)	(0.154)	(0.118)	(0.162)	(0.0987)
Data privacy regulation	0.202	0.0223	0.160	0.140	0.0152	-0.108
	(0.170)	(0.197)	(0.141)	(0.154)	(0.188)	(0.0815)
Observations	529	529	529	529	529	529
II. Automotive						
Panel C. All Treatments Combined						
Any AI related regulation	-0.0857	0.106	0.391**	0.524**	0.362	0.0809
	(0.191)	(0.202)	(0.193)	(0.260)	(0.251)	(0.149)
Panel D. Treatment Specific Effects						
General AI regulation	-0.253	-0.0605	0.330	0.326	0.169	0.248
	(0.367)	(0.345)	(0.303)	(0.290)	(0.319)	(0.188)
Agency specific AI regulation	-0.0779	0.146	0.697**	0.668**	0.531	0.0548
	(0.204)	(0.267)	(0.304)	(0.311)	(0.340)	(0.180)
Existing AI related regulation	-0.0746	0.0721	0.438	0.555	0.166	-0.0667
	(0.280)	(0.285)	(0.278)	(0.338)	(0.273)	(0.218)
Data privacy regulation	-0.0355	0.192	-0.00433	0.395	0.506	0.250
	(0.295)	(0.334)	(0.283)	(0.374)	(0.397)	(0.168)
Observations	232	232	232	232	232	232
III. Retail and Wholesale						
Panel E. All Treatments Combined						
Any AI related regulation	0.134	0.0562	0.181	0.0703	0.166	-0.236***
	(0.143)	(0.129)	(0.154)	(0.135)	(0.102)	(0.0836)
Panel F. Treatment Specific Effects						
General AI regulation	0.0545	-0.112	0.149	-0.170	-0.0336	-0.249**
	(0.181)	(0.151)	(0.194)	(0.145)	(0.158)	(0.124)
Agency specific AI regulation	-0.0198	0.0709	0.118	-0.0384	0.308**	-0.213*
	(0.170)	(0.165)	(0.210)	(0.179)	(0.129)	(0.109)
Existing AI related regulation	0.257	0.0197	0.207	0.184	0.194	-0.240**
	(0.173)	(0.190)	(0.155)	(0.138)	(0.150)	(0.108)
Data privacy regulation	0.221	0.233	0.244	0.299	0.183	-0.244***
	(0.185)	(0.186)	(0.208)	(0.200)	(0.147)	(0.0734)
Observations	484	484	484	484	484	484

Notes: Firm level controls include state, industry, firm size, and firm revenue fixed effects. Individual controls include gender, race, education, and age fixed effects. Management controls include management practice variables related to promotion and firing, and organizational role fixed effects. Budget experience includes dummy variables that control for the largest budget previously managed. Current AI adoption includes dummy variables indicating whether the business currently uses natural language processing, computer vision, or machine learning. Standard errors clustered at the state-industry level are presented in parentheses. Columns (1) to (5) are ordered probit regression results and Column (6) is censored poisson regression results. ***, **, and * denote statistical significant at 1%, 5%, and 10% level.

Article II

Article II

A Framework for Understanding AI-Induced Field Change: How AI Technologies are Legitimized and Institutionalized

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Abstract

Artificial intelligence (AI) systems operate in increasingly diverse areas, from healthcare to facial recognition, the stock market, autonomous vehicles, and so on. While the underlying digital infrastructure of AI systems is developing rapidly, each area of implementation is subject to different degrees and processes of legitimization. Building on institutional- and information systems (IS) theory, this paper presents a conceptual framework to analyze and understand AI-induced field change. The introduction of novel AI agents into new or existing fields creates a dynamic in which algorithms shape organizations and institutions. At the same time, existing institutional infrastructures determine the scope and speed at which organizational change is allowed to occur. Where institutional infrastructure and governance arrangements, such as standards, rules, and regulations, still are unelaborate, the field can move fast but is also more likely to be contested. The institutional infrastructure surrounding AI-induced fields is generally little elaborated, which could be an obstacle to the broader institutionalization of AI systems.

Keywords: AI; Field Change; Legitimization; Digital Infrastructure; Institutional Infrastructure

JEL codes: K24 (Cyber Law), L38 (Public Policy), O33 (Technological Change: Choices and Consequences • Diffusion Processes)

1. Introduction

In recent years, the scope of information technology that complements or augments human actions has expanded rapidly. The logics embedded in AI systems already operates in diverse areas, such as the stock market (Mackenzie, 2006), mortgage underwriting (Markus, 2017), autonomous vehicles

(Hengstler et al., 2016), medical services (Davenport & Kalakota, 2019) the judicial system (Mckay, 2020), and a range of other fields. The action potentials inherent in most AI systems imply a shift in agency, moving from human actors to AI agents, which significantly shape new practices (e.g., across healthcare, agriculture, autonomous vehicles) and thereby new forms of organization.

Novel AI systems and agents are embedded in existing digital infrastructures and operate within an institutional framework that enables or constrains various activities (Baskerville et al., 2019). The socio-economic embeddedness of AI systems means that some AI agents may affect and alter existing social practices and ways of organization in swift and transforming ways. At the same time, their implementation may be subject to varying degrees of legitimacy, depending on the field and area of implementation. Digital infrastructures, however, tend to emerge more rapidly than institutional infrastructures (e.g., laws and regulations), which is commonly referred to as the pacing problem (Hagemann et al., 2018). This may create extensive issues if negative externalities are associated with fast-moving technological implementation that is at odds with existing structures or norms for specific actors or groups of a population (Buolamwini & Gebru, 2018; Obermeyer et al., 2019). Tensions also arise as human actions increasingly have become subject to 'informatization' where behavior is tracked, sometimes unknowingly, through the collection of new data points (Kallinikos, 2011; Zuboff, 1988; Zuboff, 2019). Data is derived from social networks and online interactions, facial recognition technologies, driving behavior, apps recording location data, and so on. The wide range of AI implementations and some of the associated tensions captured by the pacing problem guide and motivate the research question of this paper, which seeks to understand how AI-induced fields are subject to varying degrees of legitimacy as well as processes of institutionalization.

Views from institutional- and information systems (IS) theory are combined to conceptualize how AI fields achieve socio-technological legitimacy. Attention is placed on how AI diffusion is accepted or rejected under varying socio-economic conditions.

Elements from information systems theory elaborate on the notion of digital infrastructure (Constantinides et al., 2018; Henfridsson & Bygstad, 2013; Yoo et al., 2010), which signifies a range of interconnected technologies (e.g., Internet, Platforms, IoT) that contribute to realizing the action potentials of novel AI agents and associated processes of information collection.

Institutional theory introduces the concept of fields, which denote distinct areas of AI implementation and organization by a diverse range of actors. Elements from institutional theory, i.e., institutional work (Lawrence & Suddaby, 2006), logics (Thornton et al., 2012), and infrastructure (Hinings et al., 2017), are applied in order to conceptualize how processes of AI-induced digitization affect the evolution and governance of organizations (Powell et al., 2017). Theory surrounding institutional work is applied to understand how actors accomplish the social construction of logics, i.e., rules, scripts, schemas, and cultural accounts. These areas signify where human actors and AI agents may challenge existing organizational or institutional practices and boundaries, which may result in difficulties associated with legitimization. Adding the institutional perspective is about how "digitally-enabled institutional arrangements emerge and diffuse both through fields and organizations" (Hinings et al., 2017, p. 53). The paper's primary focus is placed on the interplay between existing and new and emerging institutional arrangements and the role of AI in altering ways of organization.

Building on institutional- and information systems (IS) theory, the paper proposes a novel conceptual framework for analyzing and understanding AI-induced field change. The framework builds on Zietsma et al.'s. (2017) concept of pathways of change, which outlines how a field is likely to move between states from emerging/aligning to fragmented, contested, and established, depending on the coherency in logics and elaboration of institutional infrastructure. The proposed framework adds the notion of digital infrastructure elaborated through the constructs of technological maturity, data, and AI autonomy, which enables an assessment of the impact of AI systems on existing forms of institutional infrastructure. Where digital and institutional infrastructure is well-elaborated in terms of organizational practices, rules, and processes, the field can be considered established. If a field is emerging or aligning, on the other hand, its digital and institutional infrastructure will be nascent and unelaborate. The developed framework is illustrated through application to the field of facial recognition technologies in the United States.

The paper contributes by elaborating on existing information systems theory by adding the institutional perspective to understand the dispersion of AI technologies. Clarity is gained in assessing how AI technologies move within and between fields, which is interpreted through a technology's elaboration of institutional and digital infrastructure, which in combination informs a technology's perceived degree of legitimacy.

The paper is structured as follows. Section 2 elaborates on institutional theory and the characteristics of digital infrastructure. Section 3 presents a framework for understanding AI-induced field change. Section 4 applies the framework through illustration. Section 5 deliberates on pathways of change, referring to how AI fields become institutionalized, and section 6 discusses obstacles to legitimacy and paths forward in terms of governance. Section 7 concludes.

2. Institutional Theory and AI Agents

In organization theory, the idea of institutional infrastructure reflects the embeddedness of organizations within fields and the structuration of fields that occurs through interactions and activity among actors (Dacin et al., 1999). Over the last few decades, organizational fields have become more dynamic and boundaries between fields have become more porous, due to the introduction of new digital infrastructures, such as the Internet (Powell et al., 2017, p. 336).

Early institutional theory developed the notion that organizations come to resemble each other due to socio-cultural pressures, which provide a source of legitimacy (Meyer & Rowan, 1977). A central process is isomorphism, demonstrating that organizations are likely to converge through normative, mimetic, and coercive pressures (DiMaggio & Powell, 1983). Mimetic isomorphism holds that organizational legitimacy is achieved by copying other organizations and their technologies and practices. Coercive legitimacy refers to societal legitimacy, which often is achieved through legislation. In contrast, normative legitimacy can be viewed as derived from appropriate professional standards and social acceptance of new technologies. Socio-cultural beliefs and practices thus play an essential role in the adoption of new technologies and innovations and contingent processes of legitimization (Hinings et al., 2018).

Competing institutions may lie within individual populations that inhabit a field, while fields may be contested by multiple institutional logics (Reay & Hinings, 2005; 2009; Greenwood, Raynard, Kodeih, Micelotta, & Lounsbury, 2011; Gawer & Phillips, 2013; Scott, 2014). Institutional logics describe a field's "socially constructed, historical patterns of material practices, assumptions, values, beliefs, and rules" (Thornton & Ocasio, 1999: 804). The institutional logics perspective deals with the interrelationships among individuals, institutions, and organizations, i.e., the actors of a field.

Institutional work, on the other hand, emphasizes a conceptual shift towards individuals and organization's actions that are "dependent on cognitive (rather than affective) processes and structures and thus suggests an approach… that focuses on understanding how actors accomplish the social construction of rules, scripts, schemas, and cultural accounts" (Lawrence & Suddaby, 2006: 218).

When the two approaches are held together, i.e., logics and interrelationships, and structures and practices, these can be expressed as the institutional infrastructure of a field. Institutional infrastructure is established through adjacent activities such as rules, regulations, certifications, and reporting against principles, codes, and standards (Waddock, 2008). Institutional infrastructure can be clarified in terms of its degree of elaboration (high, low), as well as coherency in logics (unitary, competing) (Hinings et al., 2017).

Novel AI agents operating in varying systems also embody distinct logics and cognitive functions (Floridi & Sanders, 2004). While these functions are defined by human actors (e.g., engineers in a company), AI agents remain autonomous in varying degrees, i.e., they are to some extent able to act independently based on intrinsic flows of information. This implies that AI agents have the autonomy to act on (e.g., judicial evidence, road conditions, etc.) and interact with (e.g., speech recognition, chatbots) their environments. This new form of artificial agency confounds the paradox of embedded agency, i.e., how actors can change institutions when their actions are conditioned by those same institutions (Holm, 1995), by the implication of an AI's ability to shape human behavior and ways of organization – sometimes simultaneously. In other words, algorithms can affect how we conceptualize the world while modifying socio-political forms of organization (Floridi, 2014).

Algorithms can be seen as non-human agents endowed with the ability to evaluate, rank, and reward or punish individuals' actions and positions based on pre-programmed instructions that shape social relationships (Curchod, Patriotta, Cohen, & Neysen, 2020; Orlikowski & Scott, 2008). Algorithms, however, are often compressed and hidden, and we do not encounter them in the same way that we encounter traditional rules (Lash, 2007; Beer, 2017). The increasing reliance on algorithms as instruments for the regulation of social relationships, coupled with the obscurity of algorithmic evaluation systems, is evidence of new yet subtle ways of exercising power, which alters existing power-dependencies, e.g., through surveillance, online interaction, and so on. Algorithms are therefore implicated in the constitution and reproduction of power asymmetries that regulate individuals' behaviors and ensure their compliance with predefined standards, which in turn can affect human agency (Curchod et al., 2020). It is difficult, however, to identify ex-ante what the socio-economic effects of scaling an AI-system will be (Henfridsson et al., 2018; Rai, Constantinides, &

Sarker, 2019), which warrants that extensive experimentation through application may be necessary before AI-based technological diffusion and legitimization are likely to take place.

Institutional logics and institutional work provide a foundation to understand the rationalities and practices of actors that implement novel AI agents and the AI agents' systemic impact on their surroundings through their socio-economic embeddedness. An analysis of AI agents predicated on institutional work and logics can be placed either at the micro-level, seeking to understand the impact of individual AI agents on specific socio-economic practices, or at the meso-level, seeking to understand how actors influence the legitimacy of AI applications in a field. That is, how AI diffusion is adopted and accepted, or rejected, under varying socio-economic and technological conditions.

2.1 *Digital Infrastructure*

Digital infrastructure is made from a multitude of digital building blocks and is defined as the computing and network resources that allow multiple stakeholders to orchestrate their service and content needs (Constantinides et al., 2018). Digital infrastructures are distinct from traditional infrastructures because of their ability to collect, store, and make digital data available across many systems and devices simultaneously (Constantinides et al., 2018). Examples of digital infrastructures include the Internet (Hanseth & Lyytinen, 2010; Monteiro, 1998); data centers; open standards, e.g., IEEE 802.11 (Wi-Fi); and consumer devices such as smartphones.

Henfridsson et al. (2018, p. 90) describe "digital resources" as entities that serve as building blocks in the creation and capture of value from information. While AI technologies are assembled as digital building blocks, a distinction needs to be made between traditional software systems (i.e., ERP, CRM, WordPress, etc.) and novel AI systems (computer vision, machine learning, etc.). This distinction is important, as a new kind of embedded agency is inherent in most AI systems and renders these as "organizers," "predictors," or "controllers" of data flows that are captured by digital infrastructures (Russell & Norvig, 2010).

Most digital building blocks are made accessible through online platforms or are proprietarily assembled through open-source code. Digital building blocks are transformational due to the innovative patterns that can be established through "use-recombination" (Henfridsson et al., 2018), while there needs to be separate legitimacy for each building block, as well as collective legitimacy for a new institutional arrangement to emerge (Hinings et al., 2018). It may, for example, be that a platform-based building block holds legitimacy (e.g., a cloud-based AI facial recognition system) because it performs within a predefined level of accuracy. However, for the organizational or broader institutional arrangement to gain legitimacy, the embeddedness of the building block into a socio-economic system needs to be accepted at a much broader level of implementation.

As digital building blocks are created by engineers, and as humans are subject to bias (Parasuraman & Manzey, 2010), this means that the values of the designer can be "frozen into the code, effectively institutionalizing those values'' (Macnish, 2012: 158). Friedman and Nissenbaum (1996) argue that bias in computer systems can arise in three distinct ways, referring to (1) pre-existing social values found in the ''social institutions, practices, and attitudes'' from which technology emerges, (2) technical constraints, and (3) emergent aspects that arise through usage, which only can be known ex-post. The distinction between social and technical bias has also been referred to as normative and epistemic concerns (Mittelstadt et al., 2016) or structural and functional risks (Nuno et al., 2021). Functional risks refer to technical areas such as the design and operation of an AI system, including datasets, bias, and performance issues. In contrast, structural risks refer to the ethical implications of an AI system, including the societal effects of automated decisions.

Based on a synthesis of the above considerations, I propose using three analytical constructs, referring to technological maturity, data, and AI-autonomy, to signify a field's relative elaboration of digital infrastructure. The constructs have been selected as they embody some of the main features of AI-induced digital infrastructure associated with (1) the algorithm, (2) its use of data, and (3) its ability to act, as well as the likely ramifications of those actions. Each of the three constructs is elaborated in greater detail below.

2.2 *Technological Maturity, Data, and AI Autonomy*

2.2.1 *Technological Maturity*

AI systems can be associated with different degrees of technological maturity, both in terms of the accuracy of the system (Zhu et al., 2018) and the elaboration of adjacent technological standards (Garud et al., 2002). The accuracy of an AI model refers to whether it operates within a predefined 'acceptable' level of performance. In the case of autonomous vehicle safety, for instance, an AI-controller is expected to hold the ability to locate persons and objects from a distance of 100 meters with an accuracy of +/– 20 cm, within a false negative rate of 1% and false-positive rate of 5% (Grigorescu et al., 2020). High accuracy alone may not be sufficient in some areas that involve high-stakes decisions (e.g., autonomous driving, credit applications, judicial decisions, and medical recommendations), as these applications require greater trust in their associated services (Arnold et al., 2019). In high-risk areas, the functional aspects of a model (i.e., accuracy, data, etc.) must be further elaborated through measures such as certification, testing, auditing, and the elaboration of technological standards, which refers back to the institutional infrastructure of a field.

Depending on the context and the area of use, a range of quantitative measures can be used to evaluate the technological maturity of an AI-induced field. Some suggestions include the measures of scientific output, e.g., research papers, citations, and the intellectual property rights that surround a given field. Important questions relate to whether emerging algorithmic capabilities are under development and going through testing stages or already being widely deployed by a small or a large number of actors. For structural implications, it is essential to ask questions such as: how does the technological maturity and elaboration (of immature/mature) AI-induced digital infrastructures affect a field? For example, the implementation of chatbots, which may have performed with sufficient accuracy under test environments, has proved to display racial biases and prejudices, as the algorithm continues to learn during actual implementation, which aggravates social harm for certain groups of the population (Schlesinger et al., 2018). The elements used to evaluate and decide whether an AI system is mature or immature are therefore dependent on the system's context of implementation, which renders technical aspects alone insufficient when assessing the technological maturity of AI models and associated digital infrastructure.

Several methods have been proposed to evaluate predictive models, such as "model cards for model reporting" (Mitchell et al., 2019), "nutrition labels for rankings" (Yang et al., 2018), "algorithmic impact assessment" forms (Reisman et al., 2018), as well as "fact sheets" (Arnold et al., 2019). These frameworks can help organizations establish new organizational practices that characterize model specifications more coherently while paying special attention to attributes such as accuracy, bias, consistency, transparency, interpretability, and fairness.

At a general level, when dominant standards are in place and the accuracy of an AI system is deemed safe, reliable, and trustworthy, digital infrastructure is considered elaborate and, therefore, higher field legitimacy is expected. If a technology is considered immature, inaccurate, or insufficiently tested, the surrounding digital infrastructure would be considered unelaborate.

2.2.2 *Data*

The nature of the data that feeds into an AI model or system is also essential. Data can be classified as sensitive (e.g., health-related) or non-sensitive (e.g., weather-related), and the nature of the data can be private (i.e., individual data) or public (common/pooled data) (Coyle et al., 2020). Data can also be biased, which makes AI systems prone to inherit either individually coded forms of bias or biases that result from historical or cultural practices, which are reflected in the training data, and could be adopted by the algorithm (Barocas & Selbst, 2014). For an algorithm to be effective, its training data must be representative of the communities that it impacts. The use of digital infrastructures by individuals, machines, and communities requires institutions to negotiate how bits containing various information legitimately can be utilized and (re)arranged by organizations.

Several methods have been proposed to evaluate data and machine learning models under a variety of conditions. For data, these include "data statements" (Bender & Friedman, 2018), "datasheets for data sets" (Gebru et al., 2020) and "nutrition labels for data sets" (Stoyanovich & Howe, 2019), which seek to evaluate the data that goes into a model across training, testing, and post-implementation scenarios.

Sound data practices that are transparent, well-documented, and privacy-preserving are generally associated with a more elaborate digital infrastructure. Data practices that are biased, undocumented, or otherwise disputed could be considered a sign of unelaborate digital infrastructure.

2.2.3 *AI Autonomy*

AI agents act with varying degrees of autonomy. The explorative actions of an autonomous learning agent may, however, not always be known and can be subject to change depending on the data that is fed into the model (Amodei et al., 2016). An AI agent can have limited or extensive autonomy to make decisions, while the decisions of an AI agent can have a lenient (e.g., recommender engine, smart speaker) or a severe (e.g., autonomous vehicle, incarceration system, facial recognition) impact on individuals as well as its surroundings, if the algorithm is inaccurate, fails, or is otherwise at fault. In the case of facial recognition systems, that could include excessive collection of data or unwilling intrusion of privacy, for example. The categorization of an agent's autonomy, therefore, includes its ability to act and the possible ramifications of its actions. The perceived risk of an AI agent can be understood as the probability that a disruptive event occurs, multiplied by the severity of potential harm to an individual or form of organization (Nuno et al., 2021). The definition of 'harm' and the computation of probability and severity is context-dependent and varies across sectors. For instance, the impact of an autonomous decision in medical diagnosis could, arguably, be more significant than that of a product recommendation system (Personal Data Protection Commission, 2020). Relevant questions include: what risks may be present in model usage, as well as identification of the potential recipients, likelihood, and magnitude of harm (Amodei et al., 2016). Where risks are taken into consideration and are sufficiently mitigated to avoid potential harms, the digital infrastructure could be considered elaborate.

The elaboration of AI-associated digital infrastructure across the constructs of technological maturity, data, and AI autonomy, remains subject to qualitative and quantitative judgments and measures, which are field-dependent and linked to idiosyncrasies across functional (technical) as well as structural (ethical) risks and considerations.

2.3 *Governance*

Since field-level advancements in AI are context-dependent, this means that the existing institutional infrastructure and logics negotiate the actual impact that a technology is allowed to have within a given social context, which differs across geographies. In other words, the flexibility of a digital infrastructure is often restricted by socio-technical and regulatory arrangements (e.g., restrictions on autonomous vehicles, regulations on the use of patients' medical data, etc.). Often, layered and interoperable standards and common definitions of application and service interfaces guide the use and growth of digital infrastructures (Tilson et al., 2010) and are necessary for digital infrastructure's wider processes of institutionalization. As large technology companies usually are the leading innovators of a field, these also carry a crucial weight in the direction of new technology standards (Pisano & Teece, 2007), which generally affect how an industry or a field continues to evolve. Typically, private actors orchestrate ecosystems and associated digital infrastructures, which brings issues to the forefront, such as the challenge of establishing a governance system, reproducing social order, and incorporating aspects of value appropriation and control (Botzem & Dobusch, 2012; Djelic & Sahlin-Andersson, 2006; Garud et al., 2002; Garud & Karnøe, 2003; Raynard, 2016).

The process that renders digital infrastructures institutional occurs when innovators infuse specific norms, values, and logics, as well as forms of governance and technological control, into the infrastructure as the infrastructure becomes more widely adopted and legitimized over time (Gawer & Phillips, 2013; Orlikowski, 2007; Orlikowski & Scott, 2008). Digital institutional infrastructure can thus be viewed as the integration of digital infrastructure and institutional infrastructure, which is defined as "standard-setting digital technologies that enable, constrain and coordinate numerous actors' actions and interactions in ecosystems, fields, or industries" (Hinings et al., 2018, p. 54).

3. A Conceptual Framework for Understanding AI-Induced Field Change

By integrating insights from institutional theory (work, logics) with information systems theory (digital infrastructure), I propose the use of a novel framework for analyzing AI-induced field change (Table 1). The framework builds on Zietsma et al.'s (Zietsma et al. 2017) conceptualization of pathways of change, which hypothesizes how actors drive change across different sets of field circumstances. The proposed framework extends existing work (Zietsma et al., 2017) by incorporating the notion of AI-associated digital infrastructures, which has implications for the structure and organization of (digital) institutions going forward.

The framework constrains the analyst first to consider varying actors and their position in a field before elaborating on their abilities to affect the direction of a field, either through the introduction of new technology, regulation, or a social movement. Next, the relationship among actors and their coherency in logics is considered. When logics are unitary, greater field alignment is expected, whereas competing logics means that a field is unsettled. The elaboration of institutional infrastructure is considered by looking at the practices and actions of individual actors and organizations in terms of creating, maintaining, and disrupting institutions over time. The notion of field structuring events is particularly important, both in terms of logic formation or disruption and the elaboration of the institutional infrastructure of a field.

The AI-associated digital infrastructure of a field is signified by the proposed constructs of technological maturity, data specification, and the relative autonomy of an AI system. Technological maturity refers to the perceived accuracy of an AI agent and the elaboration of areas such as standards, research, and intellectual property. The data linked to a model is another important source of institutional legitimacy, both functionally (e.g., non-biased data) and structurally (e.g., how an organization is engaged in practices of data collection and usage). Autonomy refers to the relative impact of an AI agent on its general environment and its potential for exacerbating structural risks and creating harm. At last, the governance of a field and the mechanisms that guide algorithmic implementation are considered.

Table 1. Framework for Analyzing AI-Induced Field Change and Legitimization

<table>
<tr><th colspan="2">ACTORS</th></tr>
<tr><td colspan="2">-Subject position: central, middle status, and peripheral actors
-Characterized by roles or functions, i.e., field-structuring or governing organizations, formal governance units, field coordinators, etc.</td></tr>
<tr><th colspan="2">DIGITAL INSTITUTIONAL INFRASTRUCTURE</th></tr>
<tr><td colspan="2">-Standard-setting digital technologies that enable, constrain, and coordinate numerous actors' actions and interactions in ecosystems, fields, or industries (Hinings et al., 2018).</td></tr>
<tr><th>INSTITUTIONAL INFRASTRUCTURE</th><th>DIGITAL INFRASTRUCTURE</th></tr>
<tr><td>Established through activities such as: certifying, assuring, and reporting against principles, codes, rules, and standards, as well as through the formation of new associations and networks among organizations, including official rules and regulations (Waddock, 2008).

Logics: refers to the relationships among individuals and organizations in the field. Logics can be competing or unitary. They may be based on market, social, and other considerations.
Work: refers to the practices and actions of individuals and organizations that have implications for creating, maintaining, and disrupting institutions over time. Looks at the effect of institutional change on areas such as hierarchies of status and influence, as well as subsequent power relations. Incorporates the notion of field structuring events, which informs or disrupts logic formation.</td><td>Established from a multitude of digital building blocks, defined as the computing and network resources that allow multiple stakeholders to orchestrate their service and content needs (Constantinides et al., 2018).

Technological Maturity: refers to the elaboration of hardware and software-based infrastructures and associated technological standards. Includes the perceived accuracy, safety, and reliability of an AI system/agent.
Data: refers to the data that is used in a model, which either can be sensitive or non-sensitive, private or publicly available, centralized or decentralized, and may be linked to varying forms of ownership.
Autonomy: refers to whether the AI agent holds limited or extensive autonomy to act and whether the agent's actions have a negligible or a considerable impact on its environment and surroundings.</td></tr>
<tr><th colspan="2">GOVERNANCE</th></tr>
<tr><td colspan="2">-Combinations of public and private, formal and informal systems that exercise control within a field.
-Units and processes that ensure compliance with rules and facilitate 'the functioning and reproduction of the system (e.g., standards, regulations, and social control agents that monitor and enforce these).</td></tr>
</table>

Based on coherency in logics (unitary, competing) (Hinings et al., 2017) and the elaboration of institutional infrastructure (high, low) (Greenwood et al., 2011), a four-fold classification of field conditions is produced. The classification is used to consider whether there are settled or unsettled logic prioritizations and limited or elaborated digital and institutional infrastructure (Figure 1) (Zietsma et al., 2017).

Where digital and institutional infrastructure is highly elaborate and there is a unitary dominant logic within the field, the field can be described as established and relatively stable, i.e., the institutional infrastructure is coherent (Zietsma et al., 2017). Formal governance and informal infrastructure elements are elaborate and likely to reinforce each other, leading to a coherent sense of what is legitimate or not within the organizational field (Zietsma & Lawrence, 2010).

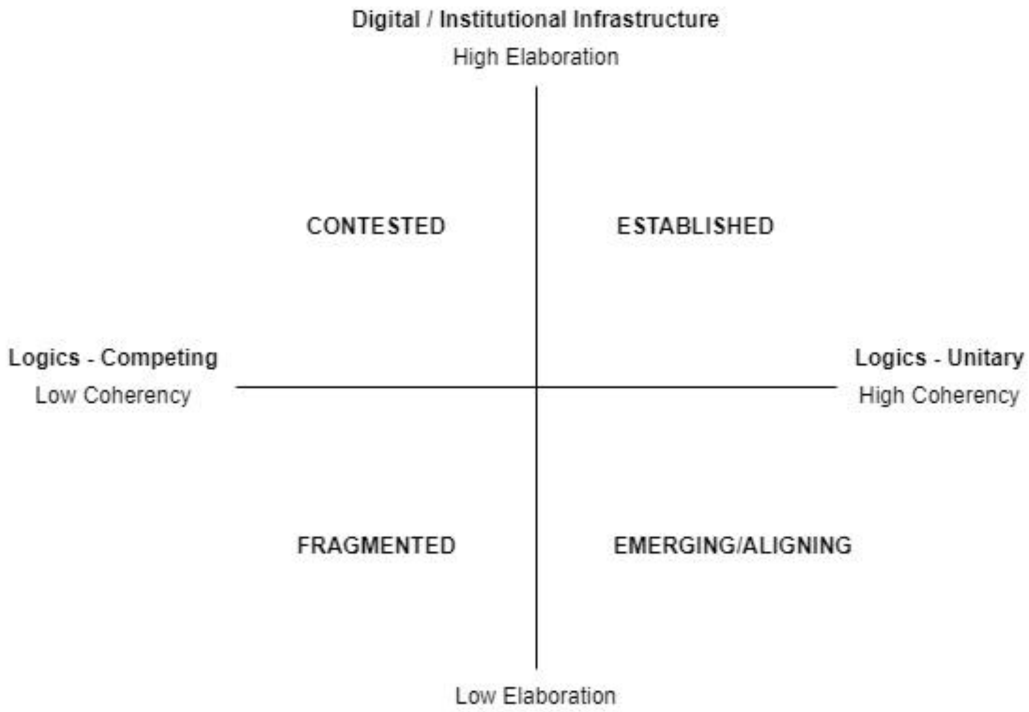
In fields with highly elaborate institutional infrastructure but competing logics (low coherency), there could be multiple governance and digital and institutional infrastructure arrangements (Zietsma et al., 2017). These arrangements may conflict with one another or compete for dominance, making the field contested (Reay & Hinings, 2005; Rao, Morrill, & Zald, 2000). Contested refers both to competing digital infrastructures (e.g., technological standards, varying models, and levels of algorithmic accuracy) and to stakeholders with opposing views.

Fields with low coherency and limited elaboration of digital and institutional infrastructure are described as fragmented, with competing conceptions of what is legitimate. Fields may be fragmented if they emerge in intermediate positions (e.g., biotechnology), which draw on logics and practices from diverse but neighboring fields (Powell & Sandholtz, 2012). A field may also be fragmented as new actors enter an existing field with innovative ideas and designs about products, courses of action, behaviors, and new structures and ways of organizing (Patvardhan et al., 2015). For instance, in the field of facial recognition technology, multiple competing logics move across stakeholders and demonstrate incoherent views over technical accuracy and the ability of FRT to enhance public safety. Many differing views paired with a limited (but expanding) digital infrastructure situates the field in the fragmented quadrant.

When infrastructure has a low degree of elaboration but a high degree of coherency in logics, the field is described as emerging or aligning (Hinings et al., 2017). While the lack of digital and institutional infrastructure in an emerging field may create room for experimentation and change, it may also limit field members’ ability to define and acquire legitimacy. This contributes to ambiguity and the need to draw on inappropriate infrastructure from adjacent fields. One example could be the emergence of autonomous vehicles, the governance of which draws on existing legal frameworks regarding liability that may be ill-suited to cover accompanying changes in agency and responsibility.

Categorizing a field’s present condition and its potential trajectories enables us to get a deeper understanding of possible areas of contestation, fragmentation, or alignment, as well as what it takes for an AI-induced field to grow established over time. Before these conditions are further discussed in section 5, the following section applies the developed framework (Table 1) to the field of facial recognition technologies in the United States. The application briefly illustrates the utility of the framework in terms of assessing field elaboration; future studies may apply the framework to analyze specific case studies at greater depths.

Figure 1: Digital / Institutional Infrastructure and Logics: Framework for Field-Change. Modified from (Zietsma et al., 2017).



4. Analyzing AI-Induced Field Change and Legitimization: Facial Recognition Technology

4.1 *Actors*

The proliferation of facial recognition technologies in the United States has been supported by large technology companies, which are the central actors in the field (e.g., Apple, Amazon, Google, Microsoft, IBM). While these companies provide their own applications directly to the market, they also modularize facial-recognition technologies and make them accessible for complementors on their platforms. This makes them field structuring organizations, since the modularization of FRT systems embodies best practices and de-facto industry standards with which other companies align. Central actors include adopters of FRT systems, while many of these are US public sector agencies. Contractors that specialize in delivering FRT technology to law-enforcement agencies and the National Institute of Standards and Technology (NIST) hold intermediate positions. Peripheral actors include multistakeholder organizations such as the Partnership on AI, non-profit research organizations such as the Center for Data and Society, and research institutes such as The AI Now Institute (NYU). These actors affect the field through public reports and commentaries, paying particular attention to issues of technological implementation and social ramifications. Peripheral actors also include opponents of FRT systems, both in the form of activists and civil society organizations such as The American Civil Liberties Union (ACLU).

4.2 *Logics*

The dominant logics behind FRTs has been driven by private sector companies focused on gaining market share. The logic behind adoption is motivated by enhancing public safety measures, e.g., identifying criminals, screening travelers, and processing border immigration. Both logics are highly contested by peripheral actors, e.g., company activists and civil rights organizations (Hao, 2020b), citing that inaccurate technologies hold the potential of exacerbating racial and social biases and inequities. This signifies that emergent dominant logics are at odds with existing social arrangements, including structures of power and governance, which makes the technology heavily resisted (Furnari, 2016).

