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Evidence from Public Healthcare

Sun, Tara Qian; Medaglia, Rony

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Qian Sun and Rony Medaglia

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Mapping the challenges of Artificial Intelligence in the public sector: Evidence from public healthcare

Tara Qian Sun

Sino-Danish College

University of Chinese Academy of Sciences

19(A) Yuquan Road, Shijingshan District

100049 Beijing, China

qs.digi@cbs.dk

Rony Medaglia

Department of Digitalization

Copenhagen Business School

Howitzvej 60

2000 Frederiksberg, Denmark

rony@cbs.dk

Highlights

- We map how stakeholders frame challenges of AI adoption in the public sector
- We investigate the adoption of IBM Watson in public healthcare in China
- We identify challenges in seven dimensions as framed by three stakeholder groups
- Stakeholders have diverse framings of AI adoption in the public sector
- We suggest future research and provide four governance recommendations

Mapping the challenges of Artificial Intelligence in the public sector: Evidence from public healthcare

ABSTRACT

The nascent adoption of Artificial Intelligence (AI) in the public sector is being assessed in contradictory ways. But while there is increasing speculation about both its dangers and its benefits, there is very little empirical research to substantiate them. This study aims at mapping the challenges in the adoption of AI in the public sector as perceived by key stakeholders. Drawing on the theoretical lens of framing, we analyse a case of adoption of the AI system IBM Watson in public healthcare in China, to map how three groups of stakeholders (government policy-makers, hospital managers/doctors, and IT firm managers) perceive the challenges of AI adoption in the public sector. Findings show that different stakeholders have diverse, and sometimes contradictory, framings of the challenges. We contribute to research by providing an empirical basis to claims of AI challenges in the public sector, and to practice by providing four sets of guidelines for the governance of AI adoption in the public sector.

Keywords: Artificial Intelligence, public sector, healthcare, challenges, framing, China

1 INTRODUCTION

Artificial Intelligence (AI) technologies refers to any device that perceives its environment and takes actions that maximize its chance of success at some goal (Russell & Norvig, 2016). Such technologies include machine learning, rule-based systems, natural language processing, and speech recognition (Eggers, Schatsky, & Viechnicki, 2017).

After a series of rises and falls in popularity, AI technologies are now experiencing a surge in diffusion. In parallel with the emergence of the concepts of web 3.0 (Fuchs et al., 2010), the Internet of Things (IoT) (Brous & Janssen, 2015), open innovation (Kankanhalli, Zuiderwijk, & Tayi, 2017; Zhang, Zhao, Zhang, Meng, & Tan, 2017), and big and open data (Janssen & van den

Hoven, 2015), AI has recently gained momentum as a potentially disruptive set of technologies in many industry areas, such as financial, automotive, retail, travel, and media (Chui, 2017).

AI technologies are now also beginning to be adopted in areas of the public sector (K. C. Desouza, 2018). For example, in the education area, systems identified as AI can draw on algorithms that support the prediction of which school teacher will have the greatest value added (Rockoff, Jacob, Kane, & Staiger, 2010). In social policy, AI is being used to support the prediction of high risk youth for targeting interventions (Chandler, Levitt, & List, 2011). In regulation, AI systems are targeting health inspections in restaurant businesses (Kang, Kuznetsova, Luca, & Choi, 2013).

In this nascent phase, the hype linked to the introduction of AI technologies in the public sector is inevitably accompanied by some degree of uncertainty, as the public sector trails the explosion of AI in the private sector. On the one hand, AI applications are seen as enablers of increased efficiency and effectiveness, by automating cognitive labour, freeing up high-value work, augmenting predictive capabilities for decision-making, and improving services to citizen queries (Eggers et al., 2017). On the other hand, the introduction of AI is accompanied by fuzzily defined challenges related to the destruction of jobs caused by automation, the infringements of privacy caused by digital surveillance (The Economist, 2016), and the reinforcement of biases in policy-making caused by algorithmic governance (Janssen & Kuk, 2016).

A key area of adoption of AI technologies in the public sector is healthcare. The healthcare sector is one of the public policy sectors with the highest investments in new technologies (Yang, Ng, Kankanhalli, & Luen Yip, 2012), and where AI has the most potential for doing transformative work, such as mining medical records, assisting repetitive jobs, and designing treatment plans (Meskó, 2016). Moreover, the healthcare sector presents unique characteristics linked to the complexity of its ecosystem of stakeholders, which includes not only the government agencies shaping policies, but also service-delivering public organizations (i.e., public hospitals) and private

IT firms providing the technology. The already fuzzy challenges of AI initiatives in the public sector are even harder to pinpoint in healthcare because the diverse stakeholders can be expected to have different views on what these challenges are.

Despite the media hype, there is still little research on AI in the public sector. In particular, compared to the expanding debate on potential challenges of AI adoption in the public sector, there is little to no existing empirical research to test these assumptions or provide guidelines for the governance of this emerging phenomenon. In order to fill this gap in research and in practice, in this study we tackle the following research question: *what are the perceived challenges of AI adoption in the public healthcare sector?*

We aim at answering this question by mapping the challenges of adopting an AI system, IBM Watson, as perceived by three key groups of stakeholders in a public healthcare ecosystem in China: government policy-makers, hospital managers/doctors, and IT firm managers. Public healthcare in China provides an ideal setting to investigate healthcare as a sector of government action. Different from other contexts such as healthcare in the U.S., healthcare services in China are strongly dominated by public sector intervention, in terms of regulation, strategy, and financing (Hu et al., 2008). A notable range of investments and experimentations is occurring in some regions of China with the introduction of Watson, the AI system developed by IBM to answer questions posed in natural language and design personalized treatment plans based on the state-of-the-art medical literature (IBM, 2016). Mapping the challenges of AI adoption as perceived by key stakeholders that actually use, diffuse, and regulate AI technology in the public sector can help push our understanding of AI impacts beyond the realm of speculation.

The remainder of this paper is structured as follows. In the next section, we provide the background for the study by unboxing the relevant characteristics of AI technologies, and discussing existing contributions on AI adoption in the public sector. In section 3, we present the construct of framing, which we adopt as a theoretical lens to map the way different stakeholders perceive the challenges of AI adoption in the public healthcare sector. Section 4 provides the details of our empirical research setting, describes the sources of the empirical data, and illustrates the methods used to collect and analyse the data for the study. In section 5, we report the findings from the analysis of how the three groups of stakeholders (government policy-makers, hospital managers/doctors, and IT firm managers) frame challenges of AI adoption in seven dimensions: social challenges; economic challenges; ethical challenges; political, legal, and policy challenges; organizational and managerial challenges; data challenges; and technological challenges. In the discussion section (Section 6), we summarize the findings, discuss their implications for research, provide recommendations for the governance of AI adoption in the public sector, and highlight limitations of the study. In the conclusion section, we illustrate how the findings of our study open new directions for future research on AI in the public sector.

2 BACKGROUND AND PREVIOUS RESEARCH

2.1 Opening the "black box": What is AI?

Despite recent hype, the research field of AI is not new. The term 'Artificial Intelligence' was coined in 1956 at Dartmouth College, to indicate an emerging research field bringing together researchers on brain physiology, formal analysts of propositional logic, and computer engineers (Tzafestas, 2016). Within this context, AI has been defined according to two abilities 1) as the ability of machines to carry out tasks by displaying intelligent, human-like behaviour; and 2) as the ability of machines to behave rationally (i.e., as intelligent agents) by perceiving the environment and taking actions to achieve some goals (Russell & Norvig, 2016).

The development of AI research has been characterized by ups and downs. A first wave of general enthusiasm in the late 1950s was linked to the ability to build programmes capable of proving some mathematical theorems, or playing simple games, like checkers (Russell & Norvig, 2016). Such initial enthusiasm was followed by a period of disillusion, where promises of AI systems being able to display levels of intelligence similar, or even higher, than humans were met with exemplary failures, for instance in the area of machine translation (Russell & Norvig, 2016). This was partly due to the immaturity of computing technology at the time, and partly due to the lack of a solution to the problem of how to map and incorporate contextual knowledge. The following 'AI winter', characterized by reduced funding and interest in AI research, was only punctuated by cyclical spikes in optimism in AI and, according to many, lasted until the late 1990s.

Currently, many authors refer to AI as bringing in a new revolution, as a consequence of how machines have transformed the way work is carried out by humans (Makridakis, 2017). Similar to the industrial revolution (when machines provided ways to substitute, supplement, and amplify the *manual work* performed by humans) and the digital revolution (where machines provide ways to substitute, supplement, and amplify *mental routine* tasks performed by humans), the AI revolution has been heralded as providing ways to substitute, supplement, and amplify *practically all tasks* currently performed by humans (Makridakis, 2017).

Despite increasing enthusiasm, however, most researchers agree that what we are witnessing today is the diffusion of weak AI technologies, as opposed to strong AI. *Strong AI* refers to hypothetical systems with human or superhuman intelligence, that simulate the complex human ability to think and to execute intelligent tasks such as ethical judgments, symbolic reasoning, managing social situations, and ideation (Brynjolfsson & McAfee, 2014). *Weak AI* refers to systems capable of carrying out tasks that require single human capabilities, e.g., visual perception, understanding context, probabilistic reasoning, and dealing with complexity (Russell & Norvig, 2016). Only the weak form of AI is of interest for real-world applications, as strong AI systems are still considered an area of speculation and science fiction (Russell & Norvig, 2016). Our study focuses on AI technologies in their weak form, and focuses on the under-investigated area of AI adoption in the public sector.

2.2 Research on AI in the public sector

Commercial applications of AI have attracted the majority of the research interest (Ransbotham, Kiron, Gerbert, & Reeves, 2017). The impacts of AI have been studied in the areas of high tech, the automotive industry, financial services, retail, media, education, and travel (Chui, 2017; Dirican, 2015).

However, empirical research on AI in the public sector is still scarce. This is surprising, as AI initiatives in the public sector are starting to take place already in public sector areas as diverse as disease surveillance, law enforcement, and tax services. For instance, in 2010 a group of hospitals in Hampshire, England adopted a disease surveillance system that relies on machine learning algorithms (MLA), which led to a reduction of outbreaks of norovirus of more than 90 percent (Mitchell, Meredith, Richardson, Greengross, & Smith, 2016). In 2011, the Santa Cruz Police Department in California piloted an AI-based analytics tool to predict hotspots of crime, contributing to a reduction of property crimes of 27 percent (Goldsmith & Crawford, 2014). In 2016, the Australian Tax Office has deployed a chatbot to help citizens with questions related to taxes, which contributed to an increase of first contact resolution rate to 80%, exceeding the industry benchmark of 60-65% (Nuance Communications, 2016).