4.3 *Work: Field-Structuring Events*

In 2019, the local government of San Francisco became the first city in the United States to ban the use of FRTs by local agencies. In the spring of 2020, nationwide protests against police brutality and racial profiling caused several central actors (IBM, Amazon, and Microsoft) to stop providing FRT technologies to law enforcement agencies altogether. IBM called for “a national dialogue on whether and how facial recognition technology should be deployed by domestic law enforcement agencies” (Krishna, 2020, p.1), and Amazon announced a one-year moratorium on police use of its facial recognition technology, giving policymakers time to set appropriate rules around the use of the technology. Microsoft declared that it would not sell FRT technology to police departments in the United States until a federal law that regulates the technology exists. These actions by some of the central actors in the field signal that the existing institutional infrastructure remains inadequate in governing and addressing the current expansion of FRT-related digital infrastructure. This indicates that even as central actors on the procurement side include many public sector agencies, the necessary institutional infrastructure to guide potential ramifications of immature technological adoption has not yet been formulated. Greater alignment between stakeholders across industry, government, and civil society is currently needed to secure ongoing legitimacy and greater field-level elaboration and use of facial recognition technologies.

4.4 *Technological Maturity*

In terms of technological maturity, verification algorithms have achieved accuracy scores of up to 99.97% on standard assessments like the National Institute for Standards and Technology (NIST) Facial Recognition Vendor Test (NIST, 2020). For identification systems, error rates tend to climb when high-quality images are replaced with the feed of live cameras that generally are utilized in public spaces. Aging is another factor that affects error rates, and accuracies of FRT systems also differ considerably across gender and race (Buolamwini & Gebru, 2018). The context, i.e., the specific area of implementation and use, has wide-reaching consequences for the accuracy rates of individual FRT systems.

4.5 *Data*

Issues of legitimacy are also inherent concerning the kinds of data used for training FRT algorithms. Many databases rely on publicly available face-annotated data, which in some cases are scraped directly from social media platforms and have raised issues over privacy and consent (Hao, 2020a). The company Clearview has, for example, assembled a database containing some 3 billion images, including many that have been scraped from public-facing social media platforms (Hill, 2020a). This raises concerns about the legitimacy of data rights and usage, and the ability of the existing institutional infrastructure to provide and safeguard associated rights. The quantity of data is, in many cases, necessary for algorithmic training and for retaining high levels of accuracy post-deployment. This means that private and public actors have an incentive to create rich and centralized databases (e.g., new biometric data). In several states (e.g., Texas, Florida, and Illinois), the FBI is allowed to use facial recognition technology to scan through the Department of Motor Vehicles (DMV) database of drivers' license photos (Ghaffary & Molla, 2019) in order to generate a more coherent and centralized biometric database. As these kinds of data contain personal information, they are classified as being sensitive and vulnerable, both in terms of misuse and in relation to cybersecurity breaches and possible identity theft (Coyle et al., 2020).

4.6 *Autonomy*

AI in facial recognition systems is perceived as a new kind of social control agent, which may exert autonomy over law-enforcement officers in relation to issuing arrest orders. If the accuracy of a system is flawed, an officer's actions are likely to cause social harm whenever an innocent citizen is arrested (Hill, 2020b). The adoption of facial recognition systems for use in law enforcement alters existing power dependencies, as officers have to trust in and act on the information rendered to them by the system. Facial recognition systems are thus shaping entirely new practices and forms of organization in which the autonomy of the AI agent is dependent on the delivery of accurate information, which could reinforce a drive towards data centralization.

4.7 *Governance*

The field of facial recognition technology is fragmented and exhibits low coherency and limited elaboration in terms of institutional infrastructure. A lack of governance is most readily seen in the absence of coherent rules and regulations, while the field is currently going through a shift from self-regulation toward more formalized governance arrangements. This shift has been called for by peripheral actors and, more recently, by central actors from the private sector, which demands new rules to guide legitimate implementation. The case of facial recognition technologies used by law-enforcement highlights the critical role of culture and politics involved in the organization of markets and in creating the governing 'rules of the game' (North, 1990; Fligstein, 2001; Fligstein & McAdam, 2013).

5. Pathways of Change: How AI Fields Move and Gain legitimacy

In order to move from a static to a more dynamic analysis of the conditions related to field change, this section applies the concept of 'pathways of change' to several AI systems and technologies. As evident, each area of AI implementation is subject to idiosyncrasies linked to a field's specific form of digital and institutional infrastructure. Pathways of change suggest that there are some commonalities in how fields are likely to evolve and where obstacles to legitimization and institutionalization may be found. In order to understand how fields move between states, special attention needs to be placed on the scope of change (i.e., which elements change and how much changes)(Maguire & Hardy, 2009), as well as the pace of change (i.e., the speed at which a field moves from one condition to another)(Amis et al., 2004).

In the case of facial recognition technologies, the field is currently moving from the fragmented towards the contested quadrant as the number of use-cases (e.g., public surveillance, airport check-ins, smartphones, doorbells, etc.) continues to expand. While digital infrastructures are expanding, the field is represented by incoherent logics and sparse institutional infrastructure. For example, verification-based FRTs (e.g., unlocking a smartphone) are well-established practices that exhibit legitimate institutionalized functions. Identification-based FRTs (e.g., public surveillance), on the other hand, are more likely to stay contested due to having a lower degree of algorithmic accuracy, which is paired with more severe social impacts linked to the autonomy of AI agents, and how these alter existing power structures. For the field to become more established, a shift from self-regulation toward formalized governance arrangements is needed. In more authoritarian settings, such as in China, the field of facial recognition is already on its way to becoming established. This signifies that a country's socio-political setting informs its institutional infrastructure, which has important implications for a technology's path towards legitimization.

A pathway that moves from an aligning or emerging field condition to an established condition usually involves a process of convergence, which is commonly observed in the institutionalization of most fields (see, e.g., Munir & Phillips, 2005). The field of autonomous vehicles, for example, is characterized by its emerging digital and institutional infrastructure, which has a low degree of elaboration but some coherency in terms of logics. While the field is currently aligning at a relatively slow pace, it is developing as an extension of an existing field (auto infrastructure) that has been elaborated over decades. However, large parts of the existing infrastructure are challenged by the introduction of novel AI agents and a transfer in autonomy from humans to machines. As the digital infrastructure is further elaborated, which entails more mixed-autonomy vehicles on the road, the field could move towards the contested quadrant, as logics associated with safety and liability are disputed. If the rules and regulations to handle negative externalities brought about by algorithmic errors are not in place, the field would likely stay in the contested quadrant. As the advent of autonomous vehicles shifts liability (Marchant & Lindor, 2012), the scope of change demands that an entirely new institutional infrastructure needs to be developed and elaborated by insurers, policymakers, legislators, and automakers. This process could take years and be subject to multiple areas of contestation among stakeholders.

Another common pathway is the movement from an established to a contested field condition. This move is likely to occur through more disruptive change, either an exogenous shock, e.g., new regulation or a strong social movement, or through the challenging of the status quo by a new or peripheral actor (Castel & Friedberg, 2010; Hensmans, 2003). The use of recommender engines (RE), which suggests products, services, and other online information to users based on prior data, is already a well-established practice but could grow more contested due to incoherent logics. RE's have, for example, been argued to create fragmentation by limiting a user's media exposure to a set of predefined interests or objectives (Sunstein, 2007). This could have undesirable social consequences as people's preferences may be guided towards echo chambers where alternate views are missing, which could impede decisional autonomy (Hosanagar et al., 2014; Newell & Marabelli, 2015). Other actors argue that existing data are inconclusive, and some research suggests that recommenders appear to create commonality, not fragmentation (Van Alstyne & Brynjolfsson, 2005), implying that there is little cause to modify the current architecture of recommender engines. This incoherency in logics is coupled with information asymmetries between the AI agent and human actors concerning how and on which information a decision to recommend specific content is made. This lack of transparency and a lack of algorithmic knowledge by the general population arguably leaves some aspects of the current digital infrastructure in the contested quadrant. The governance of data and information that goes into an RE, for example, is partially situated in the contested quadrant, which could have broader field-level implications, and possibly force a coercive change in the form of new regulation.

When a field moves from an established position to (re)aligning under the emergent quadrant, change is usually observed through incremental modifications, with central actors often managing these (Zietsma et al., 2017). This incremental change sees the field realigning around new practices or relational channels while readjusting the institutional infrastructure. The field of smart speakers (Google Assistant, Siri, Alexa, etc.) has moved from the emerging to the established field quadrant over a relatively short time horizon. However, some elements of the digital infrastructure have been linked to concerns over data-collection and data privacy practices, which could cause the field to grow more contested.

Other pathways of change include a move from a fragmented or contested condition to one that is aligning in the emergent quadrant. When looking at nascent AI areas such as Generative Pre-trained Transformer 3 (GPT-3), or deepfakes, these fields emerge in the fragmented quadrant due to incoherent logics coupled with institutional infrastructures that are unelaborate. While the inherent agency of these AI systems is emerging, their associated use of already elaborate digital infrastructure linked to the general information ecosystem makes them able to proliferate at rapid speeds. In terms of autonomy, these AI agents could have a considerable impact on their environment by exacerbating the spread of misinformation online. Therefore, a move from the fragmented quadrant toward greater alignment is needed, which may be formed as actors converge around new ideas, rules, and positions to inform and elaborate on the surrounding institutional infrastructure (Garud, 2008; Zilber, 2007).

AI is currently changing organizational practices across a wide range of fields, which implies that new applications should be carefully considered in terms of their short-term impact on human behavior and long-run influences on institutional change. Insufficiently tested implementation of unsafe or biased algorithms can foster negative externalities, which can have severe consequences or may be detrimental to societal trust. An analysis of AI-associated digital institutional infrastructure, based on logics and work, and conceptualizations of technological maturity, data, and AI autonomy, contributes to assessing where potential areas of contestation or fragmentation could be found. These findings hold important implications for AI developers and adopters (e.g., engineers, managers, firms) and policymakers that seek to define new rules going forward. The implications and main takeaways of the paper are briefly discussed below before a conclusion is offered.

6. Discussion: Commonalities of AI-Induced Field Change & Pending Issues over Governance

Through this illustration of the developed framework, three takeaways that move across varying kinds of AI-induced field change and legitimization are offered. Subject to discussion, these broadly refer to (1) altered power dependencies between humans and machines, (2) unresolved questions over data use and control, as well as (3) issues with the current elaboration of institutional infrastructure surrounding many forms of AI application.

First, the autonomy of AI agents can affect existing power dependencies, which may cause friction as human behavior and ways of organization are influenced in ways that are hard to identify ex-ante (Curchod et al., 2020). In examples such as facial recognition, judicial AI systems, and autonomous vehicles, the AI-agent gains determining power over human actors, which have to trust the identifications or predictions of the AI agent. This transfer of autonomy is contingent on systemic trust, based on conceptualizations of technological maturity and ideas of machine-augmented perception that is expected to operate at cognitive levels that are equal to – or in many cases, exceed those of a human operator. Issues with field-level legitimization and nascent institutionalization processes are likely to arise when emerging systems are inaccurate, unsafe, or non-transparent, all of which erode trust across applications and causes fields to stay fragmented and logics to grow incoherent. Analyzing the field trajectories of such cases involves assessing what it takes for altered power dependencies to be conceived as legitimate practices, which is crucial for a field to move from fragmentation or contestation toward greater alignment of digital and institutional infrastructures.

Second, an incentive for data-centralization is inherent in most digital infrastructures (based on technical and economic logics), which has implications for associated forms of organization. A lack of transparency during data collection and in markets for data leaves large populations unaware of where and how their data and information are being used, stored, and traded and for what purposes (Mittelstadt et al., 2016). The current organization of many digital infrastructures comes with the risk of deteriorating public trust in digital institutional infrastructures if data sources are used for socially disputed measures of public (e.g., safety) and private (e.g., market-based) forms of surveillance (Zuboff, 2019), or are being misused, e.g., due to large-scale data-breaches (Isaak & Hanna, 2018). This implies that the legitimacy of AI agents is highly contingent on the legitimate collection, use, and ownership of data, which otherwise could be a source of dispute that causes field-level disintegration. Regulations such as the European Union's General Data Protection Regulation

(GDPR) should be seen as the first step of elaborating institutional infrastructure that seeks to move fields engaged in data collection from the contested quadrants toward greater establishment and coherency in logics. Over time this could imply a conceptual shift of companies moving from "owners" to "custodians" of individuals' private data. Opening access to data and developing interactivity and an increased sense of ownership with users is a step that could gain traction to smoothen existing information asymmetries between central actors and individual end-users (Tene & Polonetsky, 2013). Similarly, enabling users to better understand and perhaps interact with specific AI agents (e.g., recommender engines) would empower users with a greater sense of ownership over how information is utilized and how it can influence behavior under varying circumstances.

Third, where institutional infrastructure is considered inadequate during phases of market expansion, peripheral actors, such as civil society organizations, frequently work on outlining insufficient governance arrangements (Star, 2002). In many cases, institutional infrastructure must be elaborated before negative externalities erode systemic and institutional levels of trust, which causes a field to grow fragmented. If trust is eroded past specific barriers, technology developers and adopters will likely experience severe pushback from the general public. Public pushback forces central actors from the private sector to engage in new measures of self-regulation, which in some cases means scaling back digital infrastructure until a policy vacuum is filled by new legislative provisions. When logics are at odds with existing power structures or violate existing governance arrangements, these are also more likely to be resisted (Furnari, 2016).

At the same time, the formulation of institutional infrastructure needs to emerge in more adaptive forms of organization (Taeihagh et al., 2021; Wang et al., 2018) that can consider the myriad ways in which AI systems influence and shape existing practices and ways of behavior. This warrants that new types of institutional engineering have to be embraced to keep up with rapidly expanding digital infrastructures while alleviating the pacing problem (Hagemann et al., 2018). Proposed measures of institutional adaptation to mitigate AI-induced externalities include enhanced measures of algorithmic auditing carried out by companies (Zarsky, 2016), third-party auditors (Clark & Hadfield, 2019), or external regulators (Tutt, 2016).

Auditing can create an ex-post procedural record of complex algorithmic decision-making to track inaccurate decisions or detect forms of discrimination, as well as biased data, practices, and other harms (Mittelstadt et al., 2016). When algorithms are designed without considering a population's or community's needs, it has become apparent that both the algorithm and its implementer are likely to experience public pushback or outright rejection, which may obstruct other processes of AI legitimacy and adoption (Whittaker et al., 2018).

As many fields continue to migrate from traditional forms of linear programming and further embrace autonomous learning algorithms – behavioral control is gradually transferred from the programmer to the algorithm and its operating environment (Matthias, 2004). During this process, "the modular design of systems can mean that no single person or group can fully grasp the manner in which the system will interact or respond to a complex flow of new inputs" (Allen, Wallach, & Smit, 2006: 14). In order to cope with AI-induced complexities, new governance structures have to be co-invented through greater stakeholder engagement among companies, civil society organizations, and policymakers in order to secure the inclusion of affected communities in the development of just algorithmic systems and processes going forward (Lee et al., 2019).

The tradeoffs between algorithmic accuracy, transparency, and use of data and the rights to privacy, explanation, and redress remain subject to ongoing forms of mediation concerning the concomitant organizational practices that emerge at the intersection of human-machine-based interactions. While these tradeoffs have wide-ranging implications for the kind of institutions that are likely to emerge, the devising of inclusive yet reflexive institutional infrastructures that can encompass a wide variety of AI-associated risks remains a crucial area to be further studied and understood.

7. Conclusion

The increased presence of AI agents embedded in varying forms of organization entails that a whole range of AI-induced institutions is currently emerging. This paper makes three contributions that help elicit how AI-induced fields are subject to varying degrees of legitimacy as well as processes of institutionalization. First, the paper proposes a novel conceptual framework for analyzing AI-induced field change. Second, it illustrates the utility of the framework and finds a set of common grounds for contestation associated with AI-induced field change and legitimization. Third, the paper points to the need for more adaptive organizations to emerge in response to the rapidly evolving digital infrastructures of AI systems.

The notion of pathways of change helps elicit the varying ways in which novel AI solutions are resisted, rejected, or accepted as legitimate practices over time. Assessing where a field is currently positioned, what its potential trajectories are or could be, and what needs to be done for a field to grow established and become legitimatized over time are essential considerations for stakeholders to consider. Such deliberations contribute to securing greater alignment between digital and institutional infrastructures, which is essential in mitigating negative externalities going forward.

The logics of any algorithmic interaction and transparency with the information that guides the interaction need to be broadly examined to better understand how AI agents alter existing organizational dependencies. Only by understanding where certain negative externalities could potentially arise can organizations responsible for algorithmic development or implementation work on establishing the necessary institutional infrastructure (i.e., standards, rules, and processes) to keep such externalities in check. Transparent and reliable AI systems and enhanced human–AI interactions are crucial elements for the trajectory of most AI fields on their road to securing a broad sense of social legitimacy and growing established over time. As novel digital infrastructures continue to emerge, their road to becoming institutionalized structures of society must be thoroughly vetted and mitigated to secure fair, equitable, and trustworthy socio-technical interactions in the years to come.

References

Allen, C., Wallach, W., & Smit, I. (2006). Why machine ethics? *Machine Ethics*, 51–61. https://doi.org/10.1017/CBO9780511978036.005

Amis, J., Slack, T., & Hinings, C. R. (2004). The Pace, Sequence, and Linearity of Radical Change Author(s): *The Academy of Management Journal*, *47*(1), 15–39.

Amodei, D., Olah, C., Steinhardt, J., Christiano, P., Schulman, J., & Mané, D. (2016). Concrete Problems in AI Safety. *ArXiv*, 1–29. http://arxiv.org/abs/1606.06565

Arnold, M., Piorkowski, D., Reimer, D., Richards, J., Tsay, J., Varshney, K. R., Bellamy, R. K. E., Hind, M., Houde, S., Mehta, S., Mojsilovic, A., Nair, R., Ramamurthy, K. N., & Olteanu, A. (2019). FactSheets: Increasing trust in AI services through supplier's declarations of conformity. *IBM Journal of Research and Development*, *63*(4–5), 1–13. https://doi.org/10.1147/JRD.2019.2942288

Barocas, S., & Selbst, A. D. (2014). Big Data's Disparate Impact. *California Law Review*, *104*(671), 671–732.

Baskerville, R. L., Myers, M. D., & Yoo, Y. (2019). Digital First: The Ontological Reversal and New Challenges for IS Research. *MIS Quarterly*.

Beer, D. (2017). The social power of algorithms. *Information Communication and Society*, *20*(1), 1–13. https://doi.org/10.1080/1369118X.2016.1216147

Bender, E. M., & Friedman, B. (2018). Data Statements for Natural Language Processing: Toward Mitigating System Bias and Enabling Better Science. *Transactions of the Association for Computational Linguistics*, *6*, 587–604. https://doi.org/10.1162/tacl_a_00041

Botzem, S., & Dobusch, L. (2012). Standardization Cycles : A Process Perspective on the Formation and Diffusion of Transnational Standards. *Organization Studies*, *5–6*(33), 737–762. https://doi.org/10.1177/0170840612443626

Buolamwini, J., & Gebru, T. (2018). Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classificatio. *Proceedings of Machine Learning Research*, *81*, 1–15. https://doi.org/10.2147/OTT.S126905

Castel, P., & Friedberg, E. (2010). Institutional change as an interactive process: The case of the modernization of the French cancer centers. *Organization Science*, *21*(2), 311–330. https://doi.org/10.1287/orsc.1090.0442

Clark, J., & Hadfield, G. K. (2019). Regulatory Markets for AI Safety. *Conference Paper at ICLR 2019*.

Constantinides, P., Henfridsson, O., & Parker, G. G. (2018). Platforms and infrastructures in the digital age. *Information Systems Research*, *29*(2), 381–400. https://doi.org/10.1287/isre.2018.0794

Coyle, D., Diepeveen, S., Wdowin, J., Kay, L., & Tennison, J. (2020). The Value of Data: Policy Implications. In *Bennett Institute for Public Policy, Cambridge in partnership with the Open Data Institute.*

Curchod, C., Patriotta, G., Cohen, L., & Neysen, N. (2020). Working for an Algorithm: Power Asymmetries and Agency in Online Work Settings. *Administrative Science Quarterly*, *65*(3), 644–676. https://doi.org/10.1177/0001839219867024

Dacin, M. T., Ventresca, M. J., & Beal, B. D. (1999). The embeddedness of organizations: Dialogue & directions. *Journal of Management*, *25*(3), 317–356. https://doi.org/10.1177/014920639902500304

Davenport, T., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. *Future Healthcare Journal*, *6*(2), 94–98.
DiMaggio, P. J., & Powell, W. W. (1983). The Iron Cage Revisited : Institutional Isomorphism and Collective Rationality in Organizational Fields. *American Sociological Review*, *48*(2), 147–160.
Djelic, M., & Sahlin-Andersson, K. (2006). *Transnational governance: Institutional dynamics of regulation*. Cambridge University Press.
Fligstein, N. (2001). Social skill and the theory of fields. *Sociological Theory*, *19*(2), 105–125. https://doi.org/10.1111/0735-2751.00132
Fligstein, N., & McAdam, D. (2012). *A theory of fields*. Oxford University Press.
Floridi, L. (2014). *The Fourth Revolution: How the infosphere is reshaping human reality*. Oxford University Press.
Floridi, L., & Sanders, J. W. (2004). On the morality of artificial agents Luciano. *Minds and Machines*. https://doi.org/10.1023/B
Friedman, B., & Nissenbaum, H. (1996). Bias in computer systems. *ACM Transactions on Information Systems*, 330–347. https://doi.org/10.4324/9781315259697-23
Furnari, S. (2016). Institutional fields as linked arenas: Inter-field resource dependence, institutional work and institutional change. *Human Relations*, *69*(3), 551–580. https://doi.org/10.1177/0018726715605555
Garud, R. (2008). Conferences as venues for the configuration of emerging organizational fields: The case of cochlear implants. *Journal of Management Studies*, *45*(6), 1061–1088. https://doi.org/10.1111/j.1467-6486.2008.00783.x
Garud, R., Jain, S., & Kumaraswamy, A. (2002). Institutional entrepreneurship in the sponsorship of common technological standards: The case of Sun Microsystems and Java. *Academy of Management Journal*, *45*(1), 196–214. https://doi.org/10.2307/3069292
Garud, R., & Karnøe, P. (2003). Bricolage versus breakthrough: distributed and embedded agency in technology entrepreneurship. *Research Policy*, *32*, 277–300.
Gawer, A., & Phillips, N. (2013). Institutional Work as Logics Shift : The Case of Intel ' s Transformation to Platform Leader. *Organization Science*, *34*(8), 1035 –1071. https://doi.org/10.1177/0170840613492071
Gebru, T., Morgenstern, J., Vecchione, B., Vaughan, J. W., Wallanch, H., Daume, H., & Crawford, K. (2020). Datasheets for Datasets. *Arxiv*.
Ghaffary, S., & Molla, R. (2019, December 10). Here's where the US government is using facial recognition technology to surveil Americans. *Vox*. https://www.vox.com/recode/2019/7/18/20698307/facial-recognition-technology-us-government-fight-for- the-future
Greenwood, R., Raynard, M., Kodeih, F., Micelotta, E. R., & Lounsbury, M. (2011). Institutional complexity and organizational responses. *Academy of Management Annals*, *5*(1), 317–371. https://doi.org/10.1080/19416520.2011.590299
Greenwood, R., Suddaby, R., & Hinings, C. R. (2002). Theorizing change: The role of professional associations in the transformation of institutionalized fields. *Academy of Management Journal*, *45*(1), 58–80. https://doi.org/10.2307/3069285
Grigorescu, S., Trasnea, B., Cocias, T., & Macesanu, G. (2020). A survey of deep learning techniques for autonomous driving. *Journal of Field Robotics*, *37*(3), 362–386. https://doi.org/10.1002/rob.21918
Hagemann, R., Huddleston, J., & Thierer, A. D. (2018). Soft Law for Hard Problems: The

Governance of Emerging Technologies in an Uncertain Future. In *Colorado Technology Law Journal* (Vol. 17, Issue 1). https://heinonline.org/HOL/Page?handle=hein.journals/jtelhtel17&id=52&div=8&collection=journals%0Ahttps://ssrn.com/abstract=3118539

Hanseth, O., & Lyytinen, K. (2010). Design theory for dynamic complexity in information infrastructures: The case of building internet. *Journal of Information Technology*, *25*(1), 1–19. https://doi.org/10.1057/jit.2009.19

Hao, K. (2020a). IBM's photo-scraping scandal shows what a weird bubble AI researchers live in. *MIT Technology Review*. https://www.technologyreview.com/2019/03/15/136593/ibms-photo-scraping-scandal-shows-what-a-weird-bubble-ai-researchers-live-in/

Hao, K. (2020b). The two-year fight to stop Amazon from selling face recognition to the police. *MIT Technology Review*.

Henfridsson, O., & Bygstad, B. (2013). The generative mechanisms of digital infrastructure evolution. *MIS Quarterly: Management Information Systems*, *37*(3), 907–931. https://doi.org/10.25300/MISQ/2013/37.3.11

Henfridsson, O., Nandhakumar, J., Scarbrough, H., & Panourgias, N. (2018). Recombination in the open-ended value landscape of digital innovation. *Information and Organization*, *28*(2), 89–100. https://doi.org/10.1016/j.infoandorg.2018.03.001

Hengstler, M., Enkel, E., & Duelli, S. (2016). Applied artificial intelligence and trust-The case of autonomous vehicles and medical assistance devices. *Technological Forecasting and Social Change*, *105*, 105–120. https://doi.org/10.1016/j.techfore.2015.12.014

Hensmans, M. (2003). Social movement organizations: A metaphor for strategic actors in institutional fields. *Organization Studies*, *24*(3), 355–381. https://doi.org/10.1177/0170840603024003908

Hill, K. (2020a). The Secretive Company That Might End Privacy as We Know It. *New York Times*. https://www.nytimes.com/2020/01/18/technology/clearview-privacy-facial-recognition.html

Hill, K. (2020b). Wrongfully Accused by an Algorithm. *New York Times*. https://www.nytimes.com/2020/06/24/technology/facial-recognition-arrest.html

Hinings, B., Gegenhuber, T., & Greenwood, R. (2018). Digital innovation and transformation: An institutional perspective. *Information and Organization*, *28*(1), 52–61. https://doi.org/10.1016/j.infoandorg.2018.02.004

Hinings, B., Logue, D., & Zietsma, C. (2017). Fields, Institutional Infrastructure and Governance. In *The SAGE Handbook of Organizational Institutionalism* (pp. 163–189).

Holm, P. (1995). The Dynamics of Institutionalization: Transformation Processes in Norwegian Fisheries. *Administrative Science Quarterly*, *40*(3), 398–422.

Hosanagar, K., Fleder, D., Lee, D., & Buja, A. (2014). Will the global village fracture into tribes recommender systems and their effects on consumer fragmentation. *Management Science*, *60*(4), 805–823. https://doi.org/10.1287/mnsc.2013.1808

Isaak, J., & Hanna, M. J. (2018). User Data Privacy: Facebook, Cambridge Analytica, and Privacy Protection. *Computer*, *51*(8), 56–59. https://doi.org/10.1109/MC.2018.3191268

Kallinikos, J. (2011). *Governing through Technology: Information Artefacts and Social Practices. New York: Palgrave Macmillan.* Palgrave Macmillan.

Krishna, A. (2020). *IBM CEO's Letter to Congress on Racial Justice Reform*. https://www.ibm.com/blogs/policy/facial-recognition-sunset-racial-justice-reforms/

Lash, S. (2007). Power after Hegemony: Cultural Studies in Mutation? *Theory, Culture & Society*, *24*(3), 55–78. https://doi.org/10.1177/0263276407075956

Lawrence, T. B., & Suddaby, R. (2006). Institutions and institutional work. In *The SAGE Handbook of Organization Studies* (Issue March, pp. 215–254). https://doi.org/10.4135/9781848608030.n7
Lee, M. K., Kusbit, D., Kahng, A., Kim, J. T., Yuan, X., Chan, A., See, D., Noothigattu, R., Lee, S., Psomas, A., & Procaccia, A. D. (2019). Webuildai: Participatory framework for algorithmic governance. *Proceedings of the ACM on Human-Computer Interaction*, *3*(CSCW). https://doi.org/10.1145/3359283
Mackenzie, A. (2006). *Cutting Code: Software and Sociality*. Peter Lang Publishing.
Macnish, K. (2012). Unblinking eyes: The ethics of automating surveillance. *Ethics and Information Technology*, *14*(2), 151–167. https://doi.org/10.1007/s10676-012-9291-0
Maguire, S., & Hardy, C. (2009). Discourse and Deinstitutionalization: The Decline of DDT. *The Academy of Management Journal*, *52*(1), 148–178. https://doi.org/10.5465/amj.2009.36461993
Marchant, G. E., & Lindor, R. A. (2012). The Coming Collision Between Autonomous Vehicles and the Liability System THE COMING COLLISION BETWEEN AUTONOMOUS VEHICLES AND THE LIABILITY SYSTEM. *Santa Clara Law Review Article*, *52*(4).
Markus, M. L. (2017). Datification, Organizational Strategy, and IS Research: What's the Score? *Journal of Strategic Information Systems*, *26*(3), 233–241. https://doi.org/10.1016/j.jsis.2017.08.003
Matthias, A. (2004). The responsibility gap: Ascribing responsibility for the actions of learning automata. *Ethics and Information Technology*, *6*(3), 175–183. https://doi.org/10.1007/s10676-004-3422-1
Mckay, C. (2020). Predicting risk in criminal procedure: actuarial tools, algorithms, AI and judicial decision-making. *Current Issues in Criminal Justice*, *32*(1), 22–39. https://doi.org/10.1080/10345329.2019.1658694
Meyer, J. W., & Rowan, B. (1977). Institutionalized Organizations : Formal Structure as Myth and Ceremony. *American Journal of Sociology*, *83*(2), 340–363.
Michael, S. (2008). Interlopers and Field Change: The Entry of US News into The Field of Legal Education. *Administrative Science Quarterly*, *53*, 209.
Mitchell, M., Wu, S., Zaldivar, A., Barnes, P., Vasserman, L., Hutchinson, B., Spitzer, E., Raji, I. D., & Gebru, T. (2019). Model cards for model reporting. *FAT* 2019 - Proceedings of the 2019 Conference on Fairness, Accountability, and Transparency*, *Figure 2*, 220–229. https://doi.org/10.1145/3287560.3287596
Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. *Big Data and Society*, *December*, 1–21. https://doi.org/10.1177/2053951716679679
Möller, J., Trilling, D., Helberger, N., & van Es, B. (2018). Do not blame it on the algorithm: an empirical assessment of multiple recommender systems and their impact on content diversity. *Information Communication and Society*, *21*(7), 959–977. https://doi.org/10.1080/1369118X.2018.1444076
Monteiro, E. (1998). Scaling information infrastructure: The case of next-generation IP in the internet. *Information Society*, *14*(3), 229–245. https://doi.org/10.1080/019722498128845
Munir, K. A., & Phillips, N. (2005). The birth of the "Kodak moment": Institutional entrepreneurship and the adoption of new technologies. *Organization Studies*, *26*(11), 1665–1687. https://doi.org/10.1177/0170840605056395
Newell, S., & Marabelli, M. (2015). Strategic opportunities (and challenges) of algorithmic decision-making: A call for action on the long-term societal effects of "datification." *Journal of Strategic*

Information Systems, *24*(1), 3–14. https://doi.org/10.1016/j.jsis.2015.02.001

NIST. (2020). *FRVT 1:1 Verification*. https://pages.nist.gov/frvt/html/frvt11.html#overviewhttps://www.technologyreview.com/2019/03/15/13 6593/ibms-photo-scraping-scandal-shows-what-a-weird-bubble-ai-researchers-live-in/

North, D. C. (1990). Institutions, Institutional Change and Economic Performance. In *Institutions, Institutional Change and Economic Performance. North, Douglass C.* https://doi.org/10.1017/CBO9780511606892.012

Nuno, N., Gomes, A. de, & Kontschieder, V. (2021). *AI Impact Assessment: A Policy Prototyping Experiment*. *January*.

Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science*, *366*(6464), 447–453. https://doi.org/10.1126/science.aax2342

Orlikowski, W. J. (2007). Sociomaterial practices: Exploring technology at work. *Organization Studies*, *28*(9), 1435–1448. https://doi.org/10.1177/0170840607081138

Orlikowski, W. J., & Scott, S. V. (2008). 10 Sociomateriality: Challenging the Separation of Technology, Work and Organization. *The Academy of Management Annals*, *2*(1), 433–474. https://doi.org/10.1080/19416520802211644

Parasuraman, R., & Manzey, D. H. (2010). Complacency and bias in human use of automation: An attentional integration. *Human Factors*, *52*(3), 381–410. https://doi.org/10.1177/0018720810376055

Patvardhan, S. D., Gioia, D. A., & Hamilton, A. L. (2015). Weathering a meta-level identity crisis: Forging a coherent collective identity for an emerging field. *Academy of Management Journal*, *58*(2), 405–435. https://doi.org/10.5465/amj.2012.1049

Personal Data Protection Commission. (2020). *Model Artificial Intelligence Governance Framework Second Edition*.

Pisano, G. P., & Teece, D. J. (2007). How to Capture Value from Innovation: Shaping Intellectual Property and Industry Architecture. *California Management Review*.

Powell, W. W., Oberg, A., Korff, V., Oelberger, C., & Kloos, K. (2017). Institutional analysis in a digital era: Mechanisms and methods to understand emerging fields. In *New Themes in Institutional Analysis: Topics and Issues from European Research* (pp. 305–344). https://doi.org/10.4337/9781784716875.00016

Powell, W. W., & Sandholtz, K. W. (2012). Amphibious entrepreneurs and the emergence of organizational forms. *Strategic Entrepreneurship Journal*, *6*(2), 94–115. https://doi.org/10.1002/sej.1129

Rai, A., Constantinides, P., & Sarker, S. (2019). Editor’s comments: Next-Generation Digital Platforms: Toward Human–AI Hybrids. *MIS Quarterly*, *43*(1).