The little existing empirical research on AI in the public sector has focused on AI's capabilities to transform the workforce. Impacts of the use of AI on the work of the public sector have been categorized into four areas: *relieving*, in which AI takes over mundane tasks, and relieves public workers for more valuable tasks; *splitting up*, where AI helps to break up a job into smaller pieces, and takes over as many as possible of these, leaving humans do the remainder; *replacing*, where AI carries out an entire job performed by a human; and *augmenting*, where the AI technology makes workers more effective by complementing their skills (Eggers et al., 2017).

The scarcity of empirical studies on the impacts of AI in the public sector is particularly remarkable when we consider the unique nature of the problems of the public sector, as opposed to the private one. AI differs from existing automation technologies because it does not make decisions on pre-programmed *if-then* logic, in which the same input instructions produce the exact same results. Instead, AI goes a step further by exhibiting some learning capabilities (Russell & Norvig, 2016). AI thus represents, in principle, an ideal technology to be applied to the public-sector context, where environmental settings are constantly changing, and pre-programming cannot account for all possible cases.

Research is beginning to identify the manifold challenges faced in the adoption of AI in the public sector. First, AI is seen as having tremendous impacts on the workforce, as the jobs of doctors, nurses, managers and lawyers can increasingly be replaced (Susskind & Susskind, 2016), bringing about threats of unemployment (Ford, 2013; Roman & Anna, 2017). Second, social rules and ethical issues are increasingly focused on. How to achieve an appropriate balance between privacy and data acquisition is seen as one of the most pressing issue in AI adoption (Begg, 2009). Third, regulatory issues also need to be faced. Effective supervision (Hengstler, Enkel, & Duelli, 2016) and corresponding laws and regulations (Gulson & Webb, 2017) are needed in the different public sectors, including e.g., education and healthcare.

One of the promising area of AI application is public healthcare. While its adoption has been slow, its use is steadily increasing, partly due to the cost savings that can potentially be achieved by AI replacing face-to-face interactions, which are at the core of healthcare service delivery (Jung & Padman, 2015). The use of AI has been considered likely to redesign the healthcare sector in many aspects. This use includes a physical and a virtual branch. The *physical branch* largely overlaps with studies in robotics to, for example, assist elderly patients or attending surgeons. The *virtual branch* concerns the heart of AI, including the study of deep learning information management to control health management systems, electronic health records, and actively guide physicians in their treatment decisions. The use of AI systems to assist doctors in the diagnosis of patients, in particular, has recently received some research attention (Hamet & Tremblay, 2017). Our study focuses on the virtual branch of AI in healthcare.

Research on AI in the public sector is still in its nascent phase, and mostly concerns the expected impacts of AI, that so far are mostly speculative in nature. There is a need for empirical accounts of AI challenges as perceived by stakeholders that work with it in the public sector.

3 THEORETICAL LENS

Framing was originally defined as the active task of figuring out what is going on (that is, what frames apply), without which no utterance could be interpreted (Goffman, 1974). Framing is a widely used construct in management and organizations studies, aimed at capturing how groups and organizations construct and negotiate meaning around a general phenomenon. Drawing on this general blueprint, the construct of framing has been adopted in a wide range of research settings, including research in managerial cognition and decision-making (Hodgkinson, Bown, Maule, Glaister, & Pearman, 1999; Nutt, 1998), strategic and organizational change (Fiss & Zajac, 2006; Mantere, Schildt, & Sillince, 2012), and social movements and institutions (Benford & Snow, 2000).

To investigate how the challenges of an emerging technology are perceived by different groups of stakeholders, we draw on the concept of *technological framing*, defined as "A collectively constructed set of assumptions, knowledge and expectations regarding a technology and its uses and applications in organizations" (Cornelissen & Werner, 2014, p. 185). The initial concept of technological frames in organizations drew on the notion of cognitive frames, combined with a sociological focus, to map different groups' understanding of what a technology is ("nature of technology"), why a technology is adopted in an organization ("technology strategy"), and how a technology is used on a day-to-day basis ("technology-in-use") (Orlikowski & Gash, 1994). Studies using the concept of technological frames focus on a number of different aspects, including: how a technology is framed versus how the technology is implemented (Barrett, Heracleous, & Walsham, 2013; Kaplan & Tripsas, 2008; Leonardi, 2010); the consequences of incongruences between groups that frame a certain technology differently (Davidson, 2006; Mazmanian, 2013); and the evolution process of technology frames (Gal & Berente, 2008; Young, Mathiassen, & Davidson, 2016).

In this study, we take a different perspective on the construct of framing, by using it as a lens to map how different groups of stakeholders perceive the *challenges* in AI adoption in the public healthcare sector. We refer to challenges as any perceived obstacle or problem faced by a stakeholder when considering the adoption of AI in the public sector. Rather than systematically operationalizing one version of framing theory, we use framing as a sensitizing device (Klein & Myers, 1999) to inductively solicit different stakeholders' views on the challenges of AI technology adoption. Similar to approaches taken in analysing public policy-making (Schon & Rein, 1995), we consider framing as the work of "selecting, naming, and categorizing" (Van Hulst & Yanow, 2016, p. 99) that different groups of stakeholders – consciously or unconsciously – carry out when they highlight some features and challenges of an emerging technology.

Very few studies have adopted a theoretical lens to capture the perceptions of challenges of AI, with the exception of the seminal research by Carbonell, Sánchez-Esguevillas, & Carro (2016) on the use of metaphors to characterize AI. The use of framing as a lens for mapping the perceived challenges of an emerging technology is particularly apt in the empirical context of this study, since existing research is still at an early stage of understanding the challenges of AI adoption in the public sector, and because the adoption of AI in the public healthcare sector is enacted by a range of diverse stakeholders.

4 METHODS

4.1 Research setting

To answer our research question, *what are the perceived challenges of AI adoption in the public healthcare sector*, we draw on empirical data from a case of AI adoption in public healthcare in China. We focus on the perceived challenges of the introduction of an AI system, IBM Watson, in a public healthcare ecosystem among different groups of stakeholders: hospital managers/doctors, IT firms, and government policy-makers. The hospital involved is the Zhejiang Provincial Hospital of Traditional Chinese Medicine (ZP-TCM Hospital). The three IT firms are IBM China, Hangzhou CognitiveCare, and EWELL. The two national government agencies are the Ministry of Science and Technology (MOST) and the National Development and Reform Commission (NDRC), both of the People's Republic of China. An overview of the stakeholders is provided in Table 1.

<Table 1 here>

Watson is the name given by IBM to its question answering (QA) computing system capable of answering questions posed in natural language. Originally developed as a research experiment to determine whether a computer could be taught to read volumes of text (such as Wikipedia and newspapers) to produce reliable answers in response to natural language questions, Watson achieved global fame after a public demonstration in 2011, when it defeated two human champions in the quiz game show *Jeopardy*.

Watson is based on a massively parallel probabilistic evidence-based architecture, named DeepQA, which uses more than 100 different techniques to analyze natural language questions, identify sources, find and generate hypotheses, find and score evidence, and merge and rank hypotheses.

These techniques include syntactic and semantic structure mining, relationship graphs between extracted entities, hypotheses generation via search engine and via hypotheses ranking, and logistic regression as a classifier. Watson's capability does not draw on an original algorithm, but rather on executing hundreds of proven language analysis algorithms simultaneously (Ferrucci et al., 2010).

The first commercial application of Watson has been in the healthcare field, in areas such as drug discovery, patient engagement, and care management (IBM, 2017). The system adopted by the hospital in our study is Watson for Oncology, a version of Watson focusing on designing personalized treatments for cancer patients, originally developed by IBM in collaboration with the Memorial Sloan Lettering Cancer Center in the U.S., one of the world leading cancer centers. Watson for Oncology at the ZP-TCM Hospital (henceforth "Watson") takes information about a specific patient and matches it to a very large knowledge base that includes millions of pages of medical text literature (e.g., medical textbooks and journals, treatment guidelines, clinical trials, electronic medical record data, treatment history of similar patients, notes from healthcare providers), to assists doctors in making a decision on a personalized treatment plan for the patient. The knowledge base is updated weekly and, as Watson continuously learns, it improves its accuracy and confidence in treatment plan recommendations. Patient data in the knowledge base is owned by each hospital.

The steps in the use case of Watson in the hospital typically are: 1) the patient books an appointment with a doctor, specifying that she wants the doctor to use Watson, and paying a corresponding additional fee; 2) the doctor inputs into Watson personal patient data, including her symptoms, medical record, previous medical tests, nursing record, etc. If needed, the doctor might require additional patient data, and ask the patient to perform additional tests; 3) Watson provides a list of potential treatment options, ranked in the categories of 'recommended', 'for consideration', and 'not recommended', and includes relevant articles and clinical data as supporting evidence for the ranking, in the form of a report; 4) based on a discussion of Watson's report, a multidisciplinary team (MDT) of minimum five doctors approves a treatment plan for the patient.

As of December 2017, Watson has been adopted in 42 public hospitals in China. The ZP-TCM Hospital – founded in 1931, and located in the city of Hangzhou, in the Zhejiang province of China – has been the first hospital to adopt Watson in the country. From December 2016 to March 2017, as a test, the hospital provided the support of Watson free of charge to 50 patients and, since the official launch in March 2017, a reported average of 2-3 patients per week have requested the support of Watson, for a total of about 130 use cases, as of October 2017.

The adoption of Watson at the hospital is supported by Hangzhou CognitiveCare, the only partner company of IBM China that services hospitals in China using Watson (IBM, 2016). Since its adoption in the ZP-TCM Hospital in December 2016, CognitiveCare has trained on the use of IBM Watson ten physicians specialized in six different cancer types.

EWELL is a high-tech company focusing on R&D in the healthcare industry. Besides AI technologies, EWELL focuses on an array of products related to healthcare, such as cloud platforms on which it develops different application solutions for hospitals. EWELL provides technical support and training to the ZP-TCM Hospital, and carries out translations from English to Chinese.

IBM China takes responsibilities for research and development, marketing, and product and service development in the Chinese market under the leadership of IBM Global. IBM China provides fundamental technology support for the use of IBM Watson in China. It maintains the key technology of IBM Watson but also opens for any updates from its partners.

The Chinese government works on policies of AI and healthcare to ensure the technology development and AI application environment. MOST is responsible for drafting plans and policies on science popularization, technology market, and Science and Technology (S&T) intermediaries, as well as managing S&T assessment and statistics (Ministry of Science and Technology of the P.R.C., 2017). NDRC is responsible for drafting relevant laws and regulations concerning national economic and social development, economic system restructuring and opening up to the outside world, formulating regulations, and guiding and coordinating tenders in accordance with regulations (National Development and Reform Commission, 2017).