Rao, H., Morrill, C., & Zald, M. N. (2000). Power plays: How social movements and collective action create new organizational forms. *Research in Organizational Behavior*, *22*(June), 237–281. https://doi.org/10.1016/s0191-3085(00)22007-8

Raynard, M. (2016). Deconstructing complexity: Configurations of institutional complexity and structural hybridity. *Strategic Organization*, *14*(4), 310–335. https://doi.org/10.1177/1476127016634639

Reay, T., & Hinings, C. R. (2005). The recomposition of an organizational field: Health care in Alberta. *Organization Studies*, *26*(3), 351–384. https://doi.org/10.1177/0170840605050872

Reay, T., & Hinings, C. R. (2009). Managing the rivalry of competing institutional logics. *Organization Studies*, *30*(6), 629–652. https://doi.org/10.1177/0170840609104803
Reisman, D., Schultz, J., Crawford, K., & Whittaker, M. (2018). Algorithmic impact assessments: A practical framework for public agency accountability. *AI Now Institute*, *April*, 22. https://ainowinstitute.org/aiareport2018.pdf
Russell, S. J., & Norvig, P. (2010). Artificial Intelligence: A Modern Approach. In *Artificial Intelligence*. Prentice-Hall. https://doi.org/10.1017/S0269888900007724
Schlesinger, A., O'Hara, K. P., & Taylor, A. S. (2018). Let's talk about race: Identity, chatbots, and AI. *Conference on Human Factors in Computing Systems - Proceedings*, *2018-April*, 1–14. https://doi.org/10.1145/3173574.3173889
Scott, R. W. (2014). *Institutions and Organizations, 4th ed*.
Star, S. L. (2002). Infrastructure and ethnographic practice: Working on the fringes. *Scandinavian Journal of Information Systems*, *14*(2), 107–122.
Stoyanovich, J., & Howe, B. (2019). Nutritional Labels for Data and Models. *Data Engineering*, *1926250*, 13.
Sunstein, C. R. (2007). *Republic.com 2.0*. Princeton University Press.
Taeihagh, A., Tan, S. Y., & Taiehagh, A. (2021). Adaptive governance of autonomous vehicles: accelerating the adoption of disruptive technologies in Singapore. *Government Information Quarterly*, *November 2019*, 101546. https://doi.org/10.1016/j.giq.2020.101546
Tene, O., & Polonetsky, J. (2013). Big Data for All : Privacy and User Control in the Age of Analytics Big Data for All : Privacy and User Control in the. *Northwestern Journal of Technology and Intellectual Property*, *11*(5).
Thornton, P. H., & Ocasio, W. (1999). Institutional logics and the historical contingency of power in organizations: Executive succession in the higher education publishing industry, 1958-1990. *American Journal of Sociology*, *105*(3), 801–843. https://doi.org/10.1086/210361
Thornton, P. H., Ocasio, W., & Lounsbury, M. (2012). Introduction to the Institutional Logics Perspective. In *The Institutional Logics Perspective: A New Approach to Culture, Structure and Process*. https://doi.org/10.1093/acprof
Tilson, D., Lyytinen, K., & Sørensen, C. (2010). Digital infrastructures: The missing IS research agenda. *Information Systems Research*, *21*(4), 748–759. https://doi.org/10.1287/isre.1100.0318
Tutt, A. (2016). AN FDA FOR ALGORITHMS. *Administrative Law Review*, *69*(1).
Van Alstyne, M., & Brynjolfsson, E. (2005). Global village or cyber-balkans? Modeling and measuring the integration of electronic communities. *Management Science*, *51*(6), 851–868. https://doi.org/10.1287/mnsc.1050.0363
Waddock, S. (2008). Building a new institutional infrastructure for corporate responsibility. *Academy of Management Perspectives*, *22*(3), 87–108. https://doi.org/10.5465/AMP.2008.34587997
Wang, C., Medaglia, R., & Zheng, L. (2018). Towards a typology of adaptive governance in the digital government context: The role of decision-making and accountability. *Government Information Quarterly*, *35*(2), 306–322. https://doi.org/10.1016/j.giq.2017.08.003
Whittaker, M., Crawford, K., Dobbe, R., Fried, G., Kaziunas, E., Mathur, V., Myers West, S., Richardson, R., Schultz, J., & Schwartz, O. (2018). AI Now 2018 Report. *AI Now*, *December*, 1–62. https://ainowinstitute.org/AI_Now_2018_Report.pdf
Yang, K., Stoyanovich, J., Asudeh, A., Howe, B., Jagadish, H. V., & Miklau, G. (2018). A nutritional label for rankings. *Proceedings of the ACM SIGMOD International Conference on Management of Data*, *Section 2*, 1773–1776. https://doi.org/10.1145/3183713.3193568

Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). The new organizing logic of digital innovation: An agenda for information systems research. *Information Systems Research*, *21*(4), 724–735. https://doi.org/10.1287/isre.1100.0322

Zarsky, T. (2016). The Trouble with Algorithmic Decisions: An Analytic Road Map to Examine Efficiency and Fairness in Automated and Opaque Decision Making. *Science, Technology, & Human Values*, *41*(1), 118–132. https://doi.org/10.1177/0162243915605575

Zhu, H., Yu, B., Halfaker, A., & Terveen, L. (2018). Value-Sensitive Algorithm Design. *Proceedings of the ACM on Human-Computer Interaction*, *2*(CSCW), 1–23. https://doi.org/10.1145/3274463

Zietsma, C., Groenewegen, P., Logue, D., & Hinings, C. R. (Bob). (2017). FIELD OR FIELDS? BUILDING THE SCAFFOLDING FOR CUMULATION OF RESEARCH ON INSTITUTIONAL FIELDS. *Academy of Management Annals*, *11*(1). https://doi.org/10.1017/CBO9781107415324.004

Zietsma, C., & Lawrence, T. B. (2010). Institutional work in the transformation of an organizational field: The interplay of boundary work and practice work. *Administrative Science Quarterly*, *55*(2), 189–221. https://doi.org/10.2189/asqu.2010.55.2.189

Zilber, T. B. (2007). Stories and the discursive dynamics of institutional entrepreneurship: The case of Israeli high-tech after the bubble. *Organization Studies*, *28*(7), 1035–1054. https://doi.org/10.1177/0170840607078113

Zuboff, S. (1988). *In the age of the smart machine: the future of work and power*. Basic Books.

Zuboff, S. (2019). *The Age of Surveillance Capitalism*. PublicAffairs.

Article III

Article III

Government Mechanisms for Platform Boundary Resource Tuning: The Case of China’s National Open Innovation Platforms for AI

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Abstract

The role of digital platforms in the economy has grown substantially over the last decade. Few studies, however, have engaged with the wider platform literature to understand the mechanisms that governments have at their disposal to enable or constrain platform governance and associated forms of digital innovation. This paper's case study of China’s National Open Innovation Platforms for Artificial Intelligence illustrates how actors from the public sector engage in boundary resource tuning associated with leading AI open innovation platforms in China. The paper offers two key contributions. First, it extends existing theory on boundary resources by elaborating on a range of mechanisms that can be used to affect the generativity of platforms in areas such as data, software, and interoperability. Second, conceptual clarity is added to how governments can use such mechanisms to orchestrate the platform economy, which has implications for policymakers and managers.

Keywords: Artificial Intelligence; Platform Innovation; Governance; Boundary Resources; Government Mechanisms; Hybrid Platforms; China

JEL codes: L22 (Firm Organization and Market Structure), L52 (Industrial Policy • Sectoral Planning Methods), O36 (Open Innovation), P30 (Socialist Institutions and Their Transitions)

1. Introduction

Innovation platforms have long been an area of research due to their transformative organizational and technological capabilities, as well as how these serve as conduits for digital innovation (Constantinides et al., 2018; De Reuver, Sørensen and Basole, 2018; Gawer and Cusumano, 2013;

Jacobides et al., 2018; Yoo et al., 2012). In recent years, governments have also started to engage in a platform-induced way of thinking and organization, which has been summarized in literatures surrounding E-government (Janssen et al., 2009; Ju et al., 2019), Government as a Platform (Brown et al., 2017; Cordella & Paletti, 2019) as well as Big Data and Open Government Data initiatives (Klievink et al., 2017; Zhao & Fan, 2018), among others. While most of these studies concentrate on platform-induced ways of public value creation or optimization, few studies engage with the wider platform literature to understand how governments enable or constrain platform governance and associated forms of digital innovation.

This paper draws on existing management and information systems literature concerning digital platforms (Baldwin & Woodard, 2009; Cusumano, Gawer, & Yoffie, 2019; Ghazawneh & Henfridsson, 2013) to understand how governments affect platform governance and generativity. Generativity is defined as the 'capacity to produce unprompted change driven by large, varied and uncoordinated audiences' (Zittrain, 2006, p. 1980).

While studies have tried to bridge platform governance approaches from both public and private sector perspectives (see, e.g., Bonina & Eaton, 2020; Klievink et al., 2016), most studies treat platform governance as separate from policies and regulations.

Platform governance is most often associated with the dynamics that are present when private sector firms seek to orchestrate their boundary resources, which explains how a platform governs the generative relationship between its core and ecosystem members at the periphery (Ghazawneh & Henfridsson, 2013).

The role of digital platforms in the economy has grown substantially over the last decade, while governments have been struggling to devise new ways of addressing the growing power and reach of platforms. This is seen, for example, in terms of social media platforms' governance of information, or in the growing number of antitrust cases associated with digital and platform-based competition and market concentration (Nooren et al., 2018). National control over digital information infrastructure and underlying hardware and software components also have received increasing attention from governments around the world. These areas are often linked to the notion of digital sovereignty, which refers to "the control of data, software (e.g., AI), standards and protocols (e.g., 5G, domain names), processes (e.g., cloud computing), hardware (e.g., mobile phones), services (e.g., social media, e-commerce), and infrastructures (e.g., cables, satellites, smart cities)" (Floridi, 2020,

p. 370). By extension, digital sovereignty translates into a desire to retain national control over digital forms of innovation and infrastructure, including their generativity.

The United States, Europe, and China have all stressed the importance of digital sovereignty and retaining domestic control over data and AI innovation. These events have spurred new debate over the role of the government in affecting strategic digital resources such as data and software, which has important implications for the governance of innovation platforms. Contextual issues relate to how a government supports digital innovation in strategic domains (e.g., AI, Cloud Computing, 5G) or how, in pursuit of key national objections, a government enables or constrains digital markets (e.g., for software and hardware). In terms of AI innovation, growing disparities between large platforms and smaller SMEs regarding access to crucial inputs such as data and compute are also on the agenda of governments. The mechanisms at the government's disposal to affect digital innovation, competition, and sovereignty are often separated from the way platforms govern their boundary resources, i.e., the generative relationship between core and periphery (Ghazawneh & Henfridsson, 2013). Existing literature has been slow to deal with the growing interactions among governments and platforms, and how policies and regulations affect platform organization, including the orchestration of digital innovation. To address these concerns while highlighting the importance of aspects related to domestic governance of data, software and interoperability, the research questions of this paper ask: *what mechanisms can governments use to affect the boundary resources of innovation platforms, and how do these influence platform governance??*

Platform theory from strategic management and information systems concerning platform architecture, ecosystem, and governance is applied to address the research question. Adopting this theoretical perspective has three strengths. First, it sheds new light on the role of varying actors across public and private settings and how they jointly impact platform innovation and governance. Second, it explains the distinct mechanisms and rules, and tools used by public and private actors, respectively, and how these enable or constrain platform generativity. Finally, it enables a more granular assessment of differing national and strategic approaches to platform innovation and governance.

The case of China's National Open Innovation Platforms for AI has been chosen to illustrate how a government can affect the boundary resources of innovation platforms. The policy was implemented in 2017 to strengthen China's indigenous AI open-source and open data ecosystem. The case is supported by interview-based data and secondary sources that describe the changing relationship between a platform's private boundary resources and how China's central government can affect the process of boundary resource tuning, both directly and indirectly. The analysis is centered on how China's central government seeks to change the relationship between private platform governance and public sector orchestration and value creation.

Two key contributions are provided. First, the theory on boundary resources is extended, emphasizing the role of the government in affecting the process of platform generativity. In doing so, a new framework for understanding the mechanisms associated with government-induced boundary resource tuning is offered. This results in theory building that reorients the concept of boundary resource tuning from the role of private platforms and governance processes towards the interacting mechanisms that governments use to orchestrate digital aspects of innovation and rule-setting in the platform economy. The second set of contributions is related to practice, with several implications for policymakers and managers.

The following section introduces background on platforms and ecosystems and previous research on boundary resources (Ghazawneh & Henfridsson, 2013). Next, the case study is introduced, followed by an outline of the methodological approach of the research. This is followed by an analysis of government-induced boundary resource tuning in the presented case. A discussion breaks down a set of concrete government mechanisms for boundary resource tuning, which marks the theoretical contribution. Next, a set of practical implications for scholars, policymakers, and managers are offered. Finally, limitations and directions for future research are presented.

2. Background and Previous Research

Research on platforms tends to divide these into 1) transaction platforms, e.g., e-commerce, and 2) innovation platforms, e.g., apps and services (Bonina, Koskinen, Eaton, & Gawer, 2021; Cusumano, Gawer, & Yoffie, 2019). Transaction platforms act as intermediaries between two or more groups of agents, for example, as multi-sided platforms (MSP) that organize economic transactions (Hagiu & Wright, 2015). Examples include app stores, e-commerce platforms, dating platforms, and social media platforms. Innovation platforms emphasize the "foundations upon which other firms can build complementary products, services or technologies" (Gawer, 2009, p. 54). The technical architecture of an innovation platform contains modules, or building blocks, that represent 'accessible innovative capabilities' (Gawer, 2014). These modules can be accessed and combined by app developers (complementors) to build apps and services (known as platform complements) (Bonina et al., 2021). Innovation platforms are usually characterized by having platform owners (Boudreau & Hagiu, 2009) responsible for governing the innovation of modules in the core architecture and the innovation activities of third-party developers at the periphery (Bonina & Eaton, 2020).

The relationship between core and periphery is often contextualized through the notion of ecosystems. Ecosystems comprise the platform's sponsor and complement providers that make the platform more valuable to consumers (Ceccagnoli, Forman, Huang, & Wu, 2012; Gawer & Cusumano, 2013). Platform ecosystems take a "hub and spoke" form, with an array of peripheral firms connected to the central platform via shared or open-source technologies and technical standards, e.g., application programming interfaces (API) and software development kits (SDK). By connecting to the platform, complementors can generate complementary innovation and gain access to other members or custumers of the platform's broader ecosystem (Ceccagnoli et al., 2012; Cennamo & Santalo, 2013). Accordingly, platform ecosystems can be seen as "semi-regulated marketplaces" that foster entrepreneurial action under the coordination and direction of the platform sponsor (Wareham, Fox, & Giner, 2014, p. 1211).

Since platform creation draws on collaborative value creation rather than competition (Osterwalder & Pigneur, 2010), innovation platforms are often associated with open innovation. Open innovation is defined as "the use of purposive inflows and outflows of knowledge to accelerate internal innovation and expand the markets for external use of innovation" (Chesbrough, 2006, p. 1). Similarly, open data and open-source software (OSS) are often associated with open innovation platforms since their "free" redistribution of public goods attracts complementors from the ecosystem to the platform. Private companies may choose to adopt open source software for reasons such as reduced costs of adoption (Marsan et al., 2012), strategic considerations (Ceccagnoli et al., 2012), or a general desire to innovate (Bouras et al., 2014). Research on organizing open-source software development for generating external software contributions (Von Hippel & Von Krogh, 2003) has been tightly knit with platform ownership and governance.

2.1 *Platform governance through boundary resources*

In relation to platform governance, Ghazawneh and Henfridsson (2010) developed the theory of boundary resources to explain how platforms govern the inherent tension between openness and control. Boundary resources evolve through the governance of the production function, and are defined by the rules and tools that are used to address and constrain or enable the generativity of ecosystems (Eaton et al., 2015; Ghazawneh & Henfridsson, 2010; Henfridsson & Bygstad, 2013; Yoo, Henfridsson, & Lyytinen, 2010).

Ghazawneh and Henfridsson (2013) further develop the concepts of resourcing and securing, referring to the "software tools and regulations that serve as the interface for the arms-length relationship between the platform owner and the application developer" (Ghazawneh & Henfridsson, 2013, p. 174). Resourcing, the process by which the scope and diversity of a platform are enhanced, contributes to the expansion of the ecosystem of actors around the platform by securing the supply of new resources, knowledge, and capabilities (Iansiti & Levien, 2004). Examples of tools are APIs and SDKs that give developers access to the modular core of the platform and enable them to build software services. Securing is the process by which the platform's control is increased and contributes to governing a community of third-party developers. Platform integrity is maintained by providing rules for controlling the quality of third-party apps and services developed for the platform. One example of rules is those established by software and data licensing agreements (Boudreau & Hagiu, 2009). If rules are broken, the platform owner can take a range of actions, such as suspending a developer from using or accessing the platform (Bonina & Eaton, 2020). In combination, resourcing tools and securing rules are the key components of platform's in governing their boundary resources (Ghazawneh & Henfridsson, 2013).

Since Ghazawneh and Henfridsson (2010) proposed their theory on boundary resources, several studies have expanded on their research. Most of these are found in the information systems and management literatures and tend to be case studies that analyze how a specific platform governs its boundary resources, i.e., relationship to third parties at the periphery.

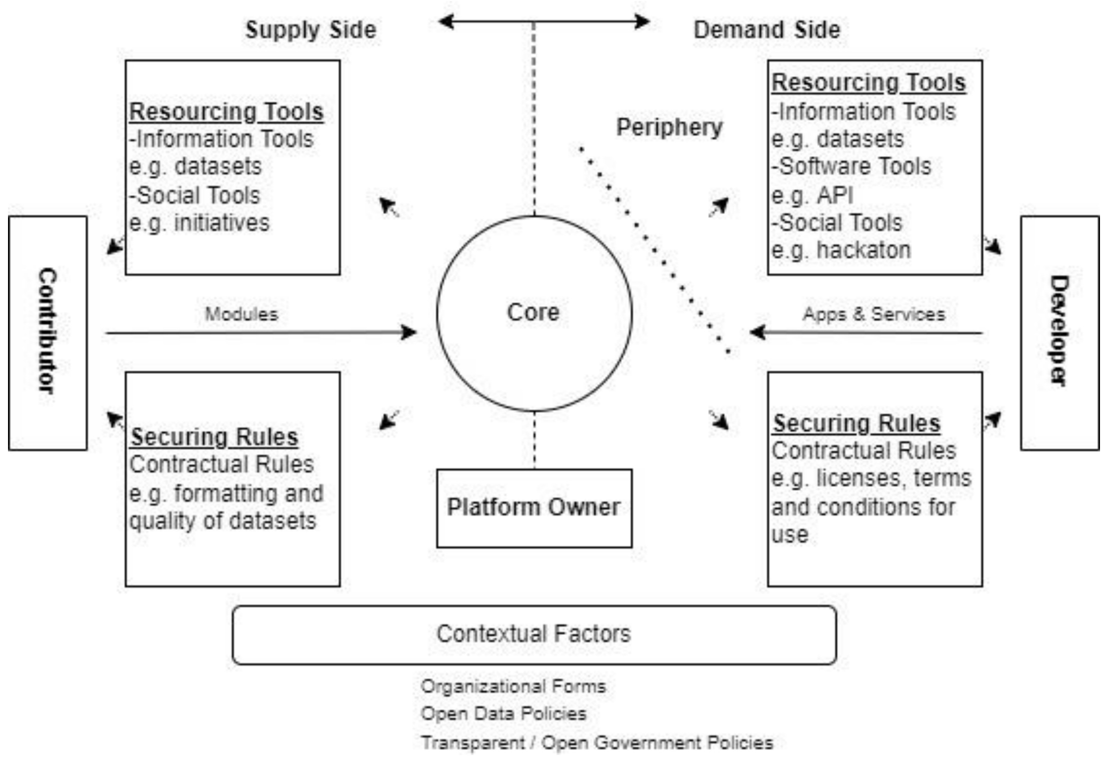
For instance, Bianco et al. (2014) add the notion of social boundary resources that transfer knowledge between the platform and developers through processes such as registering and coordination. Myllärniemi et al. (2018) find that boundary resources may influence developers' choices of software frameworks, meaning that the design of a platform's boundary resources (e.g., degree of openness) has an impact on the developer's ability to support or hinder the adaption of a particular software framework. Karhu et al. (2018) studied Google's Android platform to understand the concept of platform forking, which describes how a hostile firm bypasses a host's controlling boundary resources to exploit a platform's shared resources and create a competing competition platform business.

In studying Apple's iOS service system, Eaton et al. (2015) argues that Ghazawneh and Henfridsson's (2013) model is based on a simplistic dialectic relationship between an infrastructure owner and third-party developers at the periphery. However, this model neglects the reality that other actors also hold varying forms of power over a platform's boundary resources. By drawing on the theoretical framework of tuning (Pickering, 1993; Barrett et al., 2012), Eaton et al. (2015) describe how the co-creative and distributed dynamics of boundary resources evolve in a network of heterogeneous actors that are dealing with multiple interdependent technological artifacts. The boundary resource theory is moved from a dialectic view between a platform owner and third-party developers to a "distributed network view of actors and artifacts that are intermingled in multilayered, overlapping, and ongoing tuning processes" (Eaton et al., 2015. p. 221). In this process, human actors "seek to channel material agency to shape the actions of other human agents" (Jones, 1998, p. 297), and, as a result, boundary resources evolve and emerge. In the distributed view of boundary resource tuning, actors include developer organizations of all sizes, other boundary resource owners, user communities, regulators, partner organizations, or the public opinion, e.g., as expressed in online forums. The distributed tuning of boundary resources is simultaneously and inseparably political and material.

While Eaton et al.'s (2015) model includes external actors, few concrete examples of the rules and tools, i.e., mechanisms at their disposal, are offered. This means that the role of external actors in boundary resource tuning remains little understood and accounted for. Indeed, most studies of one or another platform's boundary resources tend to focus on platform-specific technical details situated in a Western context, without paying much attention to the role of the institutional environment in which the platform is situated. The role of external actors and how their varying forms of pressure affect the process of boundary resource tuning is an understudied phenomenon.

More recently, the role of government platforms such as Open Government Data (OGD) platforms has started to receive more attention in the literature. For example, Bonina and Eaton (2020) have researched OGD platforms in Latin America and have shifted attention towards the role of the government in formulating and shaping proprietary platform boundary resources. This has resulted in extending platform literature by incorporating a supply-side view, where ministries and other public offices contribute datasets to the OGD platform core. On the supply side, informational tools include dataset templates and social tools such as initiatives that encourage ministries and developers to engage in service innovation on the OGD platform. In terms of securing, contractual rules specify the format and quality of datasets supplied to the platform. Theoretically, these findings complement existing views of the demand side, where peripheral entrepreneurs and developers engage with data as they build tertiary apps and services. On the demand side, Bonina and Eaton (2020) find that the OGD platform owner uses informational tools (e.g., datasets and manuals), software tools (e.g., APIs and web portals), and social tools (e.g., hackathons and competitions) to resource developers. The platform owner also adopts securing rules such as licenses and conditions to govern how developers use datasets while ensuring that the platform is not abused.

Figure 1. A governance model for open government data platform ecosystem cultivation (Bonina & Eaton, 2020).



However, the policies and institutional environment in which a platform is situated are generally treated as contextual factors external to the process of boundary resource tuning. In the distributed view of boundary resources (Eaton et al., 2015), contextual factors such as organizational forms, open data policies, and open government policies link and enable functioning tools and rules to emerge (Bonina & Eaton, 2020), while little explanation is given to the mechanisms that guide this process.

The existing literature's shortcomings in addressing the role of the government in enabling or constraining the tuning processes that are associated with a platform's boundary resources motivates the research questions of this paper, which ask: *what mechanisms can governments use to affect the boundary resources of innovation platforms, and how do these influence platform governance?* In other words, how do policies, legislation, and regulations, e.g., under different national and geographic conditions, affect the boundary resources of platforms, and what does it mean for platform governance and innovation?

The size and international reach of some innovation platforms and the importance of their underlying information infrastructure, e.g., in terms of national security and digital sovereignty, prompt governments to devise new ways to affect the process of boundary resource tuning (Panchenko et al., 2020). However, the varying ways and strategies that governments devise to affect the generativity of domestic or regional platforms and information infrastructures and the constraints placed on these remain little studied.

Huhtamäki et al. (2017) provide one of few studies that incorporate the geographical angle associated with platforms' boundary resources by looking at the global API ecosystem. The authors suggest that the process of international platform governance should include four categories of governance, that is, governance related to cross-country data (e.g., country restrictions on data residency), to mash-ups (e.g., country restrictions on the combination of digital services), to technology use (e.g., country restrictions on technologies), and to API management, i.e., how to control, manage, distribute, and define APIs and their terms of service for global (public) use. These considerations may provide an additional layer to policy-related contextual factors associated with boundary resource tuning by providing context on platform design choices and how these may be affected by policies that differ across geographical and legal borders.

Given our focus on National Open Innovation Platforms for AI (NOIPAIs), Huhtamäki et al.'s (2017) proposed categories are re-purposed around 1) data governance (i.e., availability), 2) AI open source software governance (i.e., accessibility), and 3) international integration (i.e., interoperability), with an emphasis on how governments seek to affect and orchestrate the boundary resources associated with each of these dimensions.

Incorporating the geographical angle into the study of boundary resources includes paying attention to how platforms govern and structure their boundary resources domestically and globally and how varying national contexts, policies, and regulations might affect a platform's terms of operation differently. A platform's operation is usually contingent on regional or national digital innovation characteristics, such as data, labor, software, and hardware availability and accessibility on the input side, as well as laws and regulations that govern its diffusion and terms of global interoperability on the output side.

Based on these considerations, this paper seeks to shift the view of traditional boundary resources associated with a platform's core and periphery towards embedding how varying mechanisms and forms of rulemaking, which might be external to the core architecture of a platform, nonetheless can have direct implications for its process of boundary resource tuning. In this government-centered view of boundary resource tuning, threats or opportunities to platform control are no longer associated merely with competition by other boundary resource owners or third parties at the periphery; they are directly associated with varying government actors and these policies and regulatory agendas for the digital economy.

In answering the research question, the paper draws on the case of China's National Open Innovation Platforms for AI. This case is interesting for three reasons. First, it takes a public sector perspective on the role of boundary resource tuning as opposed to previous literature, which is heavily centered on individual case studies of private sector platform governance. Second, unlike most existing research, it studies platform governance outside of a Western context. The focus on China is interesting since the market structure and governing mechanisms are different from those of a liberal market economy. In the area of platform governance and control, the mechanisms China's central government utilizes to influence platform boundary resources could look very different from the mechanisms and tools used in a Western context, for instance. Due to the growing role of the digital economy, it is important to understand what these differences could mean in terms of domestic and international forms of platform governance and digital interoperability. Third and last, the National Open Innovation Platforms for AI initiative displays hybrid platform elements that have been little researched but arguably are of growing importance to the digital economy, for example, in areas associated with AI innovation and standardization.

3. Methods

3.1 *Research Setting*

Since 2017, China has engaged in a large state-led push for indigenous development of artificial intelligence. Chinese policymakers have sought to close perceived gaps in the development of AI-related to basic theory, core algorithms, key equipment, and high-end computer chips (Xinhua, 2017) by actively supporting the formation of more open ecosystems for AI innovation. The scope of supporting AI technologies is linked to upgrading existing patterns of production as well as public service delivery.

In July 2017, China's State Council released the AI Development Plan, a detailed national strategy for turning China into a world leader in AI by 2030 (Roberts et al., 2021). Later in 2017, China's Ministry of Science and Technology (MOST) issued the policy "National Open Innovation Platforms for New Generation Artificial Intelligence," which at the time endorsed four private-sector technology companies to construct National Open Innovation Platforms for AI (NOIPAI). In 2019, MOST expanded the initiative to fifteen NOIPAIs and released "Guidelines for the Construction of the National New Generation of Artificial Intelligence Open Innovation Platforms" (MOST, 2019). The guidelines detail that NOIPAIs are to be constructed by enterprises that have demonstratred leading capabilities in AI.

According to the policy plan and guidelines, the technology companies behind National Open Innovation Platforms for AI are expected to deliver results on (1) research and development, (2) ecosystem participation, (3) sharing data and open-source software (OSS), as well as (4) supporting the entrepreneurship of small and medium-sized enterprises (Wu et al., 2020).

The fifteen NOIPAIs are based on application-driven, enterprise-led, and market-oriented principles (Wu et al., 2020). MOST (2019) further specified that platform leaders are expected to advance their AI areas in close collaboration with local governments, industry participants, as well as research institutes and universities.

The companies behind each NOIPAI submit annual progress reports to MOST, while the Ministry has declared that it will actively support the construction of NOIPAIs. During this process, provincial Science and Technology authorities have been mandated to assist in the promotion of NOIPAIs in their province by providing relevant policy support, with sensitivity to regional developmental characteristics (MOST 2019). Although unspecified, channels for support include public procurement, local government initiatives, partnerships, and access to government data. How the companies choose to build their NOIPAI is little specified, however, and the architecture of each individual platform is to be designed by each leading company. Common for all NOIPAIs is that they provide open-source materials, such as open data, algorithms, open-source frameworks, as well as SDKs and APIs for their ecosystems to connect and engage with.

Table 1. Overview of the Fifteen National Open Innovation Platforms for AI

Company	National Open Innovation Platform for AI (2017)
Baidu	Autonomous Driving
Alibaba	Smart City
Tencent	Medical Imaging
iFlytek	Smart Audio
SenseTime	Smart Vision (added September 2018)
Added August 2019	
YiTu	Vision Computing
Mininglamp	Smart Marketing
Huawei	Software / Hardware
Ping'An	Inclusive Finance
HIK Vision	Video Perception
JD.com	Smart Supply Chain
Megvii	Image Perception
360 Qihoo	Cybersecurity
Tal Education	Smart Education
Xiaomi	Smart Home

3.2 *Methodology*

This study is an exploratory case analysis of China's National Open Innovation Platforms for AI. A case study is an appropriate method for studying new and emerging phenomena (Eisenhardt, 1989; Yin, 2003) and is especially suitable for exploring complex processes such as open innovation in an emerging technology paradigm (Birkinshaw, Brannen, & Tung, 2011, p. 575). A case study, grounded in empirical data, is a useful method for inductively developing theory (Eisenhardt 1989). A grounded approach to theory building is considered relevant when little is known about a phenomenon, which provides an opportunity for theory to be developed inductively (Eisenhardt 1989). Grounded theory is therefore considered an appropriate methodological approach to uncover a set of underlying processes inherent to the substantive area of inquiry (Tie et al., 2019).

Deploying a broad view on the formation of NOIPAI and governing processes, and how these are shared among several actors, increases the rigor through which knowledge of NOIPAI can be inferred (Nachum, 2012). It also enables a more precise means for identifying government mechanisms that influence the boundary resources of the initiative.

The case of National Open Innovation Platforms for AI was chosen because of its ability to inform how public actors can influence innovation platforms' process of boundary resource tuning. Furthermore, the initiative resembles a new model of public-private platform orchestration that has been little studied but is of importance to the governance of platform-based organizational settings at the intersection of public and private interests going forward.

3.3 *Data collection*

Data includes primary data from 16 semi-structured interviews collected in China during 2018 and 2019. Interviews involve key stakeholders that are directly or indirectly engaged in the NOIPAI initiative. Respondents include CEOs, directors, and managers from domestic and international technology companies and AI start-ups operating in China, and software engineers and developers directly engaged in building and maintaining AI platforms there.

The interviews consisted of open-ended questions focusing on AI innovation in China and the role of NOIPAI. The list of interview questions is included in Appendix A. All interviews were conducted in English.

Direct access to policymakers with responsibilities in the NOIPAI initiative could not be established. The reasons for this may be several, and include the sensitive nature of industrial policies in China related to emerging technology paradigms.

Secondary data relies on policy documents regarding the support of AI across national and regional levels. The documents were retrieved using a keyword search of three types of primary sources: (1) the website of the Chinese State Council (http://www.gov.cn/), providing access to all types of government policy documents (e.g., plans, opinions, notices); (2) the websites of several ministries and commissions (e.g., MOST; http://www.most.gov.cn/); and (3), reports on the development of AI in China across industry and academia (for the relevance of these sources, see, e.g., Rho, Lee, & Kim, 2015; Xue, 2018).

Additional secondary sources include online resources on platform infrastructure, which in many cases are publicly disclosed by the companies constructing NOIPAIs. Data from interviewees have been triangulated with these documentary resources.

A special focus on secondary analysis of publicly available data, such as press releases, tech blogs, and developer forums, is considered a viable approach to studying platform-based phenomena, as great levels of secrecy usually surround major platform owners. This makes reliable first-hand data on governance and design decisions hard to come by (De Reuver et al., 2018). Therefore, excerpts from public interviews and presentations by key stakeholders and related news coverage in English and Mandarin have been included as secondary sources. Finally, extensive participation in AI conferences across academia and industry was conducted in China on an ongoing basis throughout 2018 and 2019.

Table 2. Overview of interview data sources.

	Organization	**Position**	**Informant Code**	**Interview mins**	**Interview N**
NOIPAI	1 - Baidu	Manager	1NOIP1	24	1
	2 - Alibaba	Developer	1NOIP2	82	2
	3 - Tencent	Developer	1NOIP3	51	1
	4 - SenseTime	Director	1NOIP4	33	1
	5 - JD	Manager	1NOIP5	126	2
Domestic Tech Firms	6 – DiDi	Director	2DTF1	97	1
	7 – VIPSHOP	Director	2DTF2	25	1
	8 – Gridsum	Director	2DTF3	65	1
	9 – Xiaoai	President	2DTF4	44	1
Domestic AI start-ups	10 – Trio.ai	CEO	3AIST1	75	1
	11 – Meezao	Founder	3AIST2	97	1
International Tech Firms	12 – Microsoft	Director	4ITF1	55	1
	13 – Oracle	Manager	4ITF2	89	1
	14 – AI Technology Center	Co-founder	4ITF3	123	1
TOTAL				986	16

3.4 *Data analysis*

Each dataset was analyzed to answer the research questions: *What mechanisms can governments use to affect the boundary resources of innovation platforms, and how do these influence platform governance?* The data analysis aimed to identify and inductively classify government mechanisms for boundary resource tuning.

Most interviews were recorded and transcribed, while some were conducted in note form due to the collected data's sensitivity or concern for the respondent's anonymity. The interviews have been coded with the software NVivo version 12.