4.2 Data collection

For the empirical data collection, we adopted a case-study approach (Pan & Tan, 2011). We have drawn on a set of primary data, including semi-structured interviews of key stakeholders, and on secondary data, including and government policy documents, excerpts from public interviews, and presentations by key stakeholders.

The semi-structured interviews were carried out with the main stakeholders, including five hospital managers/doctors, two directors at IBM China, six managers and employees at CognitiveCare, two managers at EWELL, two policy-makers involved in AI technologies at MOST, and two policy-makers at NDRC. The interviews consisted of open-ended questions focusing on the challenges of AI adoption in healthcare and the use of IBM Watson in the hospital. The list of interview questions is included in Appendix A. Table 2 provides an overview of the interview data sources.

<Table 2 here>

Secondary data sources included an analysis of policy documents regarding the adoption of AI in the healthcare sector, in order to triangulate data from interviewing government policy-makers with documentary evidence. The documents were retrieved using a keyword search on three 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 20 ministries and commissions (e.g., NDRC; http://www.ndrc.gov.cn/); and 3) the Report on Deepening Health

Reform in China (World Bank Group, World Health Organization, Ministry of Finance of the P.R.C, National Health and Family Planning Commission of the P.R.C., & Ministry of Human Resources and Social Security of the P.R.C., 2016). Among policy documents published on a regular basis (e.g., the yearly "State Council on the Issuance of 2017 Key Tasks in Deepening the Reform of the Medical and Health System"), we only included the latest 2017 edition in our sample. We also discarded policy documents targeting only specific areas, such as traditional Chinese medicine or specific medical instruments.

The resulting 22 government policy documents focused on the following four theme groups most closely associated with AI adoption in healthcare: a) 10 policy documents on general healthcare; b) 8 policy documents on emerging Information and Communication Technology (ICT) (e.g., big data, the Internet of Things, and cloud computing); c) 2 policy documents on the overlap between these two, that is on emerging technologies in the healthcare sector; and d) 2 policy documents on Artificial Intelligence. There was no policy document explicitly tackling the topic of AI in the healthcare sector. Figure 1 provides an overview of the scope of each group of policy documents as a Venn diagram. The details of the policy documents analyzed in each of the four groups are provided in Appendix B.

<Figure 1 here>

In addition, we analysed three interviews, three conference presentations and one academic presentation concerning the challenges of AI in healthcare sector as perceived by IBM China and by Hangzhou CognitiveCare. The analysis of secondary data sources was aimed at triangulating the interviews with IT firm managers with previously published data on their framing of challenges of AI adoption. Appendix C provides an overview of the additional secondary sources of data used in our study.

4.3 Data analysis

Each dataset was analysed to answer the research question: *what are the perceived challenges of AI adoption in the public healthcare sector?* Using the concept of *framing* as a sensitizing device (Klein & Myers, 1999), we aimed at identifying and inductively classifying views on the challenges of AI technology adoption from the three groups of stakeholders: hospital managers/doctors, IT firms, and government policy-makers.

All interviews were recorded, transcribed, and translated from Mandarin Chinese to English. With the support of the software NVivo version 11, interview transcriptions were coded using two rounds. The first round of coding aimed at identifying specific challenges as framed by each group of stakeholders, in an inductive fashion (Strauss & Corbin, 1998). In the second round of coding, we re-grouped the first-order codes into more abstract second-order codes that synthesized the perceived challenges into distinct classes of challenges. Refinement was completed when the resulting framework of topic areas for each of the second-order codes reached theoretical saturation. Theoretical saturation refers to the state where the inductively derived topic areas can comprehensively account for the data, and "incremental learning is minimal because the researchers are observing phenomena seen before" (Eisenhardt, 1989, p. 545). Table 3 provides an example of the interview data coding procedure.

<Table 3 here>

We complemented the analysis of interview data with the analyses of policy documents and secondary data, all coded using the same procedure as for the interview transcripts. The analysis of the 22 policy documents provided additional insights into the framing of challenges of AI in healthcare by government policy-makers, since they indirectly represent the attitudes and considerations of the government. The analysis of the seven secondary data sources (see Appendix C) provided additional insights into the framing of challenges by the IT firms IBM China and

Hangzhou Cognitive Care. Secondary data sources ended up either confirming findings from primary data, or provided a background against which to assess the relevance of findings from the interviews, as illustrated in the next section.

5 FINDINGS

Seven dimensions of perceived challenges emerged from the analysis of the framing by the three groups of stakeholders (hospital managers/doctors, IT firm managers, and government policy-makers): social challenges; economic challenges; ethical challenges; political, legal and policy-related challenges; organizational and managerial challenges; data challenges; and technological challenges. *Social challenges* include issues related to existing societal norms and attitudes towards the adoption of AI in healthcare. *Economic challenges* include obstacles concerning profitability and economic sustainability that inhibit the adoption of AI in healthcare. *Ethical challenges* include challenges related to moral principles and moral considerations implied in the use of AI in healthcare. *Political, legal and policy-rated challenges* include issues of political principles, legal regulations, and public policy affecting the adoption of AI in healthcare. *Organizational and managerial challenges* include challenges related to each organization's strategy, human resources, and management practices in the adoption of AI in healthcare. *Data challenges* include issues related to data quality and quantity, data standards, and database development that affect the AI adoption in healthcare. *Technological challenges* refer to the nature and characteristics of AI technologies in healthcare, as perceived by each stakeholder.