The first round of coding aimed at identifying platform boundary resources (i.e., tools and rules) in an inductive fashion (Strauss & Corbin, 1998). The aims of this round included tracing the underlying policy- and firm-level justifications for establishing and engaging in the construction of a National Open Innovation Platform for AI. This step focused on how the platform owner devised rules and tools to govern the relationship between platform core and periphery and how and why the government sought to influence this process. This initial coding process fractured the data in ways that enabled a comparison of justifications for engaging in the NOIPAI initiative across public and private interests while looking for similarities and differences in data patterns that began to emerge (Strauss & Corbin, 1998). After the initial analysis of the coded material, theoretical sampling was employed to further direct additional data collection (Mills et al., 2014).

In the second coding round, first-order codes were clustered into more abstract second-order codes that synthesize how the perceived government interactions influenced platform boundary resources. A few core categories emerged at this stage and were subsequently formed into more concrete concepts and relationships surrounding a co-dependent form of boundary resource tuning. These refined first-order codes and paved the way for a more fine-grained categorization of government mechanisms for boundary resource tuning. An example of this process can be seen in Table 3.

Since policy documents often lack explicit details regarding the actual infrastructure requirements of NOIPAIs and concrete measures such as funding, the paper's analysis takes a governance-oriented approach to outlining mechanisms of boundary resource tuning. In doing so, the structural implications of the platforms, and the varying kinds of partnerships with policymakers, local governments, and businesses, are all considered. The interaction between public and private actors and the mechanisms for interaction and joint platform governance have received special attention throughout the analysis.

Table 3. Example of the interview data and coding procedure.

Empirical data	First-order coding	Second-order coding
"Universities do not have a product team, so there is no way for them to reach end-users" [4ITF1]	Lack of resources in public-sector research	Cooperation
"In China, the government […] wants this ecosystem to grow faster because they have realized that they absolutely need it" [4ITF3]	The goal is to make the domestic AI ecosystem grow faster	Communication
The companies behind National Open Innovation Platforms for AI are required to submit annual progress reports to the Ministry of Science and Technology (MOST 2019)	Legal obligation to report on progress	Contract
"Google and Facebook are not in China so we can hardly access their platform" [2DTF2]	Access to international resources restricted	Interoperability
"Most large companies have a special legal VPN so that they can access Google and things like that" [1NOIP2].	Access to international resources increased through legal VPN	Software
"The big knowledge bases like the UMLS [Unified Medical Language System] are not completely adapted to China yet, so there is infrastructural work to do" [4ITF3]	Digital AI resources still need to be developed in some areas	Infrastructure
"The size and the underdeveloped rural areas, so you could use lots of things in telemedicine and bringing better diagnosis" [4ITF3]	New solutions needed to combat social problems	Organization
"Government data often remains siloed across legacy institutions with limited access" [2DTF3]	Government data is a restricted resource	Data
"We cooperate with local governments, we offer them big data analytics, just like cloud and smart transportation" [2DTF1]	Local governments buy and adopt AI solutions	Procurement

4. Findings

The findings of this section cover platform rules and tools, and government mechanisms, which collectively inform and shape the boundary resources of National Open Innovation Platforms for AI. Special attention has been placed on NOIPAIs organization around data governance (i.e., availability), AI open source software governance (i.e., accessibility), international integration (i.e., interoperability), and how government actors seek to affect and orchestrate boundary resources associated with each of these dimensions. Finally, the findings include a set of hybrid platform elements adjacent to but interrelated with the NOIPAI initiative. These have important implications for platform governance.

4.1 *Platform rules and tools*

As clarified in policy plans such as China's AI Development Plan (2017), China's central government aims to establish greater self-sufficiency, making domestic open source projects a vital development area. An open-source White Paper released by the China AI Open-Source Software Development League in 2018 notes that: "In the development history of AI Open Source Software, due to the relatively limited participation of China, the current situation of the AI Open Source Software market is dominated by Western developed countries" (AOSS, 2018 p. 1051). A commentary positions that "China's AI open source community and technological innovation ecosystem are comparatively lagging, [and] the strength of technology platform construction needs to be reinforced. [China should] construct an independent and controllable innovation ecosystem" (Hickert & Ding, 2018, p. 1).

Regarding resourcing, NOIPAIs contribute to open source an extended range of information- (e.g., data) and software tools (e.g., deep learning frameworks). Companies endorsed to build an NOIPAI have pledged to open their computing and data platforms and allow developers from the ecosystem to improve their AI capabilities based on released open-source materials. This means that private sector platforms in the initiative are obligated to restructure their boundary resources to increase data availability and AI open-source software accessibility.

Huawei has, for example, been endorsed to build a National Open Innovation Platform for Full Stack Development of Software and Hardware and has, through its Cloud ModelArts platform, begun to open up the entire AI value chain from data processing to model development, model training, and model deployment, including open-sourcing its MindSpore deep learning framework (China Daily, 2019). All of these resourcing tools have been opened up for all individuals, companies and institutions that have an interest in them. Other companies have also open-sourced their deep learning frameworks and made these accessible on their NOIPAI, e.g., Baidu's PaddlePaddle, Alibaba's XDL, SenseTime's Parrots, and Megvii's MegEngine. Deep learning frameworks are essential for AI development as these are considered building blocks for designing, training, and validating deep neural networks through high-level APIs.

For small and medium-sized enterprises, resources such as data and AI open-source software accessibility means that they "need not start from zero. [They] can start from these platforms because they have already invested a lot. [This means that SMEs] can jump to a higher level [of innovation] and they can concentrate on the business logic level, the application level" [2DTF2].

The rationale for companies to engage in the process of providing deep learning frameworks and other software as open source, however, remains "similar to any other big tech company. […] Sometimes, something turns out to be useful and a chance to attract people or to make some PR, or it gets people closer and makes people use your services" [1NOIP2], which creates network effects and has a positive effect on innovation. Regardless of the NOIPAI status, private sector innovation platforms already have market-based incentives for engaging in boundary resource tuning that opens their platforms and increases data availability (informational tools) and open-source accessibility (software tools). In other words, greater availability of resourcing tools is a chance to attract complementors to the platform, enhancing its ecosystem's value.

In terms of increasing the availability via a NOIPAI, an interviewee noted that "data is shared as soon it will benefit [the platforms]" [1NOIP2]. Since there are no official requirements for how data and frameworks should be opened and released on NOIPAIs, the question of "how data is shared" remains a strategic company decision that is associated with a platform's unique strategy of boundary resource tuning. This means that the companies behind NOIPAIs generally control all technological interfaces regarding which parts of the platform and technology are "opened" or stay "closed."

4.2 *Government Mechanisms*

In the policy plans behind the NOIPAI initiative, a core focus is placed on R&D and close collaboration between companies, research institutes, and universities. An interviewee clarifies that, previously, "China was really concentrating on the low-hanging fruits, on the newest technologies and then copying the American models. AI researchers […] they concentrated less on the technology that would be relevant in three years. That's the weakness" [4ITF1]. Another interviewee notes that "we try to do something for the application level, but in the algorithm or the foundation level, the Chinese are still weak" [2DTF2].

Research in AI is often contingent on having access to large amounts of data and compute, which means that perceived asymmetries in access to resources between public research institutes and private innovation platforms are likely to persist.

In China, policymakers therefore seek to create more significant synergies between public and private forms of R&D. At the same time, NOIPAIs serve as a mechanism to enhance the cooperation of algorithmic research conducted in universities, with AI solutions that are applied in the private sector. “Universities do not have a product team, so there is no way for them to reach end-users [and to collect their data]” [4ITF1], which is a necessary input factor for AI innovation. Direct collaboration with universities provides the educational system with access to more data, while collaborating companies gain greater access to research capabilities. “We corporate with several universities […] They have a good engine, but they need the data. And for us, we have the data but we do not have such a big research team. So that’s why we could find a very good point to cooperate” [2DTF2]. While encouraging cooperative behavior may not directly impact the core of the open innovation platform, incentivizing greater engagement between the platform core and public research institutes does affect behavior at the periphery. The knowledge generated during such cooperative exercises might feed back into core functionalities that, in turn, affect the resources provided on the open innovation platform over time. As the government seeks to bring diverse actors together, they indirectly affect China’s domestic AI ecosystem’s boundary resources by encouraging cooperative behavior at the periphery.

Official reasons for establishing National Open Innovation Platforms for AI rest on their perceived ability to speed-up technological upgrading. “In China, the government […] want this ecosystem to grow faster because they have realized that they absolutely need it” [4ITF3]. During this process, policymakers encourage open ecosystems where data availability and deep learning frameworks are open-sourced. Even though some start-ups feel threatened by large platform integrators [3AIST2], the core idea is to empower more SMEs to become more innovative by providing greater access to open-source materials. Therefore, the National Platform emblem becomes a communication mechanism or a discursive tool used to endorse a few selected private sector platforms to build open-innovation environments. The communication mechanism signals that AI open-source developments are officially endorsed as a fruitful direction for the industry to move in.

NOIPAIs are also obligated to report on progress made in relation to R&D, the distribution of data and open-source software, and how that benefits ecosystem participation and SME-related innovation. This exemplifies a contractual mechanism whereby policymakers gain a better overview of AI innovation platforms regarding how they govern information tools (data availability) and software tools (accessibility of AI modules). Contractual mechanisms can enhance public sector oversight on platforms' governance of their boundary resources, which in the case of China, provides a clearer indication of how progress in AI is made.

Government mechanisms that affect a platform's boundary resources are also linked to control over interoperability between domestic and international ecosystems and associated data and information flows. In China, the internet environment is more tightly controlled than elsewhere due to the Great Firewall (GFW). One interviewee noted that "Google and Facebook are not in China so we can hardly access their platform" [2DTF2]. This may create idiosyncratic obstacles to AI innovation as Google and Facebook also are behind some of the most widely used deep learning frameworks, such as TensorFlow and PyTorch. While both frameworks are available as open-source software, restrictions on interoperability could be a hindrance to accessing accompanying materials. An engineer noted that "if you need to download the bigger data from some university server in the U.S. or Europe, and then it goes through the Great Firewall […] it's going to take weeks to download that" [1NOIP2]. While open-source code repositories such as GitHub or Stack Overflow are accessible inside China, "the problem is usually with these platforms […] that sometimes you have trouble accessing it due to the Great Firewall. [And so what happens] is a sort of clones or maybe delayed copies onto cloned websites [that are] easier to access from inside China. Sometimes with translations and so on" [1NOIP2].

If code repositories such as GitHub were not available in China, an interviewee speculated, "a lot of people … would be [in trouble, and] you would probably try to find another way around the Great Firewall" [1NOIP2]. The GFW is considered both an interoperability mechanism and a censorship mechanism that may present some obstacles to AI innovation by limiting connectivity with international ecosystems. This obstacle is partially solved, however, as "most large companies have a special legal VPN [virtual private network] so that they can access Google and things like that" [1NOIP2]. A special legal VPN is viewed as a software mechanism that grants special treatment to some companies. Where the Great Firewall of China creates informational constraints, the provision of a special legal VPN ensures greater interoperability with international ecosystems. However, little is known about the extent to which AI innovation by domestic SMEs without access to a special VPN is limited by the GFW.

Table 4. Government mechanisms for platform boundary resource tuning.

Type of Mechanism	Boundary Resource Characteristic	How Characteristic Affects Platform Governance
Cooperation	*Encourage cooperative behavior* at the periphery, e.g., by bridging algorithmic research in universities with research and solutions from the private sector	*Indirectly,* by bringing diverse peripheral actors together
Communication	*National Platform emblem* a communicative mechanism that is used to endorse and elevate selected private sector platforms to the status of national platforms for AI	*Indirectly,* signals AI open-source developments as a fruitful direction for the industry to move in
Contractual	*Reporting* information exchange between government and platform core whereby policymakers gain a better overview of AI innovation platforms in terms of how they govern data availability, as well as the accessibility of AI modules on their platform	*Directly,* platforms are obliged to provide annual progress reports on how data and tools are released and shared and how the platform core is being opened to outside participation as well as how it affects AI innovation
Interoperability	*The Great Firewall of China* a censorship mechanism that places limitations on the degree of information and data interoperability with international ecosystems	*Directly,* reduces data availability and software accessibility between domestic and international platforms and ecosystems
Software	*Special legal VPN* a software mechanism that grants privileged treatment to some companies, which enhances their access to international ecosystems and associated knowledge flows	*Directly,* improves data availability and software accessibility between domestic and international platforms and ecosystems
Infrastructural	*Indigenous open-source code repository (Gitee)* this makes it easier for SMEs to access open-source data and knowledge, e.g., associated with OSS	*Directly/Indirectly,* Gitee complements innovation platforms and their members at the periphery by distributing open-source materials
Hybrid platform solutions – adjacent to the NOIPAI initiative		
Organizational	*Public information infrastructure and value creation* developed by platform core, public partners, and peripheral members	*Directly,* control is negotiated between public partners and private platforms, establishing mixed ownership and control forms. The core platform usually holds leverage in devising the architecture of the solution, e.g., in terms of adjacent standards
Data	*Selective and gradual opening of government data* performed in partnership with platforms, sometimes as hybrid public-private platform solutions that provide new measures of public information infrastructure	*Directly/Indirectly,* OGD may affect firms' capabilities to innovate in AI directly through increased accessibility to novel datasets or indirectly through complementing proprietary information and data
Procurement	*Subsidies for certain kinds of AI development* includes access to government projects as well as partnerships with local government institutions	*Directly,* enables specific platform solutions to be procured, and supplies public sector data, which is released on a selective basis

On the one hand, China's domestic ecosystem is closely interconnected with and dependent on international knowledge flows linked to crucial resources such as data and open source software (OSS). At the same time, however, policymakers seek to strengthen China's domestic position by incentivizing the development and release of proprietary OSS such as deep learning frameworks, with the intention of weakening international couplings and dependencies. These developments were further emphasized in 2020, when Chinese policymakers signaled a shift away from relying on international open-source code repositories such as GitHub. The Ministry of Industry and Information

Technology (MIIT), Huawei, Tencent, and several universities endorsed the Chinese OSS platform Gitee as the domestic hub for China's open-source community. Due to the official endorsement of Gitee (a communicative mechanism) by the MIIT, the construction of an indigenous open-source code repository can be viewed as an infrastructural mechanism that targets a domestic weakness in terms of open source code accessibility. "On the one hand, the Chinese regulatory system gives an advantage to building up companies [through protection from overseas competition via censorship mechanisms], but sometimes the regulatory system can also be a hindrance [due to associated obstacles to interoperability]. China is now working very hard on striking a better balance" [4ITF3].

4.3. *Hybrid platform arrangements*

Provincial Science and Technology authorities have been mandated to assist in the promotion of NOIPAIs, contingent on regional characteristics of development (MOST, 2019). Practically, this means that collaboration with local governments often takes place through the establishment of hybrid platforms.

Alibaba, for example, is responsible for building a NOIPAI for Smart City, which is based on the Alibaba Cloud ET City Brain. ET City Brain forms the infrastructure behind a public intelligence system that can perform real-time analysis of core city functions such as transportation, energy, water, surveillance, and urban management systems.

For example, in collaboration with Shanghai's Municipal Government, ET City Brain performs digital processing and analysis of the city's urban infrastructure, including in areas such as transportation, energy, water supply, and construction. During this process, new decision-making systems for public security, public transportation, and public service authorities are being developed (Alibaba, 2021).

The creation of hybrid platforms that incorporate public and private forms of information and infrastructure is viewed as an organizational mechanism built on a negotiated form of authority and control.

As the public sector in China sits on large piles of government data, public sector agencies often seek to reorganize the boundary resources of government data repositories on the supply side (data mechanism) to enable public sector innovation and transformation. An interviewee, however, notes that "the government is reluctant to open very large repositories of data. In the UK, for example, it is different, everybody can download large public databases. In China, there is no public data of that sort. Although the state has all that knowledge, it is registered, but you cannot download knowledge that the government has" [4ITF3]. Another interviewee notes that government data often remains siloed across legacy institutions with limited forms of shared access [2DTF3]. This restricts the availability of government data and may be considered an obstacle to innovation.

However, the NOIPAI initiative indicates an alternative, supply-side way to open public data repositories, which may be contrasted with open government data initiatives elsewhere. In the city of Hangzhou, Alibaba's ET City Brain, for example, uses image recognition technology to analyze the information of 3,000 surveillance cameras connected to the operation of 128 traffic lights (Alibaba, 2021). Such initiatives and their underlying mechanisms for data sharing and governance indicate a renegotiation of public and private forms of physical and digital infrastructure and control over these.

In another example, Tencent, responsible for building a medical imaging NOIPAI, has partnered with Shenzhen's Municipal Health Planning Commission to build a Big Data Platform that integrates an intelligent healthcare service system. The cooperation relies on Tencent's Miying platform for innovation projects in medical imaging, diagnosis, teaching, standards, and medical quality control. "China still has to catch up on AI in medical. [Because] of China's size and its underdeveloped rural areas […] you could use lots of things in telemedicine and bringing better diagnosis" [4ITF3]. Tencent's partnership with Shenzhen Hospital Center includes delivering a public service where residents can engage in AI-based diabetic retinopathy screening through remote diagnosis (Tencent, 2018).

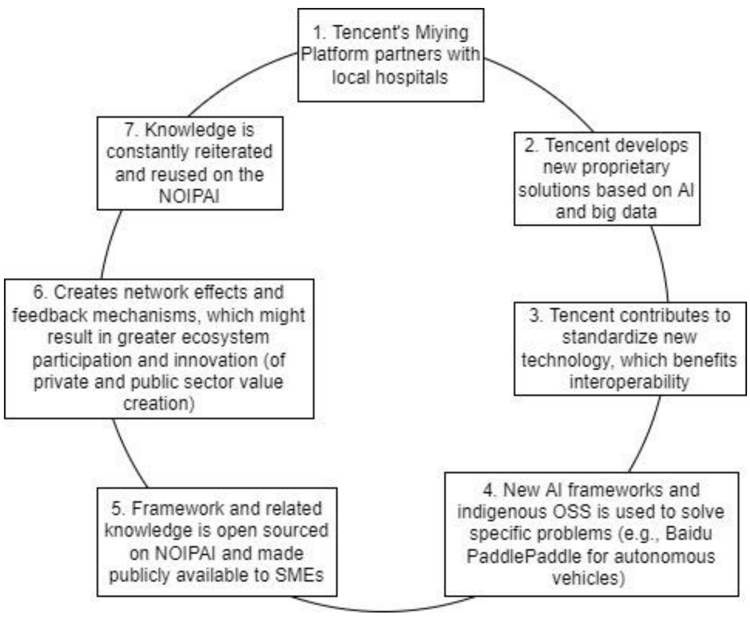
"The problem," as 4ITF3 explained,

> is still in deep learning and machine learning. [Chinese companies] can do it fast, but the infrastructure they have not yet copied. […] The big knowledge bases like UMLS [Unified Medical Language System] are not completely adapted to China yet, so there's infrastructural work to do, and people have to agree. There needs to be an agreement between the government and the medical system and research.

In the case of Tencent's NOIPAI for medical imaging, the tuning of boundary resources is done by a multitude of partners that have to agree on new ontologies linked to the creation of knowledge graphs for the medical industry. "This is not there yet, China does not have these ontologies and knowledge graphs. There, China is not so [developed], maybe because people are not so willing to share stuff" [4ITF3].

Both the Alibaba and Tencent examples include the delivery of novel forms of public service or value creation based on hybrid platform solutions and information infrastructure. While provincial Science and Technology authorities have been mandated to assist in the promotion of NOIPAIs, policy support tends to be based on procurement-based mechanisms that include access to partnerships with local institutions and associated government data. By collaborating with companies responsible for building NOIPAIs, public sector agencies and institutions are encouraged to share access to data (increase availability) and resources (increase accessibility) with private sector firms, which strengthens the supply side of platform innovation. The idea is to create reiterative feedback loops that contribute to indigenous knowledge creation, which can be linked to establishing new ontologies and knowledge graphs as well as standards on novel areas of public-private collaboration. "All these [knowledge] bases, they enable so much more. […] If you get one layer and then you immediately get a hundred companies that build on that, and then you get the next layers of knowledge on top" [4ITF3]. In the case of Tencent's Miying NOIPAI, the reiterative loop can be visualized as follows:

Figure 2. Schematic representation of the NOIPAI platform loop in the case of Tencent Miying.



The organizational mechanism of constructing hybrid platforms may result in added synergies when data and systems are open-sourced on National Open Innovation Platforms post-implementation. Application may create critical feedback loops for NOIPAIs, enabling platforms to release data and tools as open-source materials.

However, hybrid platforms and partnerships are not exclusive to the companies responsible for constructing NOIPAIs. The ride-hailing company DiDi Chuxing, for instance, has developed a range of smart city solutions connected with enhancing traffic flows and urban mobility. “We cooperate with local governments, we offer them big data analytics, just like cloud and smart transportation, there is not only DiDi’s data on the cloud but also the public transportation systems data” [2DTF1].

In embracing a platform-induced way of thinking and organization, policymakers seek to enable new kinds of information infrastructure, for example, to power smart cities, traffic flows, electricity grids, court systems, surveillance systems, healthcare, finance, and supply chains. To varying degrees, these areas of application will be connected to the data and AI modules that subsequently can be released on China’s National Open Innovation Platforms for AI (see Table 1). “All of this can be seen as infrastructure building. And so it’s a long process” [4ITF3].

5. Discussion

Several government mechanisms have been located, each of which has direct and indirect implications for the governance of platforms. The mechanisms are discussed primarily in relation to AI innovation platforms and have implications for transaction platforms. This section discusses how each mechanism affects platform boundary resources. Examples of government mechanisms from other countries are included to highlight nuances in China’s strategy of creating National Open Innovation Platforms for Artificial Intelligence. A revised model of platform boundary resources that identifies government mechanisms as contextual factors to boundary tuning processes is presented at the end of this section, before implications for research and practice and limitations and directions for future research are offered.

5.1 *Data mechanisms*

Progress in AI generally requires access to data. Policy mechanisms aim to address questions such as which entities (public and private) share their data, for what purposes, and under which conditions shared data is likely to impact AI system development. Large technology companies and their innovation platforms are both providers and gatekeepers of strategic digital resources such as infrastructure, compute, data, and access to large user bases and their data (Geradin, 2021). The business model of most platforms has been shown to be based on control over and valorization of data (see also Rahman & Thelen, 2019).

The centralizing nature of the production function of large digital platforms means that the data and AI models that are developed and deployed by these might create unique barriers to entry by startups (Bommasani et al., 2021). This is witnessed in the prohibitive costs of resources (data and compute) needed to develop, for example, innovative AI foundation models or search engines (Bommasani et al., 2021; Radinsky, 2015). Infrastructure investments can therefore be a barrier to AI development by university-based computer scientists and resource-constrained startups (Mikalef & Gupta, 2021).

Mikhaylov, Esteve, and Campion (2018) have argued that successful development of artificial intelligence capabilities relies on developing greater data-sharing relationships across government, industry, and academia. The NOIPAI initiative aims to affect information tools (data) and software tools (e.g., deep learning frameworks) on both the supply and demand sides. On the demand side, NOIPAIs are obliged, via self-enforcing contractual mechanisms, to contribute greater although unknown quantities of proprietary data, which makes information tools more available. On the supply side, government data may be provided to platforms on a procurement basis, or may be distributed freely through open government data platforms, e.g., based on licensing agreements (Cingolani, 2021).

As governments supply the data for open data ecosystems, they also embark on a transformation of existing practices and services on the demand side by increasing data availability to actors at the periphery. Novel partnerships – of public agencies on the supply side and application and content developers on the demand side – result in the formation of hybrid platforms that support the development of open-data ecosystems (Wang & Shepherd, 2020).

A data trusts is another mechanism that aims to increase data sharing among companies, the government, and individual developers. A data trust is a legal framework for managing shared data, which may promote collaboration among its members through establishing common securing rules for data security, privacy, and confidentiality on both the supply and demand sides.

The use of data trusts is, for example, a part of the United Kingdom's AI Sector Deal, a collection of policies that promote the adoption and use of AI (GOV.UK, 2019). Clearly, government mechanisms can facilitate data stewardship and bottom-up empowerment, e.g., through legislative mechanisms that establish data rights and protections, data sharing policies, and legal and infrastructural obligations on the supply side (Aapti Institute, Open Data Institute, 2021).

5.2 *Interoperability mechanisms*

In platform-based digital ecosystems, interoperability refers to the ability to transfer and render data, information, and software across systems, applications, or components (Gasser, 2015), both domestically and internationally. Governments have several mechanisms at their disposal to affect platform and ecosystem interoperability.

The NOIPAI case demonstrates that China's Great Firewall, a censorship mechanism, also limits domestic and international forms of data and information interoperability (Băzăvan, 2019), which affects platforms boundary resources by limiting access to resourcing tools from international ecosystems on the supply side. In other words, national interoperability mechanisms can be used to establish boundaries against global digital ecosystems (Tsujimoto et al., 2018). The resulting, information-limited ecosystem can be used to favor the development of domestic technology companies (Arenal et al., 2020). However, data limitations can constrain domestic companies whose developmental prospects are dependent on access to more extensive information and resources. In China, the GFW promotes development in the former group of companies and the limited provision of special legal VPNs promotes the development of at least some companies in the latter group.

Interoperability is guided by legal measures that regulate cross-border data flows and thereby restrict information tools. In Europe, for example, the adequacy approach, a legal mechanism of the General Data Protection Regulation (GDPR), defines conditions under which third-party countries are understood to provide sufficient protection for the transfer and use of personal data (Chen, 2019).

Interoperability mechanisms also relate to antitrust mechanisms that guide competition in the digital economy. In terms of innovation platforms, software-based resourcing tools accessed via APIs or SDKs can be constructed to limit interoperability between competing platforms, products, and services (Nooren et al., 2018). Antitrust mechanisms include legal measures that work to avoid that platforms construct software tools in ways that promote consumer lock-in and make it costly for users on the demand side to switch their services to competing platforms (Martens, 2016). In 2004, for example, the European Commission ordered Microsoft to provide essential interoperability information that permitted the development of competing products (Simcoe, 2012).

In relation to AI development and innovation practices, government mechanisms that address interoperability concerns relate to ensuring fair and equal competition. Forcing incumbents to share their data (resourcing tools) and intellectual property (securing rules) with new entrants has been debated as an alternative to breaking up firms out of anticompetitive concerns related to disproportionate data centralization (Chen, 2019). In terms of transaction platforms, their use of data on third-party sellers arguably has given them an unfair advantage over competitors (Lomas, 2020). However, proper organizational solutions, as well as technical (resourcing) and legal (securing) standards, have not yet been developed. To ensure that concerns over fairness and security are sufficiently addressed, new boundary resources and forms of data-sharing and interoperability need to be reconsidered by digital platforms (Chen, 2019).

5.3 *Contractual mechanisms*

Governments may directly affect the process of boundary resource tuning by using contractual mechanisms (e.g., reporting rules). As seen in the NOIPAI case, such rules may be used to provide the government with increased oversight of platform-based activities, including tools used to resource peripheral members and rules used to govern participation in the wider ecosystem. Policymakers can use such knowledge to assess the extent to which a platform has lived up to pre-specified contractual obligations (Klievink et al., 2016) or whether a platform complies with existing laws and regulations. New informational channels between public agencies and private platforms may also be established through audit-based mechanisms that seek to increase public oversight, e.g., on strategic areas of digital development and competition (Gorwa et al., 2020). Audit-based mechanisms are also relevant for launching new forms of oversight of algorithmic use and can ensure that principles such as fairness, transparency, and accuracy are sufficiently met and accounted for in the digital economy (Brown et al., 2017; Raji et al., 2020).

5.4 *Procurement mechanisms*

Procurement-based mechanisms can support AI innovation and exemplify platforms or ecosystems pull strategies on the demand side. Beraja, Yang, and Yuchtman (2021) have argued that the government may shape the direction of innovation and growth in data-intensive economies, both because the government is a key collector of data and because data is sharable across uses within firms. This may generate economies of scope when governments include supply-side data as a part of a procurement-based contract. In terms of facial recognition AI in China, government procurement contracts have been documented to be conducive to creating economies of scope arising from government data. This means that procurement-based mechanisms can lead to the development of improved commercial software in private innovation platforms (Beraja et al., 2021). Government procurement of digital technologies and services can consequently play an entrepreneurial role in promoting competition and innovation among suppliers. This has implications for the development of innovation platform's resourcing tools and contributes to shaping generativity through testing new technologies, such as facial recognition systems, for public sector use (Hanna, 2018). Advanced economies have also been documented to use government procurement to promote open standards, interoperability, and best practices in digital technology adoption (Hanna, 2018).

5.5 *Cooperation and communication mechanisms*

Several government mechanisms do not affect platform boundary resources directly, but have indirect consequences for platform governance and ecosystem participation. These include mechanisms such as cooperation and communication.

In terms of cooperation, analysis of China's NOIPAI initiative has shown that cooperative behavior may be encouraged at a platform's periphery, for example, through bridging algorithmic research in universities with research and solutions from the private sector.

In terms of communication, the NOIPAI case shows that governments may use communicative mechanisms to signal fruitful directions for the industry to move in. Pustovrh and Drnov (2020) have documented how these mechanisms may include public policy endorsing key actors' open innovation activities. Communicative mechanisms may also signal that broad and active participation can lead to shared influence and control, which facilitates productive group dynamics (Ansell & Gash, 2007).

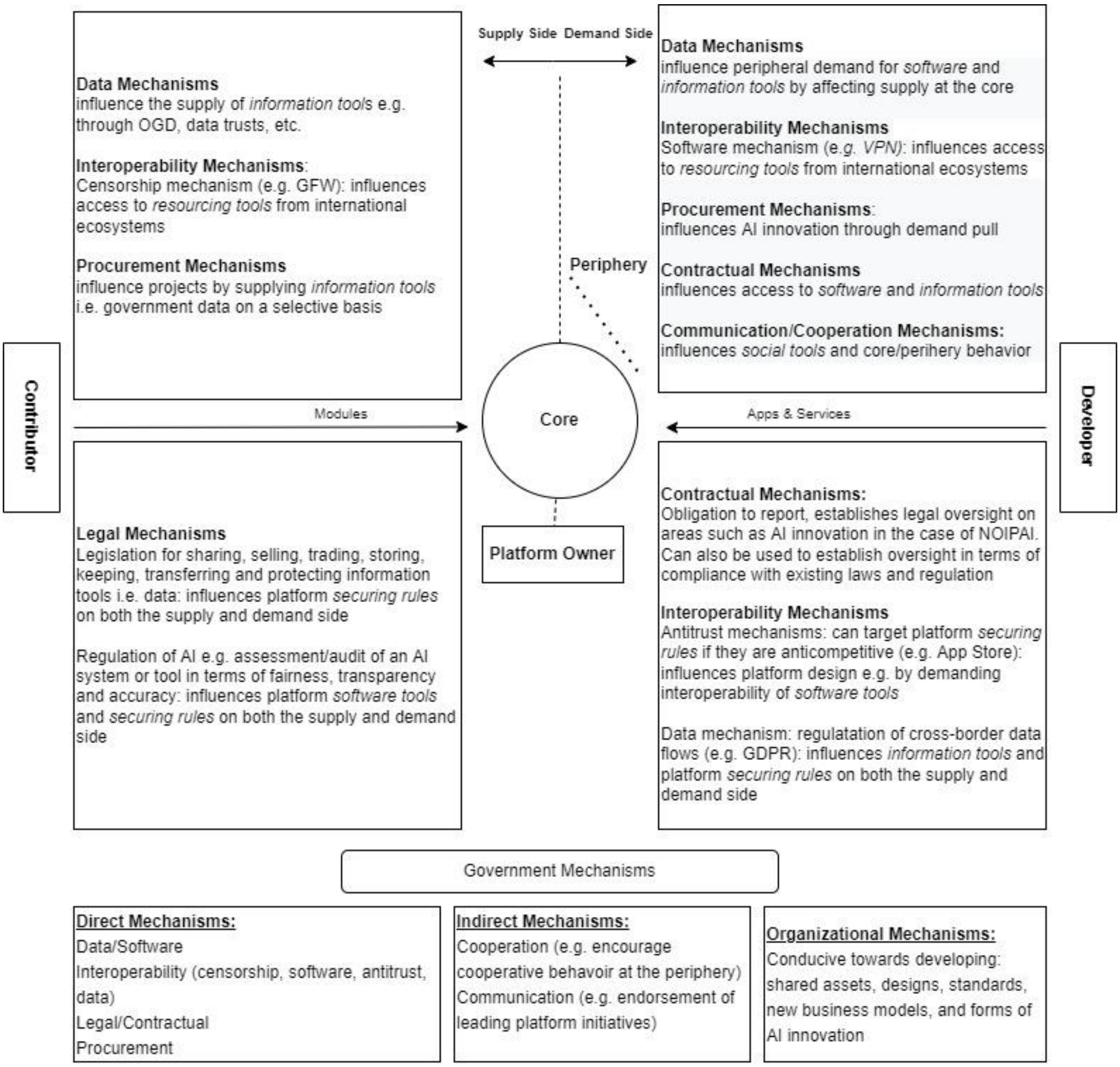
Communicative and cooperation-based alignment of goals and objectives among participants may be essential when organizations from different sectors collaborate (Ansell & Gash, 2018). Therefore, communication and cooperation-based mechanisms have important effects on social tools, especially in terms of incentivizing and guiding certain forms of platform behavior.

5.6 *Organizational mechanisms*

Organizational mechanisms, such as constructing hybrid platform solutions, have implications for platform governance and boundary resource tuning. In particular, since hybrid platforms often are constructed to create new kinds of information infrastructure in areas such as healthcare, transportation, public utilities, and so on (Kallinikos & Tempini, 2014), they may also be conducive to formulating new technology standards on emergent areas of infrastructure (Chen & Lee, 2018). Hybrid platforms consequently enable new forms of public value creation (Kim et al., 2021; Kretschmer et al., 2020; Panagiotopoulos et al., 2019) and novel governance arrangements to emerge (Chen et al., 2021). Collaborative platforms have similarly been argued to be conducive to developing shared assets, designs, and standards that may create multiplier effects among participants (Mikhaylov et al., 2018).

Hybrid platforms are distinct types of boundary resource tuning and platform orchestration. They shift platform authority in the direction of negotiated or mixed public-private control points, which jointly affect the functionality and generativity of the platform (Klievink et al., 2016). This means that resourcing tools and securing rules become subject to negotiations that determine the openness and accessibility of the hybrid platform arrangement, which contributes to a redefinition of public and private spheres of influence in the tuning process (Jacobides et al., 2019).