Table 4 provides an overview of the perceived challenges in the adoption of AI by the three group of stakeholders across the seven dimensions. The following sub-sections detail the challenges for each of the dimensions.

<Table 4 here>

5.1 Social challenges

The three groups of stakeholders (hospital managers/doctors, IT firms, and government policy-makers) express a wide range of concerns related to social challenges. In general, managers in the group of IT firms are the most vocal in relation to social challenges, while hospital managers/doctors do not express any concern in the area of social challenges.

First, managers of IT firms highlight the lack of an "innovation spirit" in Chinese society as one of the social challenges affecting the adoption of AI in the public healthcare sector. A director of IBM China, for instance, noted the lack of social driving forces on innovation in China, especially when compared to other countries, such as the U.S.: "We have to say the innovation spirit in the U.S. should be admired by us [Chinese]. […] We need to learn from them" [2IBM01].

Second, there is a perceived societal misunderstanding of the capabilities of AI technologies in the public healthcare sector. On the one hand, the general public is seen as lacking knowledge on the values and advantages of AI. As mentioned by the CEO of CognitiveCare: "this is a new thing. And most of people don't know the advantages of AI. […] What values can AI bring to clinic? […] Many people don't know." [3IT01]. On the other hand, society has overly high expectations from AI, which leads to difficulties in the acceptance of AI technology by doctors in the hospital. With the introduction of AI policies in China, social media and organizations began to talk about AI frequently, attributing "magic" qualities to AI technologies, often leading to disappointment in doctors using the IBM Watson system. As mentioned by one of the IT firm managers: "They [the doctors] have very high expectations from Watson. […] For example, doctors think it [AI] can only do some simple jobs. It is too weak" [3IT02]. Hospital managers/doctors report to experiencing frustration when facing the real technology after the societal hype: "We have difficulties on AI adoption in healthcare. […] especially for the top hospitals, they will think our doctors are much better than Watson" [3IT01].

Third, both IT firm managers and government policy makers mentioned social challenges specifically related to the unique characteristics of Chinese medical patients and health practices in China. As Watson draws on existing big data sets of patient medical records to continuously learn and deliver personalized treatment plans, its outputs are as good as the input of data it relies on. The Watson system has been originally trained by mainly North-American patient data. But different national contexts have different disease profiles (Liu, 2017; Xie, 2017c). As pointed out by one of the informants: “Because of the racial differences [between China and Western countries], the cause of a disease is different. For example, Western countries have more vascular-related diseases, while China has more hepatic diseases” [5GOV01]. As a result of this, there is less data available on disease profiles that are more widespread in China, but less frequent in Western countries, where the Watson system is originally trained.

In addition, attitudes towards how to tackle a disease are different. As remarked by one of the hospital managers/doctors:

> [For the treatment of cancer] Chinese patients think surgery is better. […] In the West, as a tumor can stay within the body for a long time, there is a greater focus on the importance of the management of cancer as a chronic disease. [In China] patients do not see it this way [as a chronic disease]. [1HP01]

This difference in medical approaches and practices is not taken into account by Watson, and this is seen as another key challenge. Watson’s base of data, on which its learning and output capabilities are largely built, is seen as challenged when used in the Chinese context.

5.2 Economic challenges

Economic challenges to the adoption of AI in healthcare are mentioned only by hospital managers/doctors. This group of stakeholders point out that treatments carried out with the support of Watson entail an expensive fee to be covered by the patients: “The price in our hospital is 2500 RMB for one appointment with Watson. They [patients] think it is too expensive.” [1HP05]. Furthermore, the adoption of IBM Watson is also costly for the hospital management, a cost that is not matched by increased profits, as hoped: “At the beginning [of introducing IBM Watson in the hospital], we wanted Watson to bring profits. But so far, we did not see any profits from Watson.” [1HP03].

Economic challenges are not mentioned by the other two groups of stakeholders: IT firm managers and government policy-makers. The government’s lack of focus on economic challenges is particularly striking when compared to the content of government policies related to healthcare and emerging technologies, such as AI. Our analysis of the 22 government policy documents shows that the most mentioned types of goals are economic, followed by social and technological, respectively. Out of a total of 88 mentions of goals, economic goals (i.e., industry development, and developing focal enterprises) are mentioned 44 times, social goals (i.e., quality of life, country innovation, smart society, and social stability) are mentioned 36 times, while technological goals are mentioned 8 times.

5.3 Ethical challenges

Ethical challenges associated with the adoption of AI in the public healthcare sector are frequently mentioned in the framings of all three stakeholder groups. As background, the analysis of national government policy documents reveals the awareness of the relevance of ethical challenges brought by AI. In these documents AI technology is framed as a disruptive technology that is expected to have a strong impact on ethical principles and which needs to be carefully monitored (State Council of the P.R.C., 2017b). As remarked by one of the government policy-maker informants: “This time, we [AI policy-makers] emphasize institutional, legal, and ethical issues. This is what we don’t have in previous plans [on other policies related to Science and Technology]” [5GOV01]. Government policy-makers all agree that AI has ethical considerations that differ from other traditional technologies [5GOV02, 6GOV01, 6GOV02].

The first ethical issue is related to trust. Both hospital managers/doctors and government policy-makers highlight the challenge of the general public's lack of trust of AI-based decisions. The new need for doctors to interact with a machine for critical decision-making poses an issue of trust, particularly in a field such as healthcare, where face-to-face interaction between patients and doctors has been historically so important [5GOV01]. The perceptions of patients are seen as challenging the adoption of AI. As highlighted by one of the IT firm informants: "They [the patients] have no idea about Watson. They will think: why do I need a machine to look at [my problem]? I prefer an expert doctor" [1HP04].

The second issue is related to unethical use of data sharing. Data is the foundation of AI adoption; at national, organizational, and personal levels, data sharing is crucial for AI industry development. However, data sharing poses challenges related to e.g., the potential misuse of patient data by commercial organizations (Xie, 2017b). IT firm managers mention the current lack of ethical guidelines for sharing data in connection to AI:

> Data comes from each person's sharing. […] But now the shared data has become a core competitive advantage for a certain organization. This [some organizations keeping the patients' data for commercial purposes] raises a number of ethical challenges. [2IBM01]

An AI system like IBM Watson requires large sets of integrated data to enable its learning and decision-making support capabilities; data-sharing lies at the core of the requirements of a functional AI system. The IT firm stakeholders highlight the worries brought on by AI adoption in treating patient data. As claimed by a top manager at IBM China: "I am worried that some firms will abuse the shared data for commercial purpose" [2IBM02].

5.4 Political, legal, and policy challenges

Challenges in the political, legal, and policy-related areas are numerous, and highlighted by all three stakeholder groups. These challenges appear at three levels: a macro-level, such as the political considerations related to possible national security threats rising from foreign AI companies managing sensitive data; at a meso-level, such as in the lack or uniqueness of market-wide policy regulations; and at a micro-level, such as in the lack of legal regulation of accountability for teams using AI for decision-making.

A first challenge, framed by government policy-makers and hospital managers/doctors, stresses the potential threat to national security when a foreign company, such as IBM, collects and stores large amounts of personal data on Chinese patients. Letting a corporation of a foreign country have access to the health records of Chinese citizens could make China more vulnerable, for instance, to biological warfare. This is considered to be no less than an existential threat for the continuation of AI in the public sector as a whole. As highlighted by one of the IT firm managers: "Once the [healthcare] data is used by bad people for evil purposes, AI will die" [1HP03]. Government policy-makers remark the importance of sensitive data not being held by foreign companies, and that, beyond limited experiments, the government will not support non-Chinese firms at a national level: "AI use in healthcare will be controlled […]. Personal information is very important. Thus, foreign firms will not get [policy] support. Experiments are ok […]. But, once there is a [security] problem, the Chinese government will close the door [on AI use]" [5GOV01].

A second challenge is related to the regulation (or lack thereof) of AI in the market. First, there is no shared official definition in the market of what AI technology is. This brings about uncertainty among competitors in the market. As remarked by the Vice CEO of EWELL, "Everyone [the firms] works on AI business […]. People [entrepreneurs] are so excited with AI. This leads to market disorder" [4IT01]. Second, there are no shared official standards in the industry for how AI can be used by organizations nor how its performance should be evaluated. This leads to uncertainty on the legitimacy of the use of AI by hospitals: “With regulation support we will feel safe […]. Without standards and regulations, they [the hospitals who use AI] will worry if it [Watson] can be used in this way” [3IT01]. Third, there is the issue of different regulations on drugs in China, compared to other countries. As pointed out by [3IT04], the IBM Watson system might design a treatment plan that includes a drug that is legal in the U.S., but not in China.

The last challenge is related to the lack of rules of accountability in the use of AI for decision-making. As AI technology replaces parts of the decision-making process traditionally carried out by humans (e.g., the design of treatment plans), there is no regulation on how to include non-human actors in the legal accountability system.

> The challenge [of AI adoption at hospitals] is: how to clarify responsibilities and what are the standards or regulations? A machine cannot take responsibility by itself, as a human being can. [2IBM02]

In China it is illegal for an AI system to make a decision [1HP05]. This is a big obstacle to the adoption of AI in the hospital. As told by one of the hospital managers/doctors:

> In our hospital, we use Watson to assist the Multidisciplinary Team (MDT). […] We discussed how to use Watson for a long time. […] As the first hospital to use Watson, we find this way [to use Watson together with the MDT]. […] But this really gives us a heavy burden! Because when we use Watson, we must have at least five doctors to work together with Watson [as required by regulation]. They [the five doctors] will sign on the report. [1HP05]

The legal requirement in China to always have a full team of human doctors fill in the paper work – even when it is Watson that designs a treatment plan – is perceived as an additional burden, and can hinder the incentive to adopt the AI system.

5.5 Organizational and managerial challenges

Organizational and managerial challenges are framed as highly relevant by government policy-makers and IT firm managers, but not by hospital managers/doctors. These challenges include the following: issues at a strategy level, such as the lack of strategy plans for AI development; issues at a management level, such as organizational resistance to data sharing; and issues at a human resource (HR) level, such as the lack of skilled workforce and the perceived threats of workforce replacement.

Top-down strategies, which require firms to have an overall plan regarding organization goals and resource distribution, are considered necessary for AI development. One IT firm manager highlights how Chinese firms lack a strategy plan for AI development: "From a tactical point of view, [Chinese firms] have good teams doing something [AI products]. But it is not from a strategy level" [3IT02].