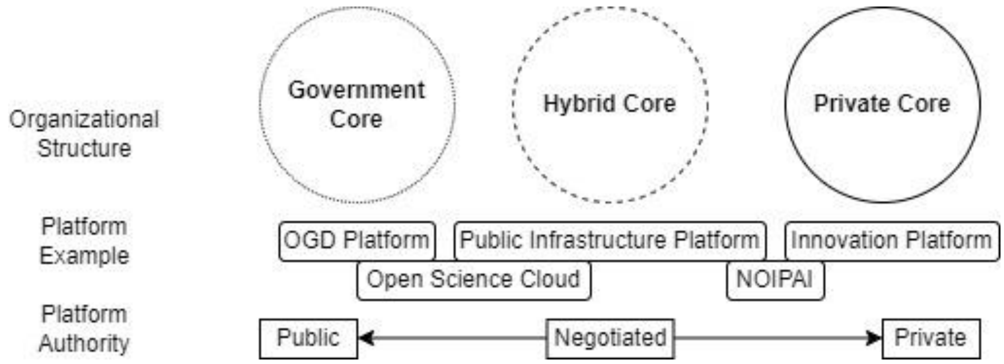
Figure 3. Government mechanisms for platform boundary resource tuning.



Hybrid platform initiatives also include establishing entirely new forms of organization with unique boundary resources that can be explicitly aimed at enhancing AI innovation. For example, in the United States, the National Research Cloud initiative aims to provide academic and non-profit researchers with enhanced access to compute and government datasets for education and research (Ho et al., 2021). In Europe, the European Open Science Cloud (EOSC) similarly aims at providing "researchers, innovators, companies, and citizens with a federated and open multi-disciplinary environment where they can publish, find and re-use data, tools, and services for research, innovation and educational purposes" (European Commission, 2020, p.1).

China has also established a national research cloud, the China Science and Technology Cloud, and the push to create NOIPAIs should be viewed as a complementary strategy that seeks to affect the boundary resources and generativity of leading private sector innovation platforms in ways that do not result in the construction of a hybrid platform arrangement. Instead, the NOIPAI policy initiative seeks to affect the AI production function by increasing the availability of private sector resourcing tools. This pulls the initiative toward a negotiated form of platform authority and control without establishing hybrid platforms. Instead, NOIPAIs continue to be based on application-driven, enterprise-led, and market-oriented principles (Wu et al., 2020). Our analysis confirms that the formation of hybrid public infrastructure platforms is only indirectly associated with the NOIPAI initiative but does have important implications for NOIPAIs in terms of creating feedback loops that may affect resourcing tools (see Fig. 2). China's NOIPAI case invites and possibly demands rethinking how policymakers seek to orchestrate open data availability and AI-related OSS accessibility without maintaining control over the value creation process itself (Janssen & Helbig, 2016).

Figure 4. The centralization of platform authority in different organizational structures.



Different government mechanisms and processes for government-induced boundary resource tuning are directly associated with organizational structure, which is argued to move across government, hybrid, and private platform constellations. As detailed throughout the paper, government mechanisms can affect resourcing tools and securing rules in a range of ways that have important direct and indirect implications for platform governance and the process of boundary resource tuning.

5.7 *Implications for research*

Based on the findings and discussion, several implications for research emerge. First, the existing theory of boundary resources has been extended (Bonina and Eaton, 2020; Eaton *et al.*, 2015; Ghazawneh and Henfridsson, 2010, 2013) through clarification of external factors as concrete government mechanisms that can be used to influence innovation platforms boundary resources. Government mechanisms have important implications for how resourcing tools and securing rules are structured and governed, which has consequences for data availability, software accessibility, and digital forms of interoperability. The suggested government mechanisms reorient existing theories on platform governance (Constantinides et al., 2018; Ghazawneh and Henfridsson, 2010, 2013) towards the role of the government in shaping and affecting platform boundary resources. For governments, the toolkit on how to influence platform boundary resources remains nascent, which means that the findings presented here have important implications for how governments continue to engage in a platform-induced way of thinking and organization (Brown et al., 2017; Cordella & Paletti, 2019; Ju et al., 2019; Klievink et al., 2017; Zhao & Fan, 2018). The findings of the paper contribute to an emerging research agenda centered on new and emergent ways in which governments seek to structure and orchestrate the platform economy while ensuring fair competition and supporting (AI) generativity.

Second, this paper has focused empirically on a case of boundary resource tuning in China. This case has provided insights into government mechanisms in a state-capitalist setting. However, some of the uncovered mechanisms are unique to China. The Great Firewall, for example, censors information and regulates the internet in ways that contrast with governance mechanisms deployed elsewhere. China's recent ban on for-profit educational-technology platforms (Chan et al., 2021) and the requirement that private-sector technology companies sometimes reserve board seats for Party members (Yang & Goh, 2021) are additional examples of uniquely Chinese mechanisms to affect the platform economy in China. It is crucial to understand which elements of one country's platform boundary resource tuning mechanism are transferrable to other countries, and which are not. This paper contributes to opening this agenda by reorienting the platform literature towards how resourcing tools and securing rules are shaped by the interplay of government mechanisms and private-sector platform governance (Cordella & Paletti, 2019; Gorwa, 2019; Raunio et al., 2018).

Third, the study contributes to the literature on platform architecture and digital infrastructure by elaborating on the growing role of hybrid platforms (Constantinides et al., 2018; Klievink et al., 2016; Tilson et al., 2010). Many elements of China's National Open Innovation Platforms for AI exhibit hybrid infrastructural elements that have been little studied (Klievink et al., 2016) but have several implications for research. This paper has taken a step by demonstrating the value of treating government, hybrid and private platforms as distinct forms of organization, which have important implications for platform authority and the processes of boundary resource tuning. Authority and control over tuning mechanisms are likely to differ considerably across the three forms of organization, which makes it an area of research that needs be further studied and understood.

Finally, implications are found in relation to AI innovation and the role of governments in affecting access to resourcing tools such as data availability, software and compute accessibility, and platform openness and interoperability. How governments seek to affect the generativity associated with each area has important implications for AI innovation going forward. Therefore, the paper's findings contribute to the growing literature on the role of the government as a strategic enabler (Battisti et al., 2022) and a regulator of AI and the digital economy (Lee et al., 2019).

5.8 *Implications for practice*

For policymakers, implications revolve around how varying mechanisms may affect the boundary resources of platforms and what it means for platform innovation in areas such as AI development. Policymakers need to know how new and existing mechanisms may be used to support and regulate platforms' process of boundary resource tuning. These mechanisms have direct and indirect effects on platform resourcing tools and securing rules and can guide specific behavior in the digital economy, for example, in relation to AI generativity. Mechanisms may include information and data mechanisms (e.g., OGD, data trusts, shared data repositories), interoperability mechanisms (e.g., censorship, software, competition, data), or legal and contractual mechanisms (e.g., GDPR, reporting, auditing), among others. These mechanisms have implications for the availability of data, the accessibility of software, and domestic and international forms of interoperability. For their part, policymakers have at their disposal an extended range of organizational mechanisms (e.g., hybrid platforms and information infrastructure, procurement) that can be used to affect or create new areas of public value creation. Fruitful strategies already engage with fostering open and inclusive forms of data sharing and open-source software distribution. Policymakers should strive toward deploying mechanisms that target interoperability, participation, or anti-competitive behavior without deploying overly discriminatory measures to enhance digital sovereignty at the cost of international forms of digital integration and cooperation.

For managers of international innovation platforms, implications involve navigating among the ways platform openness and ecosystem integration can be strategized across fragmented international borders and digital ecosystems. Managerial considerations include how policy mechanisms can be a confounding factor in limiting or enabling specific resourcing tools or securing rules. Given the rise of interest in reinforcing varying forms of digital sovereignty, managers should pay special attention to local or regional, i.e., geographical platform requirements, e.g., data use, access, openness, interoperability, portability, and control. The kind of services offered on international innovation platforms and how these stay compliant with legal requirements in different countries and constituencies is a rising case in point.

6. Limitations and future research

This study has several limitations. The first limitation concerns the geographic location of the study. While China's rise to world leader status in terms of AI innovation was relatively quick (Zhang et al., 2021), many of the government's industrial policies and political interventions, e.g., in terms of strategy, financing, and AI ethics (Roberts et al., 2021), are difficult and possibly impossible for other governments to replicate. By implication, not all conclusions drawn from the analysis may be applicable to other geographical contexts. This means that government mechanisms could look different elsewhere. While the paper has nuanced its findings by articulating examples of government mechanisms from other countries, an exhaustive list of government mechanisms for boundary resource tuning has not been established. Instead, this paper has provided the foundation for establishing a more extensive research agenda on the governance of platform boundary resources at the intersection of public and private interests. More research and documentation are therefore needed in terms of how varying government mechanisms can be used to affect the process of boundary resource tuning. Future studies are encouraged to look into government mechanisms for boundary resource tuning in other geographical contexts or could try to assess what differing government mechanisms mean for international platforms' operation and organization and forms of (AI) innovation. The interrelations between international platforms' operation, and national forms of constraint, is an important area to be studied further. How varying national regimes affect the boundary resources of international platforms differently will have important implications for digital sovereignty and digital competition going forward.

The second limitation concerns data analysis. The study's classification of governance mechanisms might have been influenced by subjective bias in interpreting the empirical data. However, the adopted protocol for coding interviews and document-based data (Strauss & Corbin, 1998) should have minimized the risk of bias in interpretation. To further mitigate these concerns, future studies could engage in a replication of the uncovered government mechanisms, perhaps based on a different case study, or could seek to determine their applicability to other geographical contexts and cases. This approach would contribute to the emergence of a more stringent and generalizable set of government mechanisms, which may be more widely applied across geographical contexts. This would strengthen knowledge of the international applicability of government mechanisms for boundary resource tuning while limiting potential biases in the individual studies. That is, the proposed government mechanism categories could be further tested, elaborated, and extended in future studies.

Third, direct contact with policymakers responsible for formulating and implementing the NOIPAI initiative was not established in this study, perhaps due to the increased sensitivity of China's industrial policies or political tensions in international high-tech competition. This represents a limitation in terms of public-sector verifiability of the results. Future studies could mitigate this limitation by interviewing policymakers who are in a position to describe and explain government intentions regarding the NOIPAI initiative. This would be informative in understanding how the NOIPAI initiative continues to evolve and expand, and how the individual platforms contribute to a larger policy agenda, e.g., in terms of AI-related digital infrastructure building at a national level.

Finally, more research needs to be aimed at the role and structure of hybrid platforms, including how these are used as organizational mechanisms for novel public-private forms of interaction and governance. The findings of this paper encourage a more comprehensive research agenda to be built around the formation of hybrid platforms as a distinct form of organization and governance. In terms of AI innovation, the ongoing centralization of resourcing tools such as data and compute in large platforms could be partially alleviated by establishing hybrid platforms and research clouds that provide better and more equal access to resources. The organization of boundary resources associated with hybrid platforms and how these inform AI innovation exemplifies a nascent agenda with promising avenues for future research.

References

Aapti Institute, Open Data Institute, G. (2021). *Enabling data sharing for social benefit through data trusts An Interim Report for the 2021 GPAI Paris Summit*. 1–105.

Alibaba. (2021). *City Brain Lab*. https://damo.alibaba.com/labs/city-brain

Ansell, C., & Gash, A. (2007). Collaborative Governance in Theory and Practice. *Journal of Public Administration Research and Theory*, 543–571. https://doi.org/10.1093/jopart/mum032

Ansell, C., & Gash, A. (2018). Collaborative platforms as a governance strategy. *Journal of Public Administration Research and Theory*, *28*(1), 16–32. https://doi.org/10.1093/jopart/mux030

AOSS. (2018). White Paper on the Development of China's Artificial Intelligence Open Source Software. *China AI Open Source Software Development League*, *March*.

Arenal, A., Armuña, C., Feijoo, C., Ramos, S., Xu, Z., & Moreno, A. (2020). Innovation ecosystems theory revisited: The case of artificial intelligence in China. *Telecommunications Policy*, *44*(6). https://doi.org/10.1016/j.telpol.2020.101960

Baldwin, C. Y., & Woodard, J. C. (2009). *The Architecture of Platforms: A Unified View*. http://ink.library.smu.edu.sg/sis_research

Barrett, M., Oborn, E., Orlikowski, W. J., & Yates, J. A. (2012). Reconfiguring boundary relations: Robotic innovations in pharmacy work. *Organization Science*, *23*(5), 1448–1466. https://doi.org/10.1287/orsc.1100.0639

Battisti, S., Agarwal, N., & Brem, A. (2022). Creating new tech entrepreneurs with digital platforms: Meta-organizations for shared value in data-driven retail ecosystems. Technological Forecasting and Social Change, 175(December 2021), 121392.

Băzăvan, A. (2019). Chinese government's shifting role in the national innovation system. *Technological Forecasting and Social Change*, *148*(June). https://doi.org/10.1016/j.techfore.2019.119738

Beraja, M., Yang, D. Y., & Yuchtman, N. (2021). Data-intensive Innovation and the State : Evidence from AI Firms in China. *NBER Working Paper*. https://doi.org/10.3386/w27723

Bianco, V. D., Myllarniemi, V., Komssi, M., & Raatikainen, M. (2014). The role of platform boundary resources in software ecosystems: A case study. *Proceedings - Working IEEE/IFIP Conference on Software Architecture 2014, WICSA 2014*, *April*, 11–20. https://doi.org/10.1109/WICSA.2014.41

Birkinshaw, J., Brannen, M. Y., & Tung, R. L. (2011). From a distance and generalizable to up close and grounded : Reclaiming a place for qualitative methods in international business research. *Journal of International Business Studies*, *42*(5), 573–581. https://doi.org/10.1057/jibs.2011.19

Bommasani, R., Hudson, D. A., Adeli, E., Altman, R., Arora, S., von Arx, S., Bernstein, M. S., Bohg, J., Bosselut, A., Brunskill, E., Brynjolfsson, E., Buch, S., Card, D., Castellon, R., Chatterji, N., Chen, A., Creel, K., Davis, J. Q., Demszky, D., … Liang, P. (2021). *On the*

Opportunities and Risks of Foundation Models. 1–212. http://arxiv.org/abs/2108.07258

Bonina, C., & Eaton, B. (2020). Cultivating open government data platform ecosystems through governance: Lessons from Buenos Aires, Mexico City and Montevideo. *Government Information Quarterly*, *37*(3), 101479. https://doi.org/10.1016/j.giq.2020.101479

Bonina, C., Koskinen, K., Eaton, B., & Gawer, A. (2021). Digital platforms for development: Foundations and research agenda. *Information Systems Journal*, *October 2019*, 1–34. https://doi.org/10.1111/isj.12326

Boudreau, K. J., & Hagiu, A. (2009). Platform rules: Multi-sided platforms as regulators. *Platforms, Markets and Innovation*, *November 2008*, 163–191. https://doi.org/10.4337/9781849803311.00014

Bouras, C., Filopoulos, A., Kokkinos, V., Michalopoulos, S., Papadopoulos, D., & Tseliou, G. (2014). Policy recommendations for public administrators on free and open source software usage. *Telematics and Informatics*, *31*(2), 237–252. https://doi.org/10.1016/j.tele.2013.06.003

Brown, A., Fishenden, J., Thompson, M., & Venters, W. (2017). Appraising the impact and role of platform models and Government as a Platform (GaaP) in UK Government public service reform: Towards a Platform Assessment Framework (PAF). *Government Information Quarterly*, *34*(2), 167–182. https://doi.org/10.1016/j.giq.2017.03.003

Ceccagnoli, Forman, Huang, & Wu. (2012). Cocreation of Value in a Platform Ecosystem! The Case of Enterprise Software. *MIS Quarterly*, *36*(1), 263. https://doi.org/10.2307/41410417

Cennamo, C., & Santalo, J. (2013). PLATFORM COMPETITION: STRATEGIC TRADE-OFFS IN PLATFORM MARKETS. *Strategic Management Journal*, *34*, 1331–1350.

Chan, E., Gao, Y., & Chen, L. (2021). China Bans For-Profit School Tutoring in Sweeping Overhaul. *Bloomberg*, July. https://www.bloomberg.com/news/articles/2021-07-24/china-bans-school-curriculum-tutoring-firms-from- going-public

Chen, Pereira, I., & Patel, P. C. (2021). Decentralized Governance of Digital Platforms. *Journal of Management*, *47*(5), 1305–1337. https://doi.org/10.1177/0149206320916755

Chen, R. (2019). Policy and Regulatory Issues with Digital Businesses. *Policy and Regulatory Issues with Digital Businesses*, *July*. https://doi.org/10.1596/1813-9450-8948

Chen, Y., & Lee, J. (2018). Collaborative data networks for public service : governance , management , and performance. *Public Management Review*, *20*(5), 672–690. https://doi.org/10.1080/14719037.2017.1305691

Chesbrough, H. (2006). *Open Innovation: The New Imperative for Creating and Profiting From Technology*. Harvard Business Press.

China Daily. (2019). *Unique basic software and hardware advantages, Huawei was selected as the national AI open innovation platform China*. *September*. https://baijiahao.baidu.com/s?id=1643532703251004033&wfr=spider&for=pc

Cingolani, L. (2021). The survival of open government platforms: Empirical insights from a global sample. *Government Information Quarterly*, *38*(1), 101522. https://doi.org/10.1016/j.giq.2020.101522

Constantinides, P., Henfridsson, O., & Parker, G. G. (2018). Platforms and infrastructures in the digital age. *Information Systems Research*, *29*(2), 381–400. https://doi.org/10.1287/isre.2018.0794

Cordella, A., & Paletti, A. (2019). Government as a platform, orchestration, and public value creation: The Italian case. *Government Information Quarterly*, *36*(4), 101409. https://doi.org/10.1016/j.giq.2019.101409

Cusumano, M. A., Gawer, A., & Yoffie, D. B. (2019). *The Business of Platforms: Strategy in the Age of Digital Competition, Innovation, and Power*. Harper Business.

De Reuver, M., Sørensen, C., & Basole, R. C. (2018). The digital platform: A research agenda. *Journal of Information Technology*, *33*(2), 124–135. https://doi.org/10.1057/s41265-016-0033-3

Eaton, B., Elaluf-Calderwood, S., Sørensen, C., & Yoo, Y. (2015). Distributed tuning of boundary resources: The case of Apple's iOS service system. *MIS Quarterly*, *39*(1), 217–243. https://doi.org/10.25300/MISQ/2015/39.1.10

Eisenhardt, K. M. (1989). *Building Theories from Case Study Research*. *14*(4), 532–550.

European Commission. (2020). *European Open Science Cloud (EOSC)*. https://eosc-portal.eu/

Floridi, L. (2020). The Fight for Digital Sovereignty: What It Is, and Why It Matters, Especially for the EU. *Philosophy and Technology*, *33*(3), 369–378. https://doi.org/10.1007/s13347-020-00423-6

Gasser, U. (2015). Interoperability in the Digital Ecosystem. *Berkman Klein Center for Internet and Society Research*, *13*.

Gawer, A. (2009). *Platforms, Markets and Innovation* (Issue January). https://doi.org/10.4337/9781849803311.00006

Gawer, A. (2014). Bridging differing perspectives on technological platforms : Toward an integrative framework. *Research Policy*, *43*(7), 1239–1249. https://doi.org/10.1016/j.respol.2014.03.006

Gawer, A., & Cusumano, M. A. (2013). Industry platforms and ecosystem innovation. *Journal of Product Innovation Management*, *31*(3), 417–433. https://doi.org/10.1111/jpim.12105

Geradin, D. (2021). What Is a Digital Gatekeeper? Which Platforms Should Be Captured by the EC Proposal for a Digital Market Act? *SSRN Electronic Journal*, *June 2017*, 1–20. https://doi.org/10.2139/ssrn.3788152

Ghazawneh, A., & Henfridsson, O. (2010a). Governing third-party development through platform boundary resources. *ICIS 2010 Proceedings - Thirty First International Conference on Information Systems*.

Ghazawneh, A., & Henfridsson, O. (2010b). Governing Third-Party Development through Platform boundary Resources. *Proceedings of the International Conference on Information Systems, ICIS 2010*.

Ghazawneh, A., & Henfridsson, O. (2013). Balancing platform control and external contribution in third-party development: The boundary resources model. *Information Systems Journal*, *23*(2), 173–192. https://doi.org/10.1111/j.1365-2575.2012.00406.x

Gorwa, R. (2019). What is platform governance. *Information Communication and Society*.

Gorwa, R., Binns, R., & Katzenbach, C. (2020). Algorithmic content moderation: Technical and political challenges in the automation of platform governance. *Big Data and Society*, *7*(1). https://doi.org/10.1177/2053951719897945

GOV.UK. (2019). AI Sector Deal. *Policy Paper*, 1–16. https://www.gov.uk/government/publications/artificial-intelligence-sector-deal/ai-sector-deal

Hagiu, A., & Wright, J. (2015). Multi-sided platforms. *International Journal of Industrial Organization*, *43*, 162–174. https://doi.org/10.1016/j.ijindorg.2015.03.003

Hanna, N. (2018). A role for the state in the digital age. *Journal of Innovation and Entrepreneurship*, *7*(1). https://doi.org/10.1186/s13731-018-0086-3

Henfridsson, O., & Bygstad, B. (2013). The generative mechanisms of digital infrastructure evolution. *MIS Quarterly: Management Information Systems*, *37*(3), 907–931. https://doi.org/10.25300/MISQ/2013/37.3.11

Hickert, C., & Ding, J. (2018). What Top Chinese Officials Are Hearing About AI Competition and Policy. *New America*, *November*.

Ho, D. E., King, J., Wald, R. C., & Wan, C. (2021). Building a National Resource: A Blueprint for the National Research Cloud. *HAI - Stanford University Human-Centered AI*, *October*.

Huhtamäki, J., Basole, R. C., Still, K., Russell, M. G., & Seppänen, M. (2017). Visualizing the geography of platform boundary resources: The case of the global API ecosystem. *Proceedings of the Annual Hawaii International Conference on System Sciences*, *2017-Janua*(July), 5305–5314. https://doi.org/10.24251/hicss.2017.642

Iansiti, M., & Levien, R. (2004). Strategy as Ecology. *Harvard Business Review*, *82*(3). https://doi.org/10.1108/eb025570

Jacobides, M. G., Sundararajan, A., & Alstyne, M. Van. (2019). Platforms and Ecosystems: Enabling the Digital Economy February. *World Economic Forum*, *February*. www.weforum.org

Janssen, M., Chun, S. A., & Gil-Garcia, J. R. (2009). Building the next generation of digital government infrastructures. *Government Information Quarterly*, *26*(2), 233–237. https://doi.org/10.1016/j.giq.2008.12.006

Janssen, M., & Helbig, N. (2016). Innovating and changing the policy-cycle: Policy-makers be prepared! *Government Information Quarterly*, *35*(4), S99–S105.

https://doi.org/10.1016/j.giq.2015.11.009

Jones, M. R. (1998). Information systems and the double mangle: Steering a course between the Scylla of embedded structure and the Charybdis of material agency. *Information Systems: Current Issues and Future Challenges*, 287–302.

Ju, J., Liu, L., & Feng, Y. (2019). Public and private value in citizen participation in E-governance: Evidence from a government-sponsored green commuting platform. *Government Information Quarterly*, *36*(4), 101400. https://doi.org/10.1016/j.giq.2019.101400

Kallinikos, J., & Tempini, N. (2014). Patient data as medical facts: Social media practices as a foundation for medical knowledge creation. *Information Systems Research*, *25*(4), 817–833. https://doi.org/10.1287/isre.2014.0544

Karhu, K., Gustafsson, R., & Lyytinen, K. (2018). Exploiting and defending open digital platforms with boundary resources: Android's five platform forks. *Information Systems Research*, *29*(2), 479–497. https://doi.org/10.1287/isre.2018.0786

Kim, S., Andersen, K. N., & Lee, J. (2021). Platform Government in the Era of Smart Technology. In *Public Administration Review*. https://doi.org/10.1111/puar.13422

Klievink, B., Bharosa, N., & Tan, Y. H. (2016). The collaborative realization of public values and business goals: Governance and infrastructure of public-private information platforms. *Government Information Quarterly*, *33*(1), 67–79. https://doi.org/10.1016/j.giq.2015.12.002

Klievink, B., Romijn, B. J., Cunningham, S., & de Bruijn, H. (2017). Big data in the public sector: Uncertainties and readiness. *Information Systems Frontiers*, *19*(2), 267–283. https://doi.org/10.1007/s10796-016-9686-2

Kretschmer, T., Leiponen, A., Schilling, M., & Vasudeva, G. (2020). Platform ecosystems as meta-organizations: Implications for platform strategies. *Strategic Management Journal*, *October 2020*, 1–20. https://doi.org/10.1002/smj.3250

Lee, Y. S., Larsen, B., Webb, M., & Cuellar, M.-F. (2019). *HOW WOULD AI REGULATION CHANGE FIRMS ' BEHAVIOR ? EVIDENCE FROM THOUSANDS OF MANAGERS*. *19*.

Lomas, N. (2020). Europe lays out antitrust case against Amazon's use of big data. *TechCrunch*, November. https://techcrunch.com/2020/11/10/europe-lays-out-antitrust-case-against-amazons-use-of-big-data/?guccounter=1&guce_referrer=aHR0cHM6Ly93d3cuZ29vZ2xlLmNvbS8&guce_referrer_sig=AQAAADCF78CiWcyqEr0IVZr7CU5s8S3qBO0Q9QcDabJeyyf7jDcecWX05laW6T4PqcHj9b2sGl225wuK

Marsan, J., Paré, G., & Beaudry, A. (2012). Adoption of open source software in organizations: A socio-cognitive perspective. *Journal of Strategic Information Systems*, *21*(4), 257–273. https://doi.org/10.1016/j.jsis.2012.05.004

Martens, B. (2016). An Economic Policy Perspective on Online Platforms. *Institute for Prospective Technological Studies Digital Economy Working Paper, No. 2016/05, European Commission, Joint Research Centre (JRC), Seville*. https://doi.org/10.2139/ssrn.2783656

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information and Management*, *58*(3), 103434. https://doi.org/10.1016/j.im.2021.103434

Mikhaylov, S. J., Esteve, M., & Campion, A. (2018). *Artificial intelligence for the public sector : opportunities and challenges of cross-sector collaboration Subject Areas :*

Mills, Birks, & Hoare. (2014). Grounded theory. In: Mills J and Birks M (eds) Qualitative methodology: a practical guide. In *Qualitative methodology: a practical guide* (pp. 107–121). SAGE.

MOST. (2019). Notice of the Ministry of Science and Technology on Printing and Distributing the "Guidelines for the Construction of the National New Generation Artificial Intelligence Open Innovation Platform." *Ministry of Science and Technology*, *August*. http://www.gov.cn/xinwen/2019-08/04/content_5418542.htm

Myllärniemi, V., Kujala, S., Raatikainen, M., & Sevońn, P. (2018). Development as a journey: factors supporting the adoption and use of software frameworks. *Journal of Software Engineering Research and Development*, *6*(1). https://doi.org/10.1186/s40411-018-0050-8

Nachum, L. (2012). Global Comparative Strategy. *Global Strategy Journal*, *95*, 92–95. https://doi.org/10.1111/j.2042-5805.2011.01028.x

Nooren, P., van Gorp, N., van Eijk, N., & Fathaigh, R. (2018). Should We Regulate Digital Platforms? A New Framework for Evaluating Policy Options. *Policy and Internet*, *10*(3), 264–301. https://doi.org/10.1002/poi3.177

Osterwalder, A., & Pigneur, Y. (2010). *Business Model Generation. A Handbook for Visionaries, Game Changers, and Challengers*. John Wiley & Sons.

Panagiotopoulos, P., Klievink, B., & Cordella, A. (2019). Public value creation in digital government. *Government Information Quarterly*, *36*(4). https://doi.org/10.1016/j.giq.2019.101421

Panchenko, V., Reznikova, N., & Bulatova, O. (2020). Regulatory competition in the digital economy: new forms of protectionism. *International Economic Policy*, *33*(32–33), 49–79. https://doi.org/10.33111/iep.2020.32_33.03_eng

Pickering, A. (1993). The Mangle of Practice: Agency and Emergence in the Sociology of Science. *American Journal of Sociology*, *99*(3), 559–589.

Pustovrh, A., & Drnov, M. (2020). The role of open innovation in developing an entrepreneurial support ecosystem. *Technological Forecasting & Social Change*, *152*(November 2019). https://doi.org/10.1016/j.techfore.2019.119892

Radinsky, K. (2015). Data monopolists like Google are threatening the economy. *Harvard Business Review*.

Rahman, K. S., & Thelen, K. (2019). The rise of the platform business model and the transformation of twenty-first-century capitalism. *Politics and Society*, *47*(2), 177–204. https://doi.org/10.1177/0032329219838932

Raji, I. D., Smart, A., White, R. N., Mitchell, M., Jan, C. Y., Hutchinson, B., & Barnes, P. (2020). Closing the AI Accountability Gap : Defining an End-to-End Framework for Internal Algorithmic Auditing. *ArXiv*.

Raunio, M., Nordling, N., Kautonen, M., & Räsänen, P. (2018). Open innovation platforms as a knowledge triangle policy tool – Evidence from Finland. *Foresight and STI Governance*, *12*(2), 62–76. https://doi.org/10.17323/2500-2597.2018.2.62.76

Rho, S., Lee, K., & Kim, S. H. (2015). Limited catch-up in China's semiconductor industry: A sectoral innovation system perspective. *Millennial Asia*, *6*(2), 147–175. https://doi.org/10.1177/0976399615590514

Roberts, H., Cowls, J., Morley, J., Taddeo, M., Wang, V., & Floridi, L. (2021). The Chinese approach to artificial intelligence : an analysis of policy , ethics , and regulation. *AI & SOCIETY*, *36*(1), 59–77. https://doi.org/10.1007/s00146-020-00992-2

Simcoe, T. (2012). Standard Setting Committees: Consensus Governance for Shared Technology Platforms. *The American Economic Review*, *102*(1), 305–336.

Strauss, A., & Corbin, J. (1998). Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory. In *Management Learning* (Vol. 31, Issue 4). Sage Publications, Inc. https://doi.org/10.1177/1350507600314007

Tencent. (2018). *Miying Lab*. https://miying.qq.com/official/detailnews/642

Tie, Y., Birks, M., & Francis, K. (2019). Grounded theory research: A design framework for novice researchers. *SAGE Open Medicine*, *7*, 205031211882292. https://doi.org/10.1177/2050312118822927

Tsujimoto, M., Kajikawa, Y., Tomita, J., & Matsumoto, Y. (2018). A review of the ecosystem concept — Towards coherent ecosystem design. *Technological Forecasting and Social Change*, *136*(June 2017), 49–58. https://doi.org/10.1016/j.techfore.2017.06.032

Von Hippel, E., & Von Krogh, G. (2003). Open source software and the "private-collective" innovation model: Issues for organization science. *Organization Science*, *14*(2). https://doi.org/10.1287/orsc.14.2.209.14992

Wang, V., & Shepherd, D. (2020). Exploring the extent of openness of open government data – A critique of open government datasets in the UK. *Government Information Quarterly*, *37*(1), 101405. https://doi.org/10.1016/j.giq.2019.101405

Wareham, J. D., Fox, P., & Giner, J. L. (2014). Technology Ecosystem Governance. *Organization Science*, *June 2018*. https://doi.org/10.2139/ssrn.2201688

Wu, F., Lu, C., Zhu, M., Chen, H., Zhu, J., Yu, K., Li, L., Li, M., Chen, Q., Li, X., Cao, X., Wang, Z., Zha, Z., Zhuang, Y., & Pan, Y. (2020). Towards a new generation of artificial intelligence in China. *Nature Machine Intelligence*, *2*(6), 312–316. https://doi.org/10.1038/s42256-020-

0183-4

Xinhua. (2017). *15 ministries and commissions work together to establish the first batch of 4 national innovation platforms - focusing China's new generation of artificial intelligence development plan*. http://www.gov.cn/guowuyuan/2017-11/23/content_5241718.htm

Xue, L. (2018). *China AI Development Report 2018*. *July*.

Yang, Y., & Goh, B. (2021). Beijing took stake and board seat in key ByteDance domestic entity this year. *Reuters*, *August*. https://www.reuters.com/world/china/beijing-owns-stakes-bytedance-weibo-domestic-entities-records-show- 2021-08-17/

Yin, R. K. (2003). *Case Study Research*. SAGE.

Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). The new organizing logic of digital innovation: An agenda for information systems research. *Information Systems Research*, *21*(4), 724–735. https://doi.org/10.1287/isre.1100.0322

Zhang, D., Mishra, S., Brynjolfsson, E., Etchemendy, J., Ganguli, D., Grosz, B., Lyons, T., Manyika, J., Niebles, J. C., Sellitto, M., Shoham, Y., Clark, J., & Perrault, R. (2021). *2021 AI Index Report*. 1–222. https://aiindex.stanford.edu/report/

Zhao, Y., & Fan, B. (2018). Exploring open government data capacity of government agency: Based on the resource-based theory. *Government Information Quarterly*, *35*(1), 1–12. https://doi.org/10.1016/j.giq.2018.01.002

Zittrain, J. (2006). THE GENERATIVE INTERNET Jonathan. *Harvard Law Review*.

Appendix A. List of interview questions

- How has China's AI industry developed over time? Which factors have been important for its development?
- How is your company engaged in AI research, and how does that feed into creating innovation? And relatedly, what is the most important research or practical application of AI technologies, and how do you view this interrelationship and the feedback mechanisms between them?
- If your company has a strategic partnership with universities/research institutes, then how does this partnership/alliance work on a practical level, and how does it feed into your company's technological innovation trajectory?
- What are the main opportunities for AI entrepreneurs in China / what are their main obstacles?
- Does the government support your company in terms of AI innovation?
- How does your company engage in the construction of National Open Innovation Platforms for AI?
- Your company was recently announced as a "National Open Innovation Platform for New-Generation Artificial Intelligence"; what does that entail for the company? How is your company building this platform? What does the partnership involve, and how is your company's platform contributing to China's AI ecosystem?
- How does your company open up data and software on the platform?
- How does your company determine what the right degree of platform openness is? And what are some of the rules that your company has devised in terms of ecosystem engagement?
- What do you think the government tries to achieve through the establishment of National Open Innovation Platform for New-Generation Artificial Intelligence?
- Are certain parts of the platform governed by both the company and the government? How are these forms of joint governance negotiated?
- What does the government do to enable AI innovation? For example, does it also contribute by providing government data and so on?
- Competition on AI in China is fierce; how does your company manage to stay ahead and leverage the overall ecosystem in the development of its technology, i.e., access to talent, venture capital, acquisition of AI start-ups, etc. – what is most important to your company in this regard?
- How does innovation in AI in China compare to innovation in AI in Silicon Valley or in Europe?
- Which AI trends should we watch out for in the coming years? Which direction are we headed in?

Article IV

US–China Tech Competition and the Willingness to Share Personal Data in China

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Abstract

We examine whether invoking nationalistic sentiment surrounding the technology race and competition between the US and China influences people's willingness to share private data with companies and the central and local governments in China. We conduct a randomized online experiment to assess whether being reminded of the US–China tech competition in artificial intelligence (AI) affects respondents' willingness to share data. We also assess whether being reminded of US sanctions on Chinese tech companies or being reminded of data collection practices by Chinese government agencies affect data privacy preferences. We find that reminding Chinese internet users of the technology race with the US invokes nationalistic sentiment, which increases respondents' willingness to share data with Chinese companies and trust in these to handle their data responsibly. When people are reminded of the US–China tech competition, they also decrease the valuation they place on their facial image data, thus making data a cheaper input factor, e.g., in AI innovation. We find that males are more willing to share their data with private companies and the central and local governments when invoked with a sense of tech nationalism. As the development of China's surveillance regime on the public and private sides of the spectrum is likely to continue,

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our findings show that invoking nationalistic sentiment can increase people's willingness to share data with private companies and the government.

Keywords: Tech competition; nationalism; data privacy; China
JEL codes: F52 (National Security • Economic Nationalism), O33 (Technological Change: Choices and Consequences • Diffusion Processes), P30 (Socialist Institutions and Their Transitions)

1. Introduction

Data is fundamental to the development of digital technologies and artificial intelligence. Massive data libraries enable both businesses and governments to develop increasingly precise algorithms that, in turn, create personalized and convenient digital products and services. Firms and organizations with access to proprietary data conduct R&D and innovate at the frontier, while those without such access often lag behind. At the same time, the collection and use of data by firms and governments has raised concerns about data privacy and ethics. People are often unaware of how, when, and which data companies and governments collect. Accordingly, more calls for regulations that aim to control the collection and use of data have been proposed around the world.

The tension between innovation and privacy is inherent to such recent digital technologies as artificial intelligence, information technologies, web platforms, and smartphone applications. However, as tech firms become global, the debates surrounding data privacy and collection have moved beyond consumers and firms within a country and have recently manifested in tensions between nation-states. When the EU implemented the GDPR, there were concerns that China, with no similar data privacy regulation, would jump ahead in AI development, because new rules would raise the cost of collecting large amounts of data (Li et al., 2021). In the US, several Chinese companies have been placed on an entity list that restricts them from obtaining critical American products, sometimes associated with concerns over illegally collecting US citizens' data or that the companies could be forced to hand over such data to the Chinese Communist Party.

In the case of the US and China, conflicts involving tech companies, data privacy, and differing data regimes have evolved into a technology war that is sometimes referred to as the "great tech decoupling" (Johnson & Gramer, 2020). Nationalistic sentiment has since been fueled on both sides of the Pacific. In the US, the Trump Administration proposed the Clean Network program to safeguard citizens' privacy and companies' sensitive information from malign actors such as the Chinese Communist Party (US Department of State, 2021). In China, US foreign policy is viewed as a strategy to contain China. US actions against Chinese companies such as Huawei have been labeled "economic bullying," designed to impede the rise of China (Dupont, 2020). Disputes on trade and technology between the US and China are viewed as an accelerator of decoupling, fragmentation, and realignment throughout the digital economy (Capri, 2020). These developments could mean that governments also are more likely to devote additional resources to shaping public opinion on related issues.

The main goal of this article is to examine whether tech nationalism, understood as increasing nationalistic sentiment surrounding the technology race and competition between US and China, influences data privacy perceptions. Data privacy perceptions are understood as people's willingness to share their data with companies and the central and local governments. We ask how people in China perceive and react to various public and private forms of data collection, and whether technological competition with the United States affects data privacy preferences. To the best of our knowledge, we are the first to examine how tech nationalism affects perceptions of data privacy.

To examine this question, we surveyed 3,146 individuals in a representative sample of China's internet population. Through a randomized online experiment, we assess whether being reminded of the US–China tech competition in the area of AI affects respondents' willingness to share data with companies and with central and local governments. We also assess whether being reminded of US sanctions on Chinese tech companies affects data privacy preferences. By showing vignettes related to US–China great power contests (i.e., competition and sanctions), our survey experiment was designed to invoke a sense of nationalism and victimization. We use this mechanism to determine how tech nationalism affects people's willingness to share data with companies and the government. In addition to the two tech nationalism-related treatments, we also examine how being reminded of intrusive data collection practices by government agencies affects data privacy preferences.

We find that invoking nationalistic sentiment increases people's willingness to share their data with private companies. Furthermore, when respondents are primed with information regarding US–China technology competition, their trust in private companies to handle their data increases. Post-treatment respondents also believe more strongly that personal data helps to enable Chinese companies to take the lead in the global competition to develop AI technologies. In other words, reminding people of the technology race with the US invokes a nationalistic sentiment that increases both respondents' willingness to share data with Chinese companies and their trust in these to handle their data responsibly. When people are reminded of the US–China tech competition, they also lower the value they place on their facial image data, thus making data a cheaper input factor for AI innovation. In other words, great power competition between the US and China shifts respondents' willingness to share data with private companies. We also find that males are more willing to share their data with private companies and the central and local governments when invoked a sense of tech nationalism. Both findings are statistically significant.

The development of China's surveillance regime on the public and private side of the spectrum is likely to continue, and our findings show that invoking nationalistic sentiment could enhance people's willingness to share data with private companies and the government. Due to China's extensive control of online discourse across digital ecosystems, we posit that the central government can build support for its surveillance regime while building a distinct data protection regime that favors government centralization of data (i.e., government surveillance) in the long run.

2. Background

2.1 *China's data regime and data privacy*

China has embraced an increasing array of data-collection technologies, often powered by AI systems. The positive aspects of technology and data use in governance are already well known among the Chinese population. Private companies have long emphasized convenience, and the government has emphasized public safety. Recent papers have focused on China's government's use of data, e.g., in the social credit system (Kostka, 2019; Mac Síthigh & Siems, 2019), as an input in facial-recognition-related innovation (Beraja et al., 2021), or in the implementation of social control measures, including propaganda and censorship (King, Pan, & Roberts, 2017; Lu & Pan, 2020). Some forms of technology use come at the cost of infringements of citizen privacy. China's central government has, for example, worked to enable a range of public sector surveillance initiatives, such as facial recognition technologies. Similarly, China's private sector companies have been suspected of engaging in predatory data collection practices. These developments have caused Chinese citizens to raise concerns over data collection, hacking, illegal sale, and personal data leaks by private entities and the government (Mozur, 2018). Through lawsuits (S. Lu, 2020), citizens have contested the over-collection and abuse of personal data amassed through AI-powered facial recognition systems and other forms of surveillance technology, which expanded during the Covid-19 pandemic.

Chinese regulators have acknowledged that data misuse has been rampant in China and that it takes seriously the people's concern that their personal information must be protected (State Council, 2020). The Chinese Communist Party (CCP) and State Council even cited personal information infringement as an issue that could affect social stability during the country's 2021 Spring Festival holiday (Xinhua, 2020). China's government has therefore begun to curb data collection by companies and has launched several new laws to govern data collection and use. One of these is the Data Security Law (DSL), which went into effect in September 2021 and governs the creation, use, storage, transfer, and exploitation of data within China. The Personal Information Protection Law (PIPL), which went into effect in November 2021, mirrors the European Union's General Data Protection Regulation (GDPR) and enables individuals to decide when and how their data is used. This includes approving the use and processing of more sensitive data, such as biometrics, financial information, and location services. The law also addresses AI-related automated decision-making, requires transparency, fairness, and justice in decisions, and explains the process for cases that could have a significant impact on individuals' rights and interests. Individuals are also allowed to opt out of algorithmic targeting and automated decision-making (Liu et al., 2022).

While new laws are specifically targeted at data collection practices by the private sector, scrutiny of public sector surveillance practices remains absent (Pernot-leplay, 2020). State agencies are, for example, not required to disclose or provide others with the personal information they handle, except as provided by law and administrative regulations that remain arbitrary and subject to interpretation. Questions, therefore, remain about the extent to which state agencies are required to comply with the Personal Information Protection Law (Lee et al., 2021). While China's surveillance systems also remains subject to extensive areas of data misuse, these are much harder for citizens to contest and criticize. The inherent consequence of this political and legal framework is that the the government's perception of collective interest outweighs individual freedoms and data privacy.

In traditional Chinese society, collectivism largely ignored individual interests, including protecting individual privacy. The belief that the collective is more important than the individual differentiates China's sense of privacy from Western societies (Lü, 2005). In Western countries, laws based on human rights principles generally protect the individual from state power. In contrast, human rights in China are derived from the state itself, which means the interests of the state, the ultimate collectivity, remain above the individual's (Pernot-leplay, 2020, p. 108). This understanding explains why individuals are currently gaining significant data protection rights in the private sector but "cannot claim any remedies for the infringements of their privacy carried out by the state government" (Pernot-leplay, 2020, p. 109).

Therefore, the Chinese consumer's data privacy protection progresses, while the Chinese citizen's does not. This implies a difference between strengthening data protection at the individual level and strengthening the government's overview of an individual's data. Compared with Western democracies, the protection of a right to privacy in China is still limited, which makes it easier for the government to override this right to privacy in favor of the needs of the state, e.g., in terms of security and criminal investigations (Lü, 2005). For example, the Chinese government retains the power to request that companies provide access to an individual's personal information. A court order is not required, which illustrates the priority of government interests over rights described as fundamental in the West (Pernot-leplay, 2020, p. 107).

China, however, aims to strengthen its current data protection and data privacy regime with the objective of increasing Chinese consumers' trust in the digital economy by making the government a credible protector of consumer privacy. While pursuing this objective, the government seeks to retain control over domestic data while generating more precise rules that secure trust in how personal data is used and shared. Issues related to data privacy, with a focus on the protection of individuals' rights, especially from overreach by private-sector companies, are frequently discussed on China's official state media. Overreach on the part of the government, however, is rarely addressed in China's official media coverage (Rieger et al., 2020). The public debate surrounding facial recognition technology (FRT), for example, does not usually question the use of cameras by the police, and data-protection laws do not place any formal limits on government surveillance (Roussi, 2020). However, state-run media has also framed FRT as an instrument to detect corruption by local government officials, and Chinese newspapers have run critical articles that question some FRT use-cases, e.g., in the educational system.

China's state media plays an essential role in affecting public opinion and tends to focus mainly on the positive aspects of surveillance technologies (Rieger et al., 2020). This could be why Chinese consumers generally exhibit lower data privacy concerns than other countries (Morey et al., 2015).

Attitudes towards AI in China are also more optimistic than elsewhere, as documented in a 2020 survey on global attitudes towards AI and machine learning, which found that 59 percent of Chinese respondents consider the uses of AI to be mostly beneficial, and only nine percent consider it harmful (Neudert et al., 2020).

2.2 *Nationalism and data privacy*

Despite censorship and other controls on the free flow of information, debates over what type of political institutions are best for China and how individual freedoms should be protected continue to persist in China (King et al., 2013). This means that mass preferences remain important, as they influence policy and governance outcomes in authoritarian as well as democratic regimes (Wang, 2008; Weeks, 2008). Mass preferences associated with data gathering and data protection practices can therefore be used as indicators of the popularity of the current direction of China's data regime. Nonetheless, one might wonder about how mass preferences for data privacy in China are construed, and particularly whether ideology is associated with a distinct set of data privacy preferences.

Pan and Xu (2018), use data from a large-scale online survey to map China's ideological spectrum, and find that, while public preferences are multidimensional, some dimensions are highly correlated. For example, those who prefer authoritarian rule are also more likely to support nationalism and state intervention in the economy. Furthermore, those who prefer democratic institutions and values are more likely to support market reform but are less likely to be nationalistic. Furthermore, individuals from regions with higher economic development, trade openness, and urbanization (e.g., Guangdong, Shanghai, and Beijing) are more likely to lean towards the liberal, pro-market, and non-nationalist end of the spectrum, while those from poorer regions (e.g., Guizhou, Guangxi, and Henan) are, on average, more likely to lean towards the conservative, antimarket, and nationalist end of the spectrum.

China's central government also plays an active role in shaping how people identify with the state. One strategy is to construct an official national-historical narrative that establishes a sense of common past and shared future (Zerubavel, 1995). In the context of China, nationalism has been argued to embody a victim sentiment that exhibits a sense of humiliation and resentment (Woods & Dickson, 2017). Because Western countries threatened the survival of the Chinese nation in modern history, this feeling of victimhood naturally bears antagonism against foreign countries. The "victim" narrative in patriotic education thus depicts foreign aggression as the primary reason for China's sufferings in modern history (Gries 2004, 48–49). The victimization narrative is regularly brought up in politicians' speeches, news reports, museums, and television (Callahan, 2006). Xu and Zhao (2020) conducted an online survey experiment among 1890 urban Chinese citizens to examine the impact of historical "victimization" narratives on political attitudes. Analysis of survey responses indicates that the US–China trade dispute and US sanctions against the firm Huawei, for example, made respondents become more suspicious of the intentions of foreign governments in international disputes. This, in turn shifted attitudes toward support for more hawkish foreign policies, and, to some extent, strengthened support for the government (Xu and Zhao 2020).

Clearly, nationalism can be used to shape perceptions of China's relationship with the West and China's status on the international stage. In terms of China's articulated quest to become a world leader in AI by 2030 (Roberts et al., 2020), the nationalist narrative may prove to be of particular importance, especially as the technological race to lead in AI has intensified and as technological decoupling between the United States and China continues to deepen (Johnson & Gramer, 2020).

We use these findings to assess whether primers associated with nationalistic pride (e.g., US–China technological competition) or victimization (e.g., "unfair" sanctions placed on Chinese companies by the United States) also make people more willing to give up their data in support for the government and private sector companies.

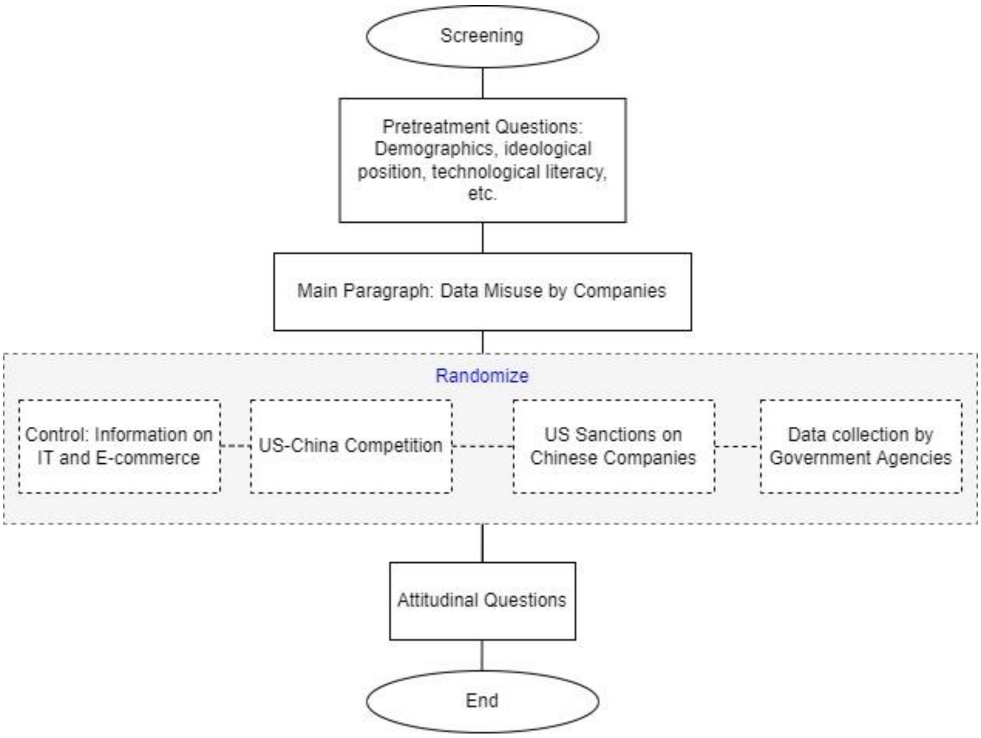
We seek to understand how ideological persuasions, especially concerning nationalistic sentiment, may correlate with data privacy preferences. We hypothesize that the narrative around nationalism could influence data privacy preferences in China and thereby assess the potential trajectory of China's current data privacy regime. We utilize people's varying persuasions and hold these together with the ongoing development of China's data protection regime. The study of ideology has important implications for how varying populations react to data privacy and data collection practices – both in China and elsewhere.

However, the Chinese Communist Party's central grip on power makes the China case unique. It sets China apart in terms of the government's ability and speed to formulate and implement new policies and to construct the public discourse, e.g., through propaganda and censorship. The limited role of civil society participation is another obstacle to effective citizen pushback against government data collection practices. In short, we expect that, compared to other states, the Chinese government has more room to carve out a centralized data collection regime that benefits the state, and it is possible that public dissent, even against existing government data collection practices, can be appeased by clamping down on private-sector practices.

3. Experimental Design

We conducted a randomized online survey experiment to study the effects of different treatments on Chinese citizens' data privacy preferences. Individuals were randomly assigned to 'treatment' and 'control' groups, and the differences in the survey responses between the groups were attributed to the treatments (Visser et al., 2000). On our instruction and with our compensation, the survey firm Qualtrics conducted the survey on a representative sample of the Chinese internet population. We collected 3,146 responses that are distributed across China's provinces. Figure 1 illustrates our experimental design.

Figure 1: Experimental Design



After respondents expressed consent and completed the screening test, we measured their prior beliefs using selected questions on ideology. Building on Pan & Xu (2020), we used three dimensions to measure ideology: (1) political liberalism, i.e., policies that pertain to political institutions and individual freedom; (2) market economy, i.e., policies about the economy and trade, and the role of the state in the allocation of resources: and (3) nationalism, i.e., policies concerning national identity and foreign affairs. We asked five questions for each dimension and, for each question, respondents expressed the extent of their agreement with the statement on a four-point Likert scale. This indicates whether they identify more strongly with liberal or conservative, pro-market or antimarket, or non-nationalist or nationalist tendencies. An example can be seen below in Figure 2, and the complete list of questions can be found in the Appendix.

Figure 2. Example of questions in the Political Liberalism domain (translated from Mandarin to English)

	<--More agree with the statement on the left			I agree more with the statement on the right -->	
In the long run, the political system of multi-party competition is not suitable for China's national conditions.	○	○	○	○	In the long run, the political system of multi-party competition can adapt to China's national conditions.
The media must adhere to the reporting policy of focusing on positive propaganda, rather than blindly exposing the dark side of society.	○	○	○	○	The job of the media is to expose the ugly side of society, and it does not need to insist on focusing on positive publicity.

The questions in each policy domain were grouped, but the order in which questions within a group are presented to each respondent was randomized. The order of the dimensions was randomized as well.

Building on Xu and Zhao (2020), we added a fourth dimension in the form of a Victim Index and a Patriot Index that build on the work of Woods and Dickson (2017) and Gries et al. (2011). The Victim index refers to China's interactions with foreign powers and captures the out-group bias against foreign countries.[33] The Patriot index reflects a respondent's sense of national pride and feelings of attachment towards China. Each index was populated on the basis of responses to five statements. Again, respondents were asked to express their agreement with the statements on a four-point Likert scale. A higher score on the respective index indicates a stronger attachment to the victim (or patriot) side of the Chinese national identity. The index is standardized with a mean of 0 and a standard deviation of 1.

Next, we assessed respondents' familiarity with technology, to gauge their level of technological literacy. We used this as a measure of comprehension of data privacy and data protection-related issues. This was followed by questions to assess our respondents' degree of overseas exposure. Then, we aimed to measure pre-treatment perceptions of technology companies by asking respondents about their perceptions of the role of large technology companies in the Chinese economy, and whether the government should do more to rein them in. We also assessed respondents' views on their data pre-treatment by asking whether they think their data has economic value and whether they are willing to share it with companies and the central and local governments. Next, we asked a set of questions related to demographics before respondents proceeded to read a paragraph that describes data privacy violations by private sector companies in China. The main paragraph was followed by a randomly assigned vignette from one control and three treatment conditions. The vignettes are similar in length (about one paragraph) and mirror the structure of factual online articles, with illustrative pictures added to increase the salience of the vignettes. Following each vignette, we included manipulation checks to ensure that respondents had paid sufficient attention to the experiment. In each subsection below, we briefly describe the main paragraph and the control and treatment conditions.

The main paragraph of the survey was designed to convey information about companies' improper use and collection of personal data. We also mentioned that the Cyber Administration of China has been cracking down on illegal and excessive data collection practices since November 2019. We provided the following examples of data misuse:

- A company collects location data and access a smartphone's camera without the user's knowledge or consent

[33] We use the victim-patriotism index to gauge whether respondents' sense of victimization i.e., unfair treatment of Chinese companies abroad, also is likely to shift respondents' willingness to share data, and thereby aiding Chinese companies and/or the government. We use the cases of US–China tech competition and US sanctions against China to invoke a sense of unfair treatment of Chinese companies abroad.

- A company sells personal data for profit without the user's consent
- An App repeatedly displays data sharing reminders or that interrupts usage until a user agrees to provide additional personal information

Three treatments and one control group follow the main paragraph. Our control group was provided with neutral, general facts about Information Technology. Content included simple descriptions of IT and how it relates to computer hardware, software, electronic products, semiconductors, the Internet, telecommunications equipment, and e-commerce.

Treatment 1 sought to invoke respondents with a sense of tech rivalry between China and the US. We reminded people of the US–China high-tech competition and how innovation in AI has intensified. We mentioned that China is developing rapidly in the area of AI and that in 2020, Chinese scholars surpassed the United States in terms of the number of citations in AI journals. We also stressed that China still lags behind the United States in terms of total investment in artificial intelligence and that to become a world leader in AI, China needs to invest more in AI. We also mentioned that the rapid development of AI in China has been buttressed by strong policy support, a solid educational system, as well as the ability of enterprises to collect consumer data. Finally, we mentioned that China's official policy goal is to become a world leader in AI development by 2030.

Treatment 2 mentioned that the trade war between China and the United States moved from corporate competition to national competition, emphasizing US policies that hinder Chinese national development. In the vignette, we stressed that since 2018, the United States has banned more than 300 Chinese companies from using American technology, which has resulted in Chinese companies losing access to critical parts for production. We described how this restricts the development of Chinese companies in science and technology and mentioned that Huawei has lost the right to use Google's Android operating system, which has caused its sales of smartphones to drop. We also mentioned how former US President Trump tried to force the Chinese company ByteDance to sell its successful TikTok business (the international version of Douyin) to a US company. Finally, we mentioned that the reason for a US ban on Chinese companies is to protect the US technology industry from Chinese exports.

Treatment 3 moved away from nationalistic sentiment and, instead, reminded respondents how the government uses personal data. We observed that local governments have installed a series of technologies to monitor and collect citizens' personal data, stressing that citizens cannot opt out and that personal knowledge or consent is unnecessary for facial recognition cameras to monitor public spaces and collect personal biometric data. We also noted that public schools can be monitored through surveillance cameras, smart wristbands, and intelligent school uniforms that track students' activities. We mentioned that China's social credit system collects and uses artificial intelligence, face recognition, big data, and other technologies and systems to monitor and analyze the data of individuals and enterprises, and that all of this may happen without their knowledge or consent.

The control and treatment scenarios were followed by questions associated with outcome variables that include respondents' willingness to share personal data with businesses and the central and local government. We also assessed whether respondents believe that businesses, the central government, and local governments will seriously protect their data. The following outcome variable assesses whether respondents believe that their data is critical for Chinese companies concerning global competition and the government's ambition to make China a world leader in developing AI technologies.

At the end of the survey, we conducted two types of choice experiments. First, we conducted a single-binary discrete-choice (SBDC) experiment (Carson et al., 2014), which involves consumers making a single choice between two options. Specifically, we asked respondents whether they would be willing to provide their facial biometric data to (A) a company or (B) the government, respectively, in exchange for financial compensation. Next, we sought to determine willingness to accept (WTA) valuations (i.e., the monetary compensation needed to compensate for various goods)(Brynjolfsson et al., 2019), by asking respondents how much money (in Chinese Yuan), they would seek from a company or the government, respectively, in exchange for their biometric facial data.

Literature on how surveys affect behavior points to self-prophecy effects, where the act of measuring itself can induce subsequent changes in respondent behavior (Morwitz et al., 1993). The literature also discusses "experimenter demand effects," which is the possibility that respondents change their behavior because they know they are subjects in an experiment (Zizzo, 2010; Di Tella & Rodrik, 2019). Zwane et al. (2011) find that surveys can affect behavior and parameter estimates, but conclude that infrequent survey visits on large samples are preferable to smaller samples with higher-frequency data collection, which is more likely to confound parameter estimates. In order to alleviate some of these previously described effects, we constructed a relatively large and representative sample of internet users in China.

4. Data and Empirical Framework

4.1 Survey Sample and Variables

We recruited internet users in China through Qualtrics. We focused on internet users since they are likely aware of the data privacy issues related to websites, apps, technology products, and services. We launched the survey in October 2021 and collected nearly 4,000 responses over seven weeks. After excluding those who did not complete the entire survey (either did not pass our attention checks or stopped before the end), those who indicated that they did not devote full attention to answering the questions, and those who finished the survey in an unreasonably short time, i.e., the first percentile of response time, we ended up with 3,146 individuals. While our sample is not representative of all individuals in China, we aimed to get a representative sample of internet users in China, which is the more relevant population for the question we study.

Table 1. Summary Statistics

Variable	Mean	Std. Dev.	Min	Max	Obs
Demographics					
Age	38.052	13.099	11	79	3,146
Male	0.498	0.500	0	1	3,146
Income below 8,000 RMB	0.455	0.498	0	1	3,146
Minority	0.056	0.23	0	1	3,146
Grew up in rural areas	0.193	0.395	0	1	3,146
Is employed	0.862	0.345	0	1	3,146
Education: below high school	0.107	0.309	0	1	3,146
Education: high school or equivalent	0.190	0.393	0	1	3,146
Education: college or equivalent	0.626	0.484	0	1	3,146
Education: above college	0.077	0.267	0	1	3,146
Work in the public sector	0.182	0.386	0	1	3,146
Work in the private sector	0.632	0.482	0	1	3,146
Unemployed/retired	0.103	0.304	0	1	3,146
Student	0.045	0.207	0	1	3,146
Affiliated with CCP	0.167	0.373	0	1	3,146
Pre-treatment: Ideology indexes					
Nationalistic index	0	1	-2.951	1.691	3,146
Conservative index	0	1	-2.807	3.089	3,146
Antimarket index	0	1	-2.747	2.827	3,146
Patriotic index	0	1	-3.683	1.545	3,146
Pre-treatment: technology savviness and data perceptions					

Technology savviness index	0	1	-3.683	1.545	3,146
Globalization index	0	1	-1.131	1.931	3,146
Tech company perception index	0	1	-3.438	4.421	3,146
Data concern index	0	1	-2.809	3.996	3,146
Post-treatment: willingness to share personal data					
Sharing with private companies:					
Willingness to share biological data and facial images	2.423	0.97	1	4	3,146
Willingness to share online shopping records	2.506	0.962	1	4	3,146
Willingness to share web browsing history	2.389	0.978	1	4	3,146
Willingness to share personal location, address, or travel information	2.454	0.956	1	4	3,146
Willingness to share personal driving record	2.576	0.941	1	4	3,146
Willingness to share medical diagnosis records	2.426	0.978	1	4	3,146
Willingness to share personal financial information	2.169	1.001	1	4	3,146
Support the use of personal data for the purpose of distributing advertisements more targeted to consumers.	2.577	0.956	1	4	3,146
Support the use of personal data for the purpose of differentiating prices for products based on users' habits, preferences, and spending power.	2.679	0.956	1	4	3,146
Willingness to share personal data for the purpose of selling data to third-party companies so that they can better understand user preferences.	2.455	1.004	1	4	3,146
Sharing with the central government:					
Willingness to share biological data and facial images	2.902	0.896	1	4	3,146
Willingness to share online shopping records	2.778	0.937	1	4	3,146
Willingness to share web browsing history	2.701	0.958	1	4	3,146
Willingness to share personal location, address, or travel information	2.887	0.914	1	4	3,146
Willingness to share personal driving record	2.96	0.878	1	4	3,146
Willingness to share medical diagnosis records	2.899	0.907	1	4	3,146
Willingness to share personal financial information	2.646	0.978	1	4	3,146
Support the use of personal data by the central government for identifying potential criminals and prevent illegal acts from happening.	3.403	0.697	1	4	3,146
Support the use of personal data by the central government for identify people with different views on the policies of the central government on the Internet and social media to prevent incidents that may cause social instability.	3.182	0.796	1	4	3,146
Support the use of personal data by the central government for controlling the spread of the epidemic.	3.422	0.705	1	4	3,146
Sharing with the local government:					
Willingness to share biological data and facial images	2.842	0.889	1	4	3,146
Willingness to share online shopping records	2.709	0.921	1	4	3,146
Willingness to share web browsing history	2.637	0.956	1	4	3,146
Willingness to share personal location, address, or travel information	2.833	0.903	1	4	3,146
Willingness to share personal driving record	2.878	0.879	1	4	3,146
Willingness to share medical diagnosis records	2.818	0.907	1	4	3,146
Willingness to share personal financial information	2.553	0.978	1	4	3,146

Support the use of personal data by the central government for identifying potential criminals and prevent illegal acts from happening.	3.344	0.715	1	4	3,146
Support the use of personal data by the central government for identify people with different views on the policies of the central government on the Internet and social media to prevent incidents that may cause social instability.	3.144	0.820	1	4	3,146
Support the use of personal data by the central government for controlling the spread of the epidemic.	3.383	0.700	1	4	3,146
Willing to share facial image with private companies	0.381	0.486	0	1.00	3,146
Valuation of facial image, sharing with private companies	23024.536	411381.536	0	10,000,000	1,199
log of valuation of facial image, sharing with private companies	0.643	0.479	-4.610	16	1,199
Willing to share facial image with the central government	2626.548	25453.579	0	1	3,146
Valuation of facial image, sharing with the central government	5.235	2.185	0	1,000,000	2,024
log of valuation of facial image, sharing with the central government	4.337	2.996	-4.610	14	2,024
Post-treatment: trust, personal data perception					
Trust in the private companies	7.015	2.281	0	10	3,146
Trust in the central government	8.476	1.578	0	10	3,146
Trust in the local government	7.987	1.671	0	10	3,146
Personal data criticality: global AI competitiveness	7.674	1.791	0	10	3,146
Personal data essential: China as the world leader AI	8.248	1.598	0	10	3,146
Post-treatment constructs: willingness, trust, and data perception					
Willingness to share personal data with private companies	0	1	-1.821	2.020	3,146
Willingness to share personal data with the central government	0	1	-2.512	1.610	3,146
Willingness to share personal data with the local government	0	1	-2.412	1.707	3,146
Support private companies for using personal data for development	0	1	-1.873	1.701	3,146
Support the central government for using personal data for development	0	1	-4.022	1.130	3,146
Support the local government for using personal data for development	0	1	-3.830	1.171	3,146
Trust in private companies	0	1	-3.076	1.309	3,146
Trust in the central government	0	1	-5.373	0.966	3,146
Trust in the local government	0	1	-4.780	1.205	3,146
Tech nationalistic sentiment: global AI competitiveness	0	1	-4.285	1.299	3,146
Tech nationalistic sentiment: China as the world leader AI	0	1	-5.163	1.096	3,146

In Table 1, we present the summary statistics of the main variables in our survey. The first set of variables presents demographic characteristics. The average age is around 38, males and females are evenly split, about 19 percent grew up in a rural area, and six percent classify themselves as minorities.[34] The share of college-educated or above is relatively high due to the nature of internet users in China. About ten percent are unemployed, and four percent are students. 17 percent of the respondents are affiliated with the Chinese Communist Party.

The next set of variables is the key control variables related to people's beliefs: ideology related to nationalism, political conservatism, anti- or pro-market beliefs, and patriotism. We createed standardized indexes that group responses to each category's four or five questions.

The final set of variables is our outcome variables related to willingness to share private data or perceptions of data privacy. Many of these are mean values from a 4-point Likert scale. Note that about 38 percent of respondents were willing to share their facial images with private companies, while nearly 64 percent were willing to share with the central government. Also, they wished to receive almost ten times as much money (23,025 vs 2,627 RMB) in exchange for providing their facial image to a private company, compared to the central government.

4.2 Treatment and Control Group Balance

Before turning to the regression results, we examined whether individual characteristics and beliefs are balanced across the control and treatment groups. Table 2 presents the mean and standard errors of the variables across each group. Panel A shows variables related to personal background and Panel B shows variables related to personal beliefs. The sample sizes for the control group and each of the three treatment groups are 891, 789, 683, and 783, for a total of 3,146. The resulting distribution after the sample restrictions reflects a relatively even distribution, though the control group is larger and Treatment 2 group slightly smaller.

Table 2 also shows the variable balance across the different treatment groups. Overall, the variables are generally well balanced, but we do find that that the average age, share of minority, share of people with less than high school education to be slightly lower for the Treatment 1 group. In terms of beliefs, the nationalism, patriotism, and tech savviness indexes were lower for the Treatment 2 group.

[34] According to the 2020 census, 91.11% of the population was Han Chinese, and 8.89% were minorities.

Table 2 Summary statistics by treatment

	Control Group		Treatment Groups						Full Sample	
			China-US competition		Sanction by the US		Gov't use of data			
	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.
Panel A: Demographics										
Age	38.452	0.452	36.954**	0.433	38.965	0.496	37.905	0.486	38.052	0.234
Male	0.488	0.017	0.494	0.018	0.521	0.019	0.494	0.018	0.498	0.009
Income below 8,000 RMB	0.460	0.017	0.445	0.018	0.449	0.019	0.466	0.018	0.455	0.009
Minority	0.056	0.008	0.033**	0.006	0.075	0.010	0.063	0.009	0.056	0.004
Grew up in rural areas	0.201	0.013	0.167*	0.013	0.204	0.015	0.202	0.014	0.193	0.007
Is employed	0.860	0.012	0.888*	0.011	0.868	0.013	0.831*	0.013	0.862	0.006
Education: below high school	0.118	0.011	0.079***	0.010	0.120	0.012	0.112	0.011	0.107	0.006
Education: high school or equivalent	0.178	0.013	0.209	0.014	0.180	0.015	0.194	0.014	0.19	0.007
Education: college or equivalent	0.633	0.016	0.619	0.017	0.624	0.019	0.626	0.017	0.626	0.009
Education: above college	0.071	0.009	0.094*	0.010	0.076	0.010	0.068	0.009	0.077	0.005
Work in the public sector	0.168	0.013	0.194	0.014	0.190	0.015	0.178	0.014	0.182	0.007
Work in the private sector	0.645	0.016	0.638	0.017	0.637	0.018	0.605*	0.017	0.632	0.009
Unemployed/retired	0.103	0.010	0.089	0.010	0.114	0.012	0.107	0.011	0.103	0.005
Student	0.037	0.006	0.042	0.007	0.037	0.007	0.064***	0.009	0.045	0.004
Affiliated with CCP	0.150	0.012	0.163	0.013	0.176	0.015	0.180	0.014	0.167	0.007
Panel B: Pre-treatment characteristics										
Nationalistic Index	0.047	0.033	0.047	0.036	-0.097***	0.038	-0.016	0.035	0	0.018
Conservative Index	-0.019	0.034	-0.033	0.035	-0.021	0.039	0.074*	0.035	0	0.018
Antimarket Index	-0.002	0.034	0.002	0.035	-0.017	0.038	0.015	0.036	0	0.018
Patriotic Index	0.031	0.033	0.012	0.035	-0.109***	0.040	0.047	0.035	0	0.018
Technology savviness index	0.031	0.033	0.012	0.035	-0.109***	0.040	0.047	0.035	0	0.018
Globalization index	-0.001	0.033	0.031	0.036	-0.018	0.039	-0.014	0.036	0	0.018
Tech company perception index	0.017	0.033	0.003	0.037	-0.032	0.038	0.005	0.035	0	0.018
Data concern index	-0.007	0.033	-0.020	0.035	0.070	0.040	-0.032	0.035	0	0.018
No. of observations	891		789		683		783		3,146	

*p<0.1; **p<0.05; ***p<0.01

In the regression analysis, we control for all of the variables in Table 2. The key assumption in identifying the impact of the treatment is that there are no unobservable differences between the control group and treatment groups. A well-randomized experiment would address this by balancing out unobserved characteristics between treatment and control. Since randomization may not be perfect in real-world settings, we include all the control variables to increase the precision of the treatment effect.

4.3 Empirical framework

The most basic model we examine in the empirical analysis is the following equation:

$$y_i = \alpha + \beta_1 T1_i + \beta_2 T2_i + \beta_3 T3_\mathrm{i} + \mathrm{X_i}\pi + \varepsilon_i \quad (1)$$

where y_i represents individual i's intent to share personal data, perception of data privacy, or valuation of one's biometric data. $T1_i$ is a dummy variable indicating the US–China competition treatment group, $T2_i$ is a dummy variable indicating the US sanctions treatment group, and $T3_i$ is a dummy variable indicating the government data misuse treatment group. $\mathrm{X_i}$ is the vector of control variables, including individual demographic controls (gender, race, education, age, employment, urban-rural, etc.), personal beliefs (nationalism, conservatism, antimarket, patriotism, technology savviness, globalization, tech company perception, data privacy concern), and province fixed effects. The coefficient β estimates the impact of each treatment on the outcome variables.

We then examine the treatment effects heterogeneity by interacting the treatment dummy variable(s) with key characteristic and beliefs variables. That is, we examine the following variant of equation (1)

$$y_i = \sum_{j=1,2,3} \beta_{j,k} Tj_i * K_i + \mathrm{X_i}\pi + \varepsilon_i \qquad (2)$$

where K_i represent different groups, e.g., males, college-educated or above, or individual characteristics or beliefs, e.g., nationalization. The coefficient estimate $\beta_{j,k}$ captures the heterogeneous treatment effect based on K_i.

5. Results

5.1 Impact on willingness to share personal data for different purposes

We first examine how being exposed to the treatment vignettes affect people's willingness to share their data with private companies (Table 3A), the central government (Table 3B), and the local government (Table 3C). We also show the coefficient estimates in Figures 3A to 3C. We find that being reminded of the US–China technology competition or US sanctions against Chinese companies significantly increased willingness to share their data with private companies. Respondents significantly increased their willingness to share personal data across most types of data that we survey (i.e., biological and facial data, online shopping records, location & travel information, driving records, medical records, financial information) when exposed to the US–China technology competition vignette. This broad-based effect is also found among respondents who received the US sanctions treatment. Consistent with these changes, we find that both treatments significantly increase support for private company use of data as they target advertisements to consumers and differentiate prices for products. Overall, we find that invoking nationalistic sentiment increases people's willingness to share their data with private companies in China.

When people are reminded of government data use, people's willingness to share personal data does not change. However, people are more willing to share their medical records with private companies when primed with information about local government monitoring and collection of citizen data, sometimes without their knowledge or consent. This could suggest that when people are primed with information that limits their perceived autonomy over, for example, sensitive medical data, they feel compelled to place greater trust in private companies regarding having these handle their medical data. It may also be that public healthcare institutions (i.e., the government) are not considered good protectors of citizens' sensitive medical data, e.g., due to risks of leaking or vulnerability to hacking. Private companies are considered better equipped to safeguard such sensitive data.

The results are less pronounced when it comes to impacts on people's willingness to share data with central and local governments. We find that the US sanctions treatment significantly increases people's willingness to share data with the central government (i.e., biological and facial data, medical records, and online shopping records)(Table 3B). People are also more willing to share

Table 3A Impact of treatments on willingness to share with private companies (with controls)

	Willingness to share with private companies								Support use of personal data for:			
	Biological and facial data	Online shopping records	Web browsing history	Location & travel informati on	Driving records	Medical records	Financial informati on	Willingne ss to share index	Targeting Ads to consumers	Differentia ting prices for products	Better understand user preference	Support use of personal data index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment Groups:												
US–China competition	0.101**	0.079*	0.049	0.100**	0.097**	0.073*	0.108**	0.108***	0.121***	0.102**	0.03	0.097**
	(0.042)	(0.043)	(0.042)	(0.043)	(0.043)	(0.043)	(0.042)	(0.039)	(0.042)	(0.043)	(0.043)	(0.040)
Sanction by the US	0.074*	0.056	0.089**	0.108**	0.057	0.069	0.119***	0.101**	0.085*	0.096**	0.071	0.097**
	(0.044)	(0.044)	(0.044)	(0.044)	(0.045)	(0.044)	(0.044)	(0.040)	(0.044)	(0.045)	(0.044)	(0.042)
Gov't use of data	0.045	-0.033	-0.004	0.043	-0.015	0.090**	0.04	0.03	0.022	-0.018	-0.079*	-0.029
	(0.042)	(0.043)	(0.042)	(0.043)	(0.043)	(0.043)	(0.042)	(0.039)	(0.042)	(0.043)	(0.043)	(0.040)
Observations	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146
R-square	0.269	0.249	0.270	0.250	0.229	0.250	0.270	0.382	0.263	0.242	0.250	0.331
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nationalism controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Conservativeness controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Antimarket controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Patriotic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology savviness controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Globalization controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tech company perception controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01

Notes: demographic controls include age, gender (1 = male), income (1 = monthly income is below 8000 RMB), minority (1 = yes), grew up in rural areas (1 = yes), is employed (1 = yes), education level (did not finish high school, high school or equivalent, college or equivalent, above college), job type (public, private, unemployed/retire, student), CCP affiliated (1 = yes).

Table 3B Impact of treatments on willingness to share with the central government (with controls)

	Willingness to share with the central government								Support use of personal data for:			
	Biological and facial data	Online shopping records	Web browsing history	Location & travel informati on	Driving records	Medical records	Financial informati on	Willingne ss to share index	Identifying criminals and prevent illegal acts	Identifying people with different political views	Controllin g the spread of the epidemic	Support use of personal data index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment Groups:												
US–China competition	0.070	0.064	0.038	0.016	0.055	0.040	0.031	0.057	0.009	0.021	0.002	0.013
	(0.044)	(0.044)	(0.043)	(0.044)	(0.044)	(0.045)	(0.044)	(0.041)	(0.046)	(0.044)	(0.046)	(0.043)
Sanction by the US	0.082*	0.078*	0.057	0.047	0.075	0.094**	0.057	0.089**	0.064	0.048	-0.004	0.045
	(0.046)	(0.046)	(0.045)	(0.046)	(0.046)	(0.047)	(0.046)	(0.043)	(0.048)	(0.046)	(0.047)	(0.045)
Gov't use of data	0.057	0.011	-0.025	-0.023	0.024	0.055	0.002	0.018	-0.007	-0.006	-0.009	-0.01
	(0.044)	(0.044)	(0.043)	(0.044)	(0.044)	(0.045)	(0.045)	(0.041)	(0.046)	(0.044)	(0.046)	(0.043)
Observations	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146
R-square	0.196	0.207	0.231	0.211	0.195	0.163	0.185	0.306	0.141	0.211	0.143	0.240
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nationalism controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Conservativeness controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Antimarket controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Patriotic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology savviness controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Globalization controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tech company perception controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01

Notes: demographic controls include age, gender (1 = male), income (1 = monthly income is below 8000 RMB), minority (1 = yes), grew up in rural areas (1 = yes), is employed (1 = yes), education level (did not finish high school, high school or equivalent, college or equivalent, above college), job type (public, private, unemployed/retire, student), CCP affiliated (1 = yes).

Table 3C Impact of treatments on willingness to share with the local government (with controls)

	Willingness to share with the local government								Support use of personal data for:			
	Biological and facial data	Online shopping records	Web browsing history	Location & travel informati on	Driving records	Medical records	Financial informati on	Willingne ss to share index	Identifying criminals and prevent illegal acts	Identifying people with different political views	Controllin g the spread of the epidemic	Support use of personal data index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment Groups:												
US–China competition	0.053	0.026	0.072*	0.087**	0.058	0.059	0.042	0.071*	0.023	-0.015	-0.018	-0.004
	(0.044)	(0.043)	(0.043)	(0.044)	(0.044)	(0.044)	(0.044)	(0.041)	(0.046)	(0.044)	(0.045)	(0.043)
Sanction by the US	0.057	0.026	0.077*	0.039	0.054	0.073	0.027	0.064	0.020	0.033	-0.001	0.021
	(0.046)	(0.045)	(0.045)	(0.045)	(0.046)	(0.046)	(0.046)	(0.042)	(0.048)	(0.046)	(0.047)	(0.045)
Gov't use of data	0.062	-0.033	-0.002	0.007	0.026	0.069	0.029	0.028	0.051	0.027	0.028	0.043
	(0.044)	(0.043)	(0.043)	(0.044)	(0.045)	(0.044)	(0.044)	(0.041)	(0.046)	(0.044)	(0.045)	(0.043)
Observations	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146
R-square	0.207	0.229	0.239	0.214	0.185	0.192	0.200	0.321	0.119	0.198	0.152	0.222
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nationalism controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Conservativeness controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Antimarket controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Patriotic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology savviness controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Globalization controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tech company perception controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01

Notes: demographic controls include age, gender (1 = male), income (1 = monthly income is below 8000 RMB), minority (1 = yes), grew up in rural areas (1 = yes), is employed (1 = yes), education level (did not finish high school, high school or equivalent, college or equivalent, above college), job type (public, private, unemployed/retire, student), CCP affiliated (1 = yes).

their data with the local government (Table 3C) after being told about US–China technology competition (i.e., web browsing history, location, and travel information) and US sanctions (web browsing history). The overall estimates are generally positive for both the central and the local governments, as shown in Tables 3B and 3C, although most estimates are not statistically significant. Furthermore, none of the treatments change people's support for the use of personal data for identifying criminal/illegal activities or for ideological or public health purposes by the government (columns 9 to 11 of Table 3B and 3C).

5.*2 Potential mechanisms*

Next, we examine potential mechanisms. Specifically, we examine whether the willingness to share data is due to the change in trust in private companies or the government and/or the change in nationalistic sentiments related to private companies or the government (Table 4 and Figure 4). We find that the US–China tech competition treatment increases the degree of trust that people place on private companies to handle their data responsibly and increases people's belief that personal data is important for Chinese companies to lead in the global competition to develop AI technologies. In other words, reminding people of the technology race with the US (i.e., Treatment 1, which invokes nationalism) increases respondents' level of trust in Chinese companies and their general level of nationalistic sentiment.

The information that Chinese companies are sanctioned by the US (Treatment 2), on the other hand, does not increase respondents' trust in Chinese companies. In short, victimization (i.e., unfair sanctioning of Chinese companies) may invoke nationalistic sentiment but does not affect respondents' general level of trust in Chinese companies in the same way that US–CH technology competition does. The US sanctions treatment seems to increase the belief that personal data is important for Chinese companies to lead the global competition to develop AI technologies. However, the estimate is not statistically significant at the ten percent level (although it is significant at the 15% level).

Treatments 1 and 2 do not affect people's trust in either the central government (column 2) or local government (column 3), nor do they affect nationalistic sentiment (column 5). Reminding people of government data use seems to reduce trust in all entities, though the estimates are not significant.

Table 4 Impact of treatments on trust and technology nationalistic sentiments (with controls)

	Trust			Tech nationalistic sentiment	
	Trust in private companies	Trust in the central government	Trust in the local government	Global AI competitiveness	China as the world leader AI
	(1)	(2)	(3)	(4)	(5)
US–China competition	0.067*	0.012	0.027	0.081*	-0.019
	(0.040)	(0.042)	(0.042)	(0.044)	(0.044)
Sanction by the US	0.028	0.038	-0.04	0.072	-0.036
	(0.041)	(0.044)	(0.043)	(0.046)	(0.046)
Gov't use of data	-0.017	-0.034	-0.015	0.071	0.021
	(0.040)	(0.042)	(0.042)	(0.044)	(0.044)
Observations	3,146	3,146	3,146	3,146	3,146
R-square	0.346	0.266	0.285	0.206	0.210
Demographic controls	Yes	Yes	Yes	Yes	Yes
Nationalism controls	Yes	Yes	Yes	Yes	Yes
Conservativeness controls	Yes	Yes	Yes	Yes	Yes
Antimarket controls	Yes	Yes	Yes	Yes	Yes
Patriotic controls	Yes	Yes	Yes	Yes	Yes
Technology savviness controls	Yes	Yes	Yes	Yes	Yes
Globalization controls	Yes	Yes	Yes	Yes	Yes
Tech company perception controls	Yes	Yes	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01

Notes: demographic controls include age, gender (1 = male), income (1 = monthly income is below 8000 RMB), minority (1 = yes), grew up in rural areas (1 = yes), is employed (1 = yes), education level (did not finish high school, high school or equivalent, college or equivalent, above college), job type (public, private, unemployed/retire, student), CCP affiliated (1 = yes).

5.3 Valuation of facial image data

We examine how the treatments affect people's willingness to share their facial images and valuation of their facial images (Table 5 and Figure 5). In general, we find that the treatments do not affect people's willingness to share their facial image at the external margin, that is, those who were unwilling to share their facial image maintain that they are unwilling to share their facial image. Interestingly, when respondents were reminded that the US is sanctioning Chinese companies for data security concerns, they decreased their willingness to share their facial image data. However, among those willing to share their biometric facial data, the valuation of their facial image decreased, and the magnitudes were larger for private companies. Most notably, when people are reminded of the US–China tech competition, they decrease the valuation of their facial image, as measured by the value they are willing to accept to share their biometric facial data with private companies.

Table 5 Impact of treatments on willingness to share facial image and valuation (with controls)

	Sharing with private companies:			Sharing with the central government:		
	Willing to share facial image	Valuation of facial image	Valuation of facial image (log scale)	Willing to share facial image	Valuation of facial image	Valuation of facial image (log scale)
	(1)	(2)	(3)	(4)	(5)	(6)
US–China competition	0.015	-65,544.370**	-0.282*	-0.008	-2,682.489*	-0.057
	(0.022)	(32610.100)	(0.167)	(0.021)	(1542.252)	(0.179)
Sanction by the US	-0.0005	-55,379.21	-0.125	-0.038*	-2,288.14	0.203
	(0.023)	(34466.050)	(0.176)	(0.022)	(1652.714)	(0.192)
Gov't use of data	-0.006	-59,701.710*	0.108	0.005	-2,050.83	0.023
	(0.022)	(33002.000)	(0.169)	(0.021)	(1537.693)	(0.178)
Observations	3,146	1,199	1,199	3,146	2,024	2,024
R-square	0.131	0.024	0.097	0.189	0.021	0.051
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Nationalism controls	Yes	Yes	Yes	Yes	Yes	Yes
Conservativeness controls	Yes	Yes	Yes	Yes	Yes	Yes
Antimarket controls	Yes	Yes	Yes	Yes	Yes	Yes
Patriotic controls	Yes	Yes	Yes	Yes	Yes	Yes
Technology savviness controls	Yes	Yes	Yes	Yes	Yes	Yes
Globalization controls	Yes	Yes	Yes	Yes	Yes	Yes
Tech company perception controls	Yes	Yes	Yes	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01

Notes: demographic controls include age, gender (1 = male), income (1 = monthly income is below 8000 RMB), minority (1 = yes), grew up in rural areas (1 = yes), is employed (1 = yes), education level (did not finish high school, high school or equivalent, college or equivalent, above college), job type (public, private, unemployed/retire, student), CCP affiliated (1 = yes).

5.4 Heterogeneous effects

Finally, we examine whether the findings presented above differ by individual characteristics or beliefs. We first examine gender (Table 6). When males are exposed to vignettes that invoke nationalism, we now find that males increase their willingness to share their private data with private companies and the central and local government.

Table 6: Impact of treatments with gender interaction (with controls)

	Willingness to share personal data with:			Support using personal data for development			Trust in handling personal data			Tech nationalistic sentiments	
	Private companies	Central gov't	Local gov't	Private companies	Central gov't	Local gov't	Private companies	Central gov't	Local gov't	Global competitiveness	World leader AI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
US–China competition	0.098*	-0.003	-0.008	0.096*	-0.065	-0.097	0.048	-0.096	-0.083	0.069	-0.081
	(0.054)	(0.058)	(0.057)	(0.057)	(0.060)	(0.061)	(0.056)	(0.059)	(0.058)	(0.062)	(0.061)
Sanction by the US	0.067	0.02	0.003	0.063	0.003	0.002	0.024	-0.017	-0.059	0.102	-0.064
	(0.057)	(0.061)	(0.060)	(0.060)	(0.064)	(0.064)	(0.059)	(0.063)	(0.062)	(0.065)	(0.065)
Gov't use of data	0.024	-0.016	-0.032	-0.038	0.002	0.057	-0.026	-0.094	-0.078	0.057	0.015
	(0.054)	(0.058)	(0.057)	(0.057)	(0.060)	(0.061)	(0.056)	(0.059)	(0.058)	(0.062)	(0.062)
Male (1 = yes)	-0.071	-0.067	-0.088	-0.125**	-0.129**	-0.053	-0.013	-0.115**	-0.074	-0.026	-0.049
	(0.054)	(0.057)	(0.056)	(0.056)	(0.060)	(0.060)	(0.055)	(0.058)	(0.058)	(0.061)	(0.061)
US–China competition x Male	0.019	0.121	0.162**	0.003	0.159*	0.190**	0.039	0.221***	0.223***	0.024	0.125
	(0.077)	(0.082)	(0.081)	(0.081)	(0.086)	(0.087)	(0.080)	(0.084)	(0.083)	(0.088)	(0.088)
Sanction by the US x Male	0.068	0.137	0.122	0.066	0.083	0.041	0.008	0.113	0.043	-0.057	0.056
	(0.081)	(0.085)	(0.084)	(0.084)	(0.089)	(0.090)	(0.083)	(0.088)	(0.087)	(0.091)	(0.091)
Gov't use of data x Male	0.012	0.071	0.123	0.019	-0.023	-0.025	0.019	0.122	0.129	0.029	0.013
	(0.078)	(0.082)	(0.081)	(0.081)	(0.086)	(0.087)	(0.080)	(0.085)	(0.083)	(0.088)	(0.088)
Observations	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146
R-Square	0.382	0.307	0.322	0.331	0.241	0.224	0.346	0.267	0.287	0.206	0.211
Other demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nationalism controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Conservativeness controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Antimarket controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Patriotic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology savviness controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Globalization controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tech company perception controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01

Male respondents' trust that the central and local government will handle their data responsibly increases significantly. On the other hand, post-treatment females are less likely to share their data with private companies, the central government, and the local government, compared to males. Females increase their willingness to share their data with private companies but not with the government when reminded of the tech competition and nationalism. In short, the treatment effects that we found before are primarily driven by males, and males become more willing to share their data with the government after treatment.

When we examine urban-rural or education levels, we surprisingly find that people who live in urban areas and those with a college education or higher are more likely to increase their willingness to share their data when exposed to US–China competition (Treatment 1). However, we note that the estimates on the interaction terms with rural are negative but not statistically significant.

When we examine individual beliefs, we find that people's willingness to share data does not change differentially based on one's nationalism, political ideology, or patriotism. However, those who display greater antimarket beliefs also are more willing to share their data with private companies when reminded of the US–China tech competition (Treatment 1) or US sanctions on Chinese companies (Treatment 2). In contrast, they become less willing to share their data with the government.

6. Discussion and Conclusion

The main goal of this article has been to examine whether tech nationalism, understood as increasing nationalistic sentiment surrounding the technology race and competition between the US and China, can influence data privacy perceptions and respondents' willingness to share their data with companies and the government.

We find that invoking nationalistic sentiment increases people's willingness to share their data with private companies. Furthermore, when respondents are primed with information regarding US–China technology competition, their trust in private companies to handle their data increases. Respondents also increase the belief that personal data is important for Chinese companies to lead in the global competition to develop AI technologies. In other words, reminding people of the technology race with the US invokes nationalistic sentiment, which increases respondents' willingness to share data with Chinese companies and their trust in these to handle their data responsibly. When people are reminded of the US–China tech competition, they also decrease the valuation they place on their facial image data, thus making data a cheaper input factor in terms of AI innovation. In other words, great power competition between the US and China significantly shifts respondents' willingness to share data with private companies.

While these findings run contrary to perceived demands for increased data privacy protection in China, they are informative regarding the importance of nationalism and its potential effects on shifting demands for privacy. China's official state media has frequently discussed issues concerning data privacy, focusing on protecting individuals' rights, especially from overreach by private-sector companies. Moreover, while China's central government has been clamping down on Chinese firms' data collection practices, it is interesting that individuals are inclined to share more of their data with private firms when primed with nationalistic sentiment and a sense of victimization.

Concerning the government, we find that sanctions by the US tend to induce a sense of victimization, which makes people significantly more willing to share their data with the government. This could mean that China's population recognizes that the "legitimate" ownership of their data already resides with the government and that during times of crisis, people become even more willing to support national forms of data centralization and surveillance by conceding more of their data. We further interpret respondents' decrease in the valuation of their biometric facial data as a recognition of their inability to opt out of government surveillance, which makes them further decrease the value of their data. We further perceive that, since China's central government controls public discourse, e.g., through the media and censorship (Chen & Xu, 2017), continued public sector data centralization and surveillance initiatives may be legitimized by narratives that raise nationalistic sentiment.

In terms of technological governance, it is clear that a distinct model of digital authoritarianism is emerging from China (Khalil, 2020). By assessing public opinion in these areas, we have engaged with how nationalist tendencies possibly affect and shift public sentiment towards ongoing data collection practices by companies and the government.

Our findings have important implications in the context of emerging data privacy regimes globally and the ideological and value-based foundations on which data regimes are based. At the same time, the link between technology and ideological values is becoming a defining issue in the global technology policy landscape. Varying positions on the use of data and technology oftentimes demarcate opposing socio-technological positions that have wide-reaching implications for citizens' sense of data privacy and protection.

Our study of ideology and data privacy preferences in China's context holds important implications for how nationalism and new forms of rule-setting and surveillance interact with such preferences. These results are especially important as the interoperability between different data privacy and data protection regimes and which government actors have access to what kind of data and on what premises continue to be debated. The notion of digital sovereignty is especially relevant in this regard and feeds into questions over how governments support or constrain digital innovation, as well as the data that feeds into such. How some of these issues are negotiated will have important and far-reaching consequences for data privacy in the years to come.

References

Beraja, M., Yang, D. Y., & Yuchtman, N. (2021). Data-intensive Innovation and the State : Evidence from AI Firms in China. *NBER Working Paper*. https://doi.org/10.3386/w27723

Brynjolfsson, E., Collis, A., & Eggers, F. (2019). Using massive online choice experiments to measure changes in well-being. *Proceedings of the National Academy of Sciences of the United States of America*, *116*(15), 7250–7255. https://doi.org/10.1073/pnas.1815663116

Callahan, W. A. (2006). *History , identity , and security : Producing and consuming nationalism in China HISTORY , IDENTITY , AND SECURITY Producing and Consuming Nationalism in China*. *2715*. https://doi.org/10.1080/14672710600671087

Capri, B. Y. A. (2020). Techno-nationalism and diplomacy : *Foundation, Hinrich*, *October*.

Carson, R. T., Groves, T., & List, J. A. (2014). Consequentiality : A Theoretical and Experimental Exploration of a Single Binary Choice. *Journal of the Association of Environmental and Resource*, *1*, 171–207.

Chen, J., & Xu, Y. (2017). Information Manipulation and Reform in Authoritarian Regimes. *Political Science Research and Methods*, *5*(1), 163–178. https://doi.org/10.1017/psrm.2015.21

Di Tella, R., & Rodrik, D. (2019). *Labor Market Shocks and the Demand for Trade Protection: Evidence from Online Surveys*.

Dupont, B. Y. A. (2020). New Cold War: De-risking US–China conflict. *Foundation, Hinrich*, *June*.

Gries, P. H. (2004). *China's new nationalism: Pride, politics, and diplomacy*. Univ of California Press.

Gries, P. H., Zhang, Q., Crowson, H. M., & Cai, H. (2011). *Patriotism , Nationalism and China ' s US Policy : Structures and Consequences of Chinese National Identity*. https://doi.org/10.1017/S0305741010001360

Johnson, K., & Gramer, R. (2020). The Great Decoupling. *Foreign Policy*. https://doi.org/10.1111/npqu.11362

Khalil, L. (2020). Digital Authoritarianism, China and C0VID. In *Lowy Institute Analysis* (Issue November).

King, G., Pan, J., & Roberts, M. E. (2013). How censorship in China allows government criticism but silences collective expression. *American Political Science Review*, *107*(2), 326–343. https://doi.org/10.1017/S0003055413000014

King, G., Pan, J., & Roberts, M. E. (2017). How the Chinese government fabricates social media posts for strategic distraction, not engaged argument. *American Political Science Review*, *111*(3), 484–501. https://doi.org/10.1017/S0003055417000144

Kostka, G. (2019). China's social credit systems and public opinion: Explaining high levels of approval. *New Media and Society*, *21*(7), 1565–1593. https://doi.org/10.1177/1461444819826402

Lee, A., Mingli Shi, Chen, Q., Horsley, J., Schaefer, K., Creemers, R., & Webster, G. (2021). Seven Major Changes in China's Finalized Personal Information Protection Law Algorithmic discrimination, cross-border data rules, data portability, post-mortem rights, and more Alexa Lee, Mingli Shi, Qiheng Chen, Jamie P. Horsley, Kendra Schaefer, Rogier. *DigiChina*, *August 23*. https://digichina.stanford.edu/work/seven-major-changes-in-chinas-finalized-personal-information-protection-law/

Li, D., Tong, T., & Xiao, Y. (2021). Is China Emerging as the Global Leader in AI? *Harvard*

Business Review, *February*. https://hbr.org/2021/02/is-china-emerging-as-the-global-leader-in-ai

Liu, Y., Huang, L., Yan, W., Wang, X., & Zhang, R. (2022). Privacy in AI and the IoT: The privacy concerns of smart speaker users and the Personal Information Protection Law in China. *Telecommunications Policy*, *46*(7), 102334. https://doi.org/10.1016/j.telpol.2022.102334

Lu, S. (2020). Facial Recognition Is Running Amok in China. The People Are Pushing Back. *Vice*, December 9. https://www.vice.com/en/article/4adnyq/facial-recognition-is-running-amok-in-china-the-people-are-pushing-back

Lü, Y. H. (2005). Privacy and data privacy issues in contemporary China. *Ethics and Information Technology*, *7*(1), 7–15. https://doi.org/10.1007/s10676-005-0456-y

Lu, Y., & Pan, J. (2020). Capturing Clicks: How the Chinese Government Uses Clickbait to Compete for Visibility. *Political Communication*, 1–32. https://doi.org/10.1080/10584609.2020.1765914

Mac Síthigh, D., & Siems, M. (2019). The Chinese Social Credit System: A Model for Other Countries? *Modern Law Review*, *82*(6), 1034–1071. https://doi.org/10.1111/1468-2230.12462

Morey, T., Theo Forbath, T., & Schoop, A. (2015). Customer data: Designing for transparency and trust. In *Harvard Business Review* (Vol. 2015, Issue May).

Morwitz, V. G., Johnson, E., & Schmittlein, D. (1993). Does Measuring Intent Change Behavior ? *Journal of Consumer Research*, *20*(1), 46–61.

Mozur, P. (2018). Inside China's Dystopian Dreams: A.I., Shame and Lots of Cameras. *New York Times*, July 8. https://www.nytimes.com/2018/07/08/business/china-surveillance-technology.html

Neudert, L., Knuutila, A., & Howard, P. N. (2020). *Global Attitudes Towards AI , Machine Learning & Automated Decision Making*. *October*.

Pan, J., & Xu, Y. (2018). China's ideological spectrum. *Journal of Politics*, *80*(1), 254–273. https://doi.org/10.1086/694255

Pan, J., & Xu, Y. (2020). Gauging Preference Stability and Ideological Constraint under Authoritarian Rule. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3679076

Pernot-leplay, E. (2020). China's Approach on Data Privacy Law: A Third Way Between the U.S. and the EU? *Penn State Journal of Law & International Affairs*, *8*(1).

Peterson, A., Zinman, J., Dusen, E. Van, Pariente, W., Null, C., & Miguel, E. (2010). *Being surveyed can change later behavior and related parameter estimates*. *11*, 1–6. https://doi.org/10.1073/pnas.1000776108

Rieger, M. O., Wang, M., & Ohlberg, M. (2020). What Do Young Chinese Think About Social Credit? It's Complicated. *Merics China Monitor*, 1–9.

Roberts, H., Cowls, J., Morley, J., Taddeo, M., Wang, V., & Floridi, L. (2020). The Chinese approach to artificial intelligence: an analysis of policy, ethics, and regulation. *AI and Society*, *0123456789*. https://doi.org/10.1007/s00146-020-00992-2

Roussi, A. (2020). Resisting the Rise of Facial Recognition. *Nature*.

State Council. (2020). *Xiaoli Changshou, Deputy Director of the Information Bureau of the State Council Information Office* (p. 25 December). http://www.gov.cn/xinwen/2020zccfh/49/wzsl.htm

US Department of State. (2021). *The Clean Network*. https://2017-2021.state.gov/the-clean-network/index.html

Visser, P., Krosnick, J., & Lavrakas, P. (2000). Survey research. In *Handbook of research methods* *in social and personality psychology* (pp. 223–252). Cambridge University Press. https://doi.org/10.4018/ijavet.2015100106

Wang, S. (2008). *Changing Models of China's Policy Agenda Setting*. 56–87.

Weeks, J. L. (2008). *Autocratic Audience Costs : Regime Type and Signaling Resolve*. 35–64.

Woods, J. S., & Dickson, B. J. (2017). Victims and Patriots_ Disaggregating Nationalism in Urban China. *Journal of Contemporary China*.

Xinhua. (2020). *The General Office of the Central Committee of the Communist Party of China and the General Office of the State Council issued the "Notice on Doing a Good Job During the New Year's Day and Spring Festival in 2021"* (p. 24 December). http://www.gov.cn/zhengce/2020-12/24/content_5573063.htm

Xu, Y., & Zhao, J. (2020). *The Power of History: How A Victimization Narrative Shapes National Identity and Public Opinion in China ∗*.

Zerubavel, Y. (1995). *Recovered roots: Collective memory and the making of Israeli national tradition*. University of Chicago Press.

Zizzo, D. J. (2010). Experimenter demand effects in economic experiments. *Experimental Economics*, *13*(1), 75–98. https://doi.org/10.1007/s10683-009-9230-z

Appendix Table 7: Impact of treatments with rural interaction (with controls)

	Willingness to share personal data with:			Support using personal data for development			Trust in handling personal data			Tech nationalistic sentiments	
	Private companies	Central gov't	Local gov't	Private companies	Central gov't	Local gov't	Private companies	Central gov't	Local gov't	Global competitiveness	World leader AI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
US–China competition	0.119***	0.076*	0.082*	0.086*	-0.017	-0.022	0.063	-0.006	0.048	0.071	-0.031
	(0.043)	(0.045)	(0.045)	(0.045)	(0.047)	(0.048)	(0.044)	(0.047)	(0.046)	(0.049)	(0.048)
Sanction by the US	0.105**	0.094**	0.069	0.089*	0.036	0.02	0.039	0.051	-0.037	0.078	-0.049
	(0.045)	(0.048)	(0.047)	(0.047)	(0.050)	(0.051)	(0.046)	(0.049)	(0.049)	(0.051)	(0.051)
Gov't use of data	0.028	0.004	0.021	-0.052	-0.008	0.041	-0.029	-0.067	-0.021	0.036	0.012
	(0.043)	(0.046)	(0.045)	(0.045)	(0.048)	(0.049)	(0.045)	(0.047)	(0.047)	(0.049)	(0.049)
Rural (1 = grew up in rural area)	-0.176***	-0.166**	-0.177**	-0.194***	-0.107	-0.089	-0.087	-0.117	0.011	-0.146*	-0.151**
	(0.068)	(0.072)	(0.071)	(0.070)	(0.075)	(0.076)	(0.070)	(0.074)	(0.073)	(0.077)	(0.076)
US–China competition x Rural	-0.068	-0.116	-0.061	0.06	0.174	0.105	0.018	0.101	-0.124	0.046	0.062
	(0.101)	(0.107)	(0.105)	(0.105)	(0.112)	(0.113)	(0.103)	(0.110)	(0.108)	(0.114)	(0.114)
Sanction by the US x Rural	-0.019	-0.029	-0.029	0.04	0.047	0.006	-0.055	-0.06	-0.018	-0.031	0.065
	(0.100)	(0.106)	(0.105)	(0.104)	(0.111)	(0.112)	(0.103)	(0.109)	(0.108)	(0.113)	(0.113)
Gov't use of data x Rural	0.006	0.07	0.037	0.117	-0.008	0.012	0.057	0.162	0.028	0.173	0.048
	(0.097)	(0.102)	(0.101)	(0.101)	(0.107)	(0.108)	(0.099)	(0.105)	(0.104)	(0.110)	(0.109)
Observations	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146
R-square	0.382	0.307	0.321	0.331	0.240	0.223	0.346	0.267	0.285	0.207	0.210
Other demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nationalism controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Conservativeness controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Antimarket controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Patriotic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology savviness controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Globalization controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tech company perception controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01

Appendix Table 8: Impact of treatments with education interaction (with controls)

	Willingness to share personal data with:			Support using personal data for development			Trust in handling personal data			Tech nationalistic sentiments	
	Private companies	Central gov't	Local gov't	Private companies	Central gov't	Local gov't	Private companies	Central gov't	Local gov't	Global competitiveness	World leader AI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
US–China competition	0.059	-0.022	-0.024	0.029	-0.027	-0.072	0.068	0.021	0.03	0.069	0.033
	(0.063)	(0.067)	(0.067)	(0.066)	(0.070)	(0.071)	(0.065)	(0.069)	(0.068)	(0.072)	(0.072)
Sanction by the US	0.135**	0.094	0.06	0.119*	-0.016	0.027	0.005	0.041	-0.028	0.055	-0.037
	(0.066)	(0.070)	(0.069)	(0.069)	(0.073)	(0.074)	(0.068)	(0.072)	(0.071)	(0.075)	(0.075)
Gov't use of data	-0.005	-0.021	0.015	-0.062	-0.074	0.029	-0.066	-0.045	-0.08	-0.05	-0.003
	(0.064)	(0.067)	(0.067)	(0.066)	(0.071)	(0.071)	(0.066)	(0.069)	(0.069)	(0.072)	(0.072)
College (1 = college or equivalent)	0.122*	(0.003)	0.024	0.162**	0.085	0.088	0.161**	0.000	0.093	0.045	0.077
	(0.073)	(0.078)	(0.077)	(0.076)	(0.081)	(0.082)	(0.075)	(0.080)	(0.079)	(0.083)	(0.083)
US–China competition x College	0.077	0.126	0.153*	0.109	0.064	0.108	-0.004	-0.013	-0.006	0.018	-0.084
	(0.080)	(0.085)	(0.084)	(0.083)	(0.089)	(0.090)	(0.082)	(0.087)	(0.086)	(0.091)	(0.091)
Sanction by the US x College	-0.054	-0.009	0.005	-0.036	0.096	-0.01	0.035	-0.003	-0.019	0.026	0.002
	(0.083)	(0.088)	(0.087)	(0.087)	(0.092)	(0.093)	(0.086)	(0.091)	(0.090)	(0.094)	(0.094)
Gov't use of data x College	0.056	0.063	0.021	0.052	0.103	0.023	0.077	0.017	0.103	0.192**	0.039
	(0.080)	(0.085)	(0.084)	(0.084)	(0.089)	(0.090)	(0.083)	(0.088)	(0.086)	(0.091)	(0.091)
Observations	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146
R-square	0.382	0.307	0.322	0.331	0.240	0.223	0.346	0.266	0.285	0.207	0.210
Other demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nationalism controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Conservativeness controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Antimarket controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Patriotic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology savviness controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Globalization controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tech company perception controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01

Appendix Table 9: Impact of treatments with nationalism interaction (with controls)

	Willingness to share personal data with:			Support using personal data for development			Trust in handling personal data			Tech nationalistic sentiments	
	Private companies	Central gov't	Local gov't	Private companies	Central gov't	Local gov't	Private companies	Central gov't	Local gov't	Global competitiveness	World leader AI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
US–China competition	0.107***	0.054	0.068*	0.095**	0.01	-0.007	0.066*	0.015	0.027	0.083*	-0.017
	(0.039)	(0.041)	(0.041)	(0.040)	(0.043)	(0.043)	(0.040)	(0.042)	(0.042)	(0.044)	(0.044)
Sanction by the US	0.101**	0.083*	0.057	0.097**	0.042	0.018	0.029	0.038	-0.039	0.078*	-0.031
	(0.040)	(0.043)	(0.042)	(0.042)	(0.045)	(0.045)	(0.042)	(0.044)	(0.043)	(0.046)	(0.046)
Gov't use of data	0.030	0.018	0.028	-0.03	-0.011	0.042	-0.018	-0.033	-0.015	0.071	0.021
	(0.039)	(0.041)	(0.041)	(0.040)	(0.043)	(0.044)	(0.040)	(0.042)	(0.042)	(0.044)	(0.044)
Nationalism (continuous index)	-0.051*	0.076**	0.014	-0.112***	0.045	-0.001	-0.094***	0.084***	0.006	-0.001	0.095***
	(0.028)	(0.030)	(0.029)	(0.029)	(0.031)	(0.031)	(0.029)	(0.030)	(0.030)	(0.032)	(0.032)
US–China competition x Nationalism	0.013	0.051	0.062	0.051	0.068	0.064	0.008	-0.043	-0.009	-0.032	-0.04
	(0.039)	(0.041)	(0.040)	(0.040)	(0.043)	(0.043)	(0.040)	(0.042)	(0.042)	(0.044)	(0.044)
Sanction by the US x Nationalism	-0.024	-0.065	-0.051	0.022	0.005	0.018	0.041	-0.026	0.027	0.097**	0.059
	(0.040)	(0.043)	(0.042)	(0.042)	(0.045)	(0.045)	(0.042)	(0.044)	(0.044)	(0.046)	(0.046)
Gov't use of data x Nationalism	-0.032	-0.008	0.023	0.001	0.024	0.05	0.033	0.004	0.025	0.044	0.0004
	(0.039)	(0.041)	(0.041)	(0.041)	(0.043)	(0.044)	(0.040)	(0.043)	(0.042)	(0.044)	(0.044)
Observations	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146
R-square	0.382	0.308	0.322	0.331	0.24	0.223	0.346	0.266	0.285	0.208	0.211
Other demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nationalism controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Conservativeness controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Antimarket controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Patriotic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology savviness controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Globalization controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tech company perception controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01

Appendix Table 10: Impact of treatments with Conservativeness interaction (with controls)

	Willingness to share personal data with:			Support using personal data for development			Trust in handling personal data			Tech nationalistic sentiments	
	Private companies	Central gov't	Local gov't	Private companies	Central gov't	Local gov't	Private companies	Central gov't	Local gov't	Global competitiveness	World leader AI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
US–China competition	0.109***	0.056	0.071*	0.098**	0.014	-0.005	0.066*	0.009	0.025	0.081*	-0.021
	(0.039)	(0.041)	(0.041)	(0.040)	(0.043)	(0.043)	(0.040)	(0.042)	(0.042)	(0.044)	(0.044)
Sanction by the US	0.103**	0.089**	0.064	0.098**	0.046	0.021	0.027	0.038	-0.042	0.072	-0.036
	(0.040)	(0.043)	(0.042)	(0.042)	(0.045)	(0.045)	(0.042)	(0.044)	(0.043)	(0.046)	(0.046)
Gov't use of data	0.031	0.018	0.028	-0.031	-0.011	0.041	-0.017	-0.037	-0.018	0.073*	0.020
	(0.039)	(0.041)	(0.041)	(0.040)	(0.043)	(0.044)	(0.040)	(0.042)	(0.042)	(0.044)	(0.044)
Conservativeness (continuous index)	0.008	0.023	0.026	-0.01	0.003	0.025	0.110***	0.106***	0.145***	0.064**	0.082***
	(0.027)	(0.028)	(0.028)	(0.028)	(0.030)	(0.030)	(0.028)	(0.029)	(0.029)	(0.030)	(0.030)
US–China competition x Conservativeness	0.042	-0.029	0.003	0.024	0.019	-0.025	-0.009	-0.114***	-0.090**	-0.011	-0.067
	(0.039)	(0.041)	(0.041)	(0.040)	(0.043)	(0.044)	(0.040)	(0.042)	(0.042)	(0.044)	(0.044)
Sanction by the US x Conservativeness	0.053	0.046	0.041	0.041	0.048	-0.028	-0.022	-0.018	-0.107**	0.007	-0.002
	(0.040)	(0.042)	(0.042)	(0.041)	(0.044)	(0.045)	(0.041)	(0.043)	(0.043)	(0.045)	(0.045)
Gov't use of data x Conservativeness	0.004	0.023	0.033	0.078*	0.058	0.019	-0.021	-0.01	-0.027	-0.032	-0.009
	(0.039)	(0.041)	(0.041)	(0.040)	(0.043)	(0.043)	(0.040)	(0.042)	(0.042)	(0.044)	(0.044)
Observations	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146
R-square	0.382	0.307	0.321	0.331	0.24	0.223	0.346	0.268	0.287	0.206	0.211
Other demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nationalism controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Conservativeness controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Antimarket controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Patriotic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology savviness controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Globalization controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tech company perception controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01

Appendix Table 11: Impact of treatments with antimarket interaction (with controls)

	Willingness to share personal data with:			Support using personal data for development			Trust in handling personal data			Tech nationalistic sentiments	
	Private companies	Central gov't	Local gov't	Private companies	Central gov't	Local gov't	Private companies	Central gov't	Local gov't	Global competitiveness	World leader AI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
US–China competition	0.108***	0.057	0.071*	0.098**	0.013	-0.004	0.067*	0.012	0.027	0.081*	-0.019
	(0.039)	(0.041)	(0.041)	(0.040)	(0.043)	(0.043)	(0.040)	(0.042)	(0.042)	(0.044)	(0.044)
Sanction by the US	0.102**	0.088**	0.063	0.098**	0.046	0.022	0.029	0.039	-0.04	0.073	-0.035
	(0.040)	(0.043)	(0.042)	(0.042)	(0.045)	(0.045)	(0.041)	(0.044)	(0.043)	(0.046)	(0.046)
Gov't use of data	0.03	0.018	0.028	-0.028	-0.009	0.044	-0.016	-0.034	-0.015	0.072	0.022
	(0.039)	(0.041)	(0.041)	(0.040)	(0.043)	(0.043)	(0.040)	(0.042)	(0.042)	(0.044)	(0.044)
Antimarket (continuous index)	-0.051*	0.059**	0.024	-0.056**	0.120***	0.101***	-0.043	0.087***	0.044	0.004	0.020
	(0.026)	(0.028)	(0.028)	(0.027)	(0.029)	(0.030)	(0.027)	(0.029)	(0.028)	(0.030)	(0.030)
US–China competition x Antimarket	0.047	-0.035	-0.004	0.085**	-0.087**	-0.035	-0.005	-0.097**	-0.05	-0.024	-0.038
	(0.039)	(0.041)	(0.041)	(0.040)	(0.043)	(0.044)	(0.040)	(0.042)	(0.042)	(0.044)	(0.044)
Sanction by the US x Antimarket	0.0001	-0.038	-0.017	0.075*	-0.002	-0.007	0.033	-0.005	-0.016	0.039	0.019
	(0.040)	(0.042)	(0.042)	(0.041)	(0.044)	(0.045)	(0.041)	(0.043)	(0.043)	(0.045)	(0.045)
Gov't use of data x Antimarket	-0.044	-0.028	-0.005	0.038	-0.098**	-0.075*	-0.048	-0.064	-0.05	-0.052	-0.031
	(0.038)	(0.041)	(0.040)	(0.040)	(0.042)	(0.043)	(0.039)	(0.042)	(0.041)	(0.043)	(0.043)
Observations	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146
R-square	0.383	0.307	0.321	0.332	0.242	0.223	0.346	0.267	0.285	0.207	0.210
Other demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nationalism controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Conservativeness controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Antimarket controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Patriotic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology savviness controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Globalization controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tech company perception controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

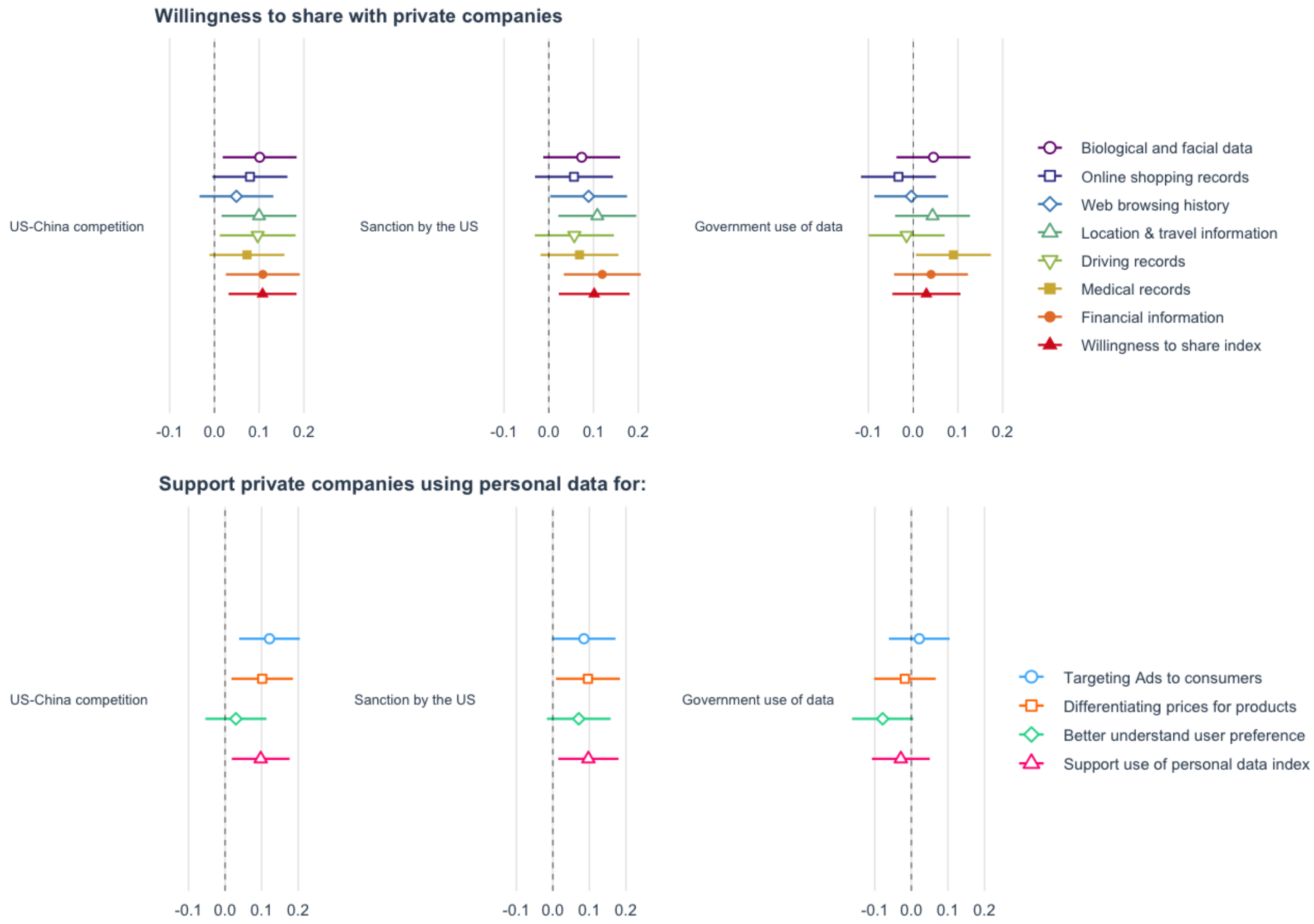
*p<0.1; **p<0.05; ***p<0.01

Appendix Table 12: Impact of treatments with patriotism interaction (with controls)

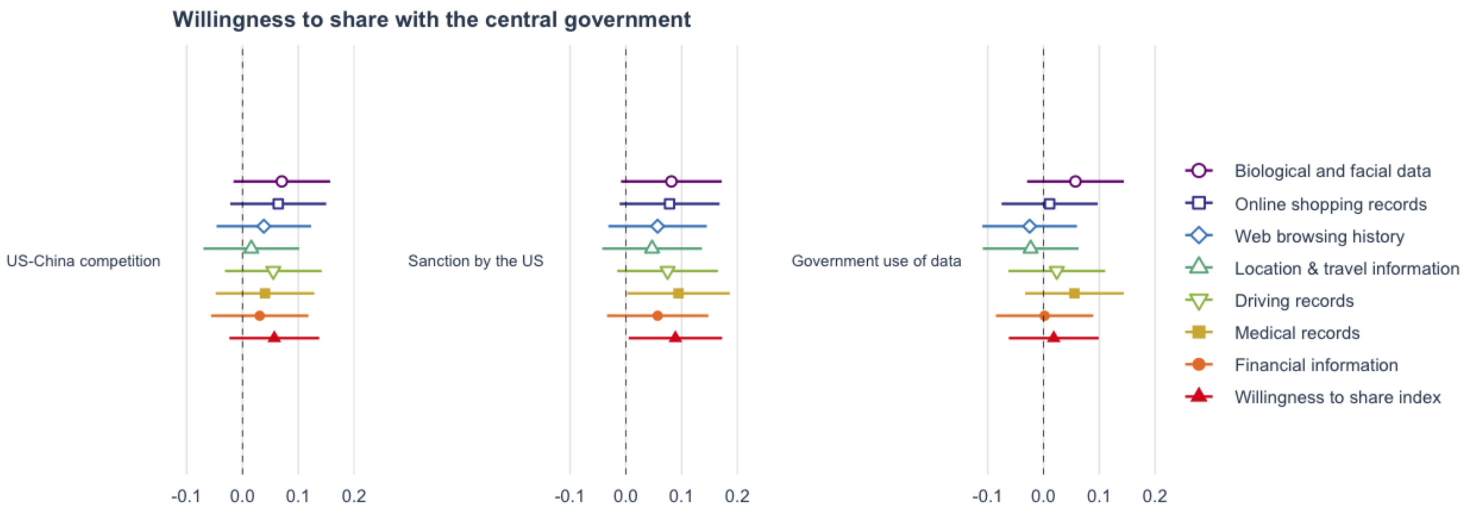
	Willingness to share personal data with:			Support using personal data for development			Trust in handling personal data			Tech nationalistic sentiments	
	Private companies	Central gov't	Local gov't	Private companies	Central gov't	Local gov't	Private companies	Central gov't	Local gov't	Global competitiveness	World leader AI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
US–China competition	0.106***	0.056	0.070*	0.097**	0.012	-0.005	0.066*	0.015	0.028	0.080*	-0.018
	(0.039)	(0.041)	(0.041)	(0.040)	(0.043)	(0.043)	(0.040)	(0.042)	(0.042)	(0.044)	(0.044)
Sanction by the US	0.102**	0.086**	0.063	0.095**	0.044	0.02	0.031	0.04	-0.036	0.075	-0.034
	(0.040)	(0.043)	(0.042)	(0.042)	(0.045)	(0.045)	(0.042)	(0.044)	(0.043)	(0.046)	(0.046)
Gov't use of data	0.031	0.019	0.028	-0.029	-0.01	0.042	-0.016	-0.032	-0.015	0.07	0.022
	(0.039)	(0.041)	(0.041)	(0.040)	(0.043)	(0.044)	(0.040)	(0.042)	(0.042)	(0.044)	(0.044)
Patriotism (continuous index)	-0.066**	0.067**	0.067**	-0.050*	0.214***	0.231***	0.039	0.293***	0.244***	0.063**	0.210***
	(0.028)	(0.030)	(0.030)	(0.029)	(0.031)	(0.032)	(0.029)	(0.031)	(0.030)	(0.032)	(0.032)
US–China competition x Patriotism	0.053	0.04	0.056	0.046	0.067	0.038	0.0002	-0.092**	-0.069	0.004	-0.044
	(0.039)	(0.042)	(0.041)	(0.041)	(0.044)	(0.044)	(0.041)	(0.043)	(0.042)	(0.045)	(0.045)
Sanction by the US x Patriotism	0.025	(0.029)	0.021	(0.009)	0.027	0.022	0.046	(0.048)	0.022	0.067	(0.000)
	(0.039)	(0.042)	(0.041)	(0.041)	(0.044)	(0.044)	(0.041)	(0.043)	(0.042)	(0.045)	(0.045)
Gov't use of data x Patriotism	-0.015	-0.014	0.005	0.000	0.02	0.039	-0.007	-0.054	-0.013	0.047	-0.027
	(0.039)	(0.042)	(0.041)	(0.041)	(0.044)	(0.044)	(0.040)	(0.043)	(0.042)	(0.045)	(0.044)
Observations	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146	3,146
R-square	0.382	0.307	0.321	0.331	0.240	0.223	0.346	0.267	0.286	0.207	0.210
Other demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nationalism controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Conservativeness controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Antimarket controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Patriotic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology savviness controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Globalization controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tech company perception controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

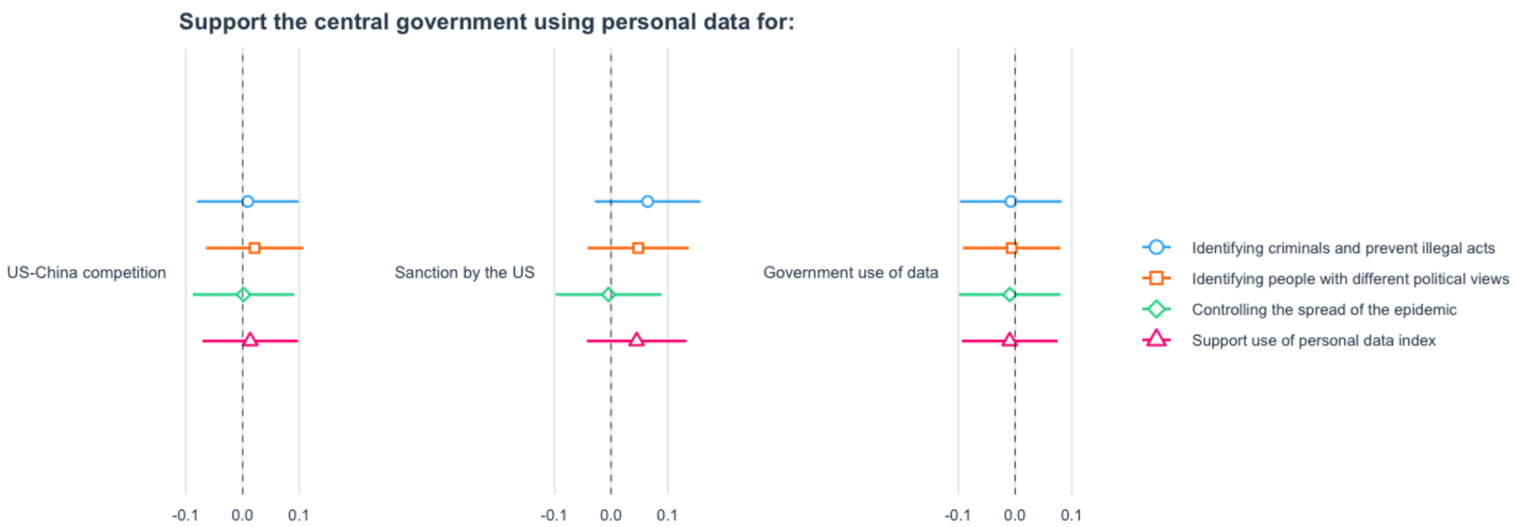
*p<0.1; **p<0.05; ***p<0.0

Appendix Figure 3A. Coefficient estimates corresponding to Table 3A

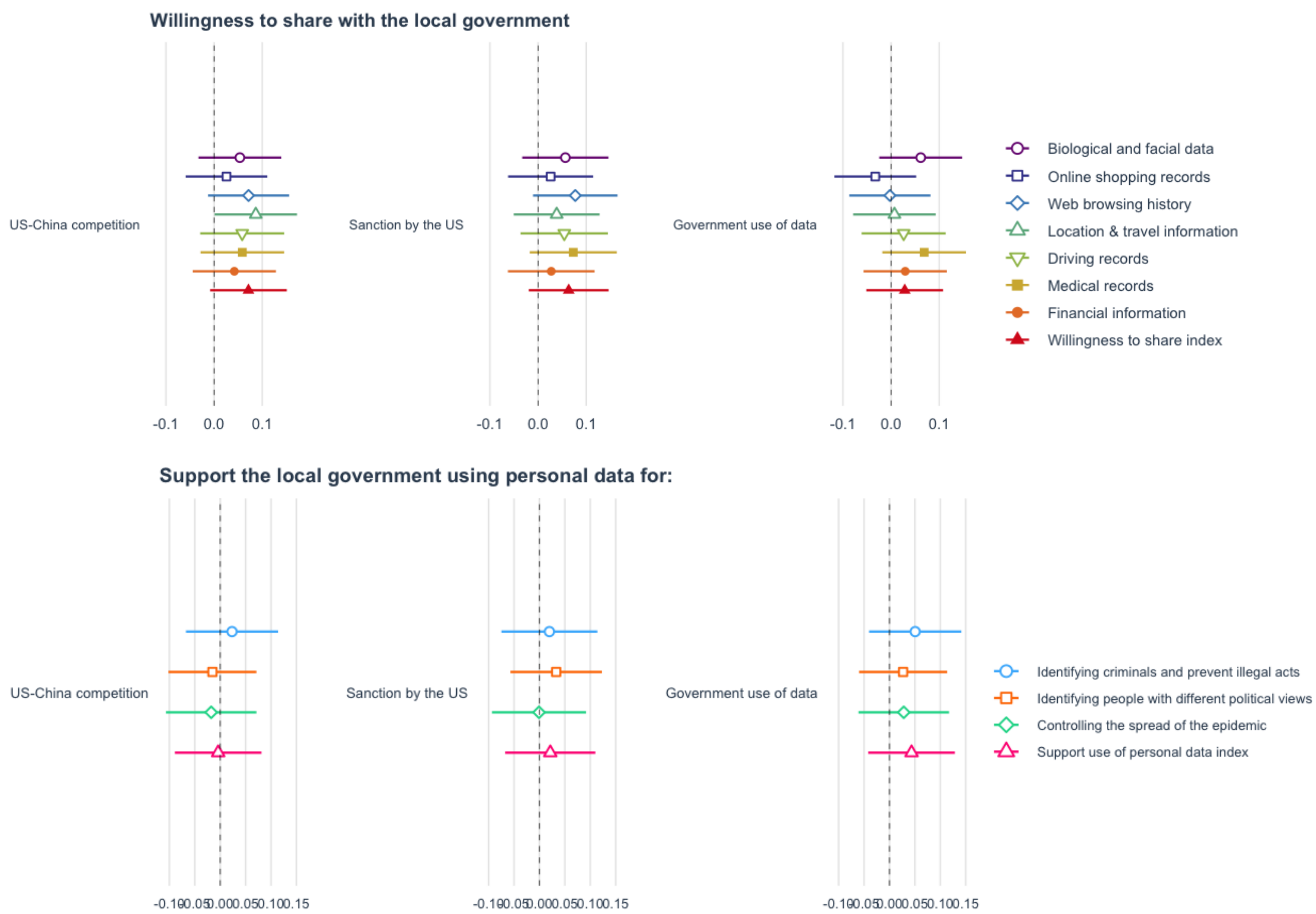


Appendix Figure 3B. Coefficient estimates corresponding to Table 3B

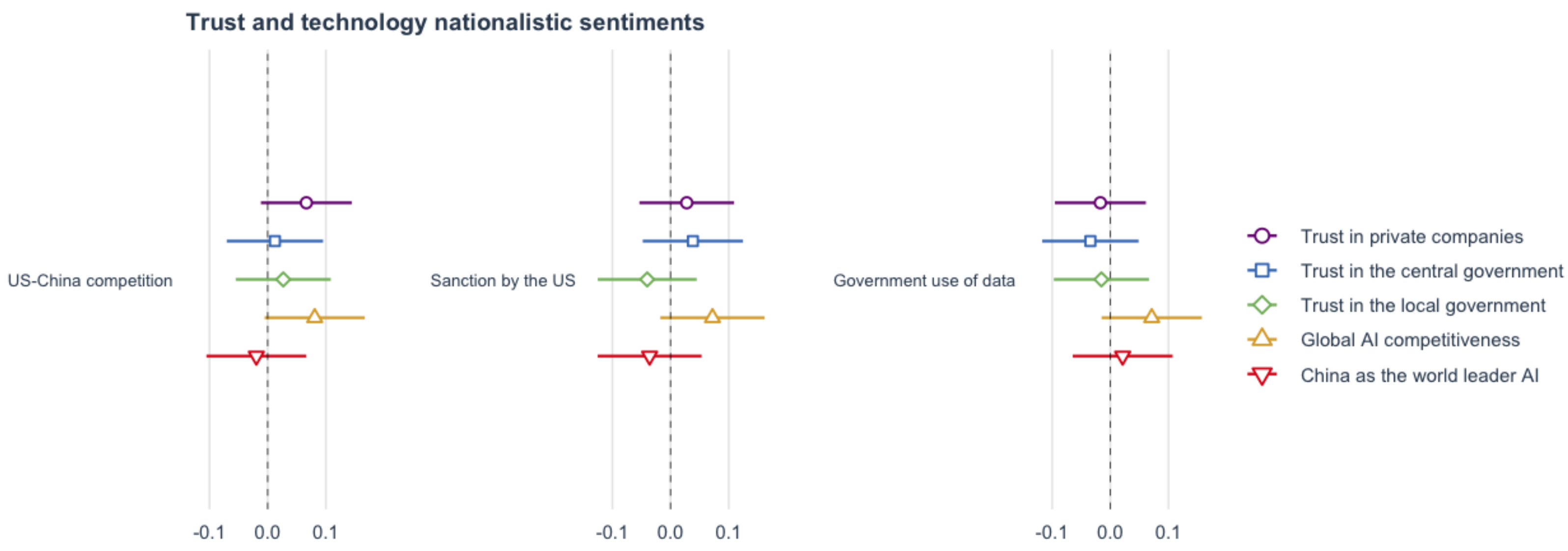




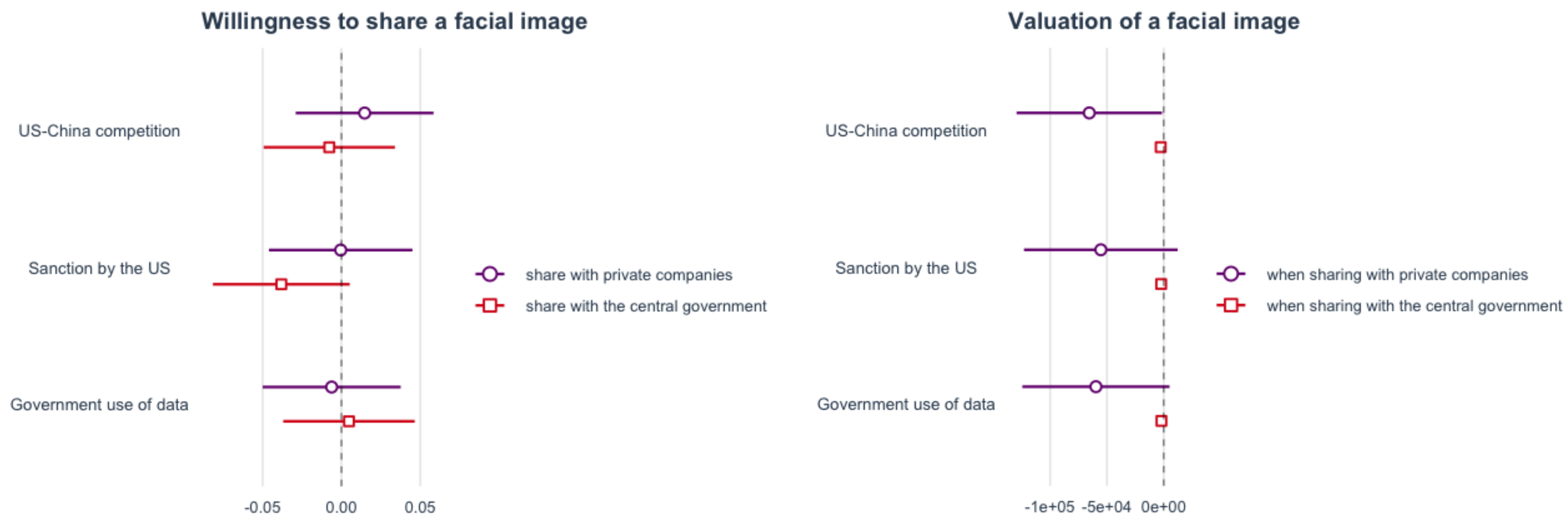
Appendix Figure 3C. Coefficient estimates corresponding to Table 3C



Appendix Figure 4 Coefficient estimates corresponding to Table 4



Appendix Figure 5. Coefficient estimates corresponding to Table 5



Declaration of co-authorship

Article I: co-authored with Mariano Florentino Cueller, Yong Suk Lee, and Michael Webb

CBS COPENHAGEN BUSINESS SCHOOL HANDELSHØJSKOLEN

CO-AUTHOR STATEMENT

Title of paper	Does Information About AI Regulation Change Manager Evaluation of Ethical Concerns and Intent to Adopt AI?
Journal and date (if published)	

1. Formulation/identification of the scientific problem to be investigated and its operationalization into an appropriate set of research questions to be answered through empirical research and/or conceptual development
Description of contribution: The PhD fellow, Benjamin Cedric Larsen, has been involved in all stages of this process.
2. Planning of the research, including selection of methods and method development
Description of contribution: The PhD fellow, Benjamin Cedric Larsen, has been involved in all stages of this process.
3. Involvement in data collection and data analysis
Description of contribution: The PhD fellow, Benjamin Cedric Larsen, has been involved in all stages of this process.
4. Presentation, interpretation and discussion of the analysis in the form of an article or manuscript
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