At a management level, the main challenge is perceived to be the one of hospitals' resistance to the data sharing that is required by the AI technology. Currently, the data of a patient is owned by the hospital in which the patient has been treated. For a hospital, data means value, even if hospital managers still don't clearly know how to use the data the hospital owns to make profits. As remarked by a government official:

> The data is in the hospital. [IT firms] cannot get the data. […] For example, Alibaba is entering the health industry. But hospitals only allow Alibaba to access data of outpatients,

> not data of inpatients. They [the IT firms] cannot get the core data [continuous data of inpatients] from hospitals. [5GOV01]

This raises a new dilemma: who should own the data? While the Chinese government has some thoughts on data storage and data using, this issue has not yet been resolved. As remarked by a government official, speculating about possible alternative ownership of the data:

> If the data belongs to the hospital, it is hard to use. If the data belongs to a firm, there may occur a monopoly problem. […] Maybe one way is for the government to develop a data center to push this issue. [5GOV01]

There is a tension between the need for data integration, and the interest of individual organizations (now the data-owning hospitals; in a hypothetic scenario, the private firms) to restrict access to data. The government faces the challenge of finding a solution to this tension.

At the HR level, one of the main challenges for the adoption of AI is the lack of required talent (Liu, 2010). AI adoption in healthcare needs staff with interdisciplinary knowledge both from technological and medical disciplines. Both government policy-makers and IT firm managers claim that in China there is an insufficient number of such in-house staff. As remarked by a government official:

> Now the in-house talent is scarce. We can learn from [Chinese big IT firms] B.A.T. [Baidu, Alibaba, and Tencent]. Most of their personnel have come from abroad. […] AI experienced three ups and downs, and China used to develop AI talent. [When AI experienced a down] people withdrew from the industry, […] universities quit developing AI talent. So, the shortage of AI talent is severe. [5GOV01]

IT firm managers also mention that they lack AI interdisciplinary medical talent [2IBM02]; [3IT04]: “Most of the IT personnel should have a PhD degree, and the same with medical personnel. It is really hard to find this kind of talent [in the local market]” [3IT04].

Last, government policy-makers and IT firm managers mention the potential challenges posed by AI’s threat to replace the workforce of doctors: “Doctors may feel they will be replaced [by Watson]. Because they [i.e., the doctors] made many efforts to achieve their status. [3IT04]”. Such a fear, however, is nuanced by the fact that AI is framed as not capable of replacing specialized, skilled work. As pointed out by a government official: “Some simple and boring work may be replaced by AI. But not all jobs” [1GOV01].

5.6 Data challenges

Data challenges are framed as highly relevant by all three stakeholder groups. AI systems, like Watson, require large data sets to train in decision-making; thus, data lies at the heart of AI functions. General data challenges include database size being too small, lack of data integration, and lack of data standards (i.e., how and what data is collected, and what format it is stored in).

The first data challenge – the insufficient size of the available data pool – is because the adoption of AI technology in healthcare is still at an experimental stage and there are no large data sets available yet (Xie, 2017a). As remarked by a government official: “It is still at the early period of research. […] There is still a long way to go to the market. […] Watson is trained by limited data. [The adoption of AI in healthcare] is still in the dark” [5GOV01].

The second challenge is the degree of data integration. Integrated data is the foundation of AI. In the adoption of AI in healthcare, data integration refers to the link between personal demographic data (e.g., age, gender) and longitudinal clinical data, including the entire clinical history of a patient (Liu, 2010, 2016). However, the Chinese system lacks integrated and continuous data sets.

As remarked by a hospital manager/doctor, and confirmed by one of the top managers at IBM China [2IBM02]:

> At each point, it can be seen as big data. But what about when we look at the whole experience? [It does not qualify as big data] […] So far, China doesn't have such good patient data from diagnosis, treatment, and observation. [1HP05]

Evidence-based medicine (EBM) requires big data with good quality integration and continuity; its lack challenges the adoption of AI in healthcare, in particular in relation to machine learning capability. EBM databases are based on scientific paper publications, reports, medical cases, etc. As remarked by the director of IBM China:

> Machine learning cannot work without an EBM database. […] The most important characteristic of healthcare is practicality. [2IBM01]

The third challenge is related to the absence of data standards, referring to what and how data is collected, and what format it is stored in. Currently, China does not have a consistent standard of healthcare data collection (Hua, 2017) in either private firms or hospitals. In private firms, this is because of the different interests each firm pursues. As stated by an IT firm manager: "Everyone [i.e., each firm] has different opinions on [health] data collection. […] Whose interests are being considered?" [3IT02]. In public hospitals across the country, data is also structured differently. As stated by a government official: "Which kind of data problem is there? […] Data structure is not consistent among hospitals" [5GOV01]. In addition, there are no standards on which data is to be included in the databases; this results in missing data that might be critical for AI decision-making. A top manager at IBM China makes an illustrative example of missing data collection and its impact on the capabilities of AI:

> For example, after a surgery treatment, a patient will not get bedsores if he/she has a son/daughter. But this information is not captured [by the AI system]. This kind of data is critical for bedsore disease, but it is not included and collected by the database. [2IBM02]

5.7 Technological challenges

Some of the stakeholders highlight perceived challenges linked to the nature and characteristics of AI technologies. These technological challenges include the lack of transparency of AI algorithms and the difficulties of the AI system in processing unstructured data. It is interesting to notice that both these technology-related concerns are voiced by either government policy-makers or by hospital managers/doctors; IT firm managers do not frame any technological challenge as relevant in the adoption of AI in healthcare.

The main technological challenge perceived by government policy-makers is the lack of transparency regarding the algorithms at the base of AI technology. AI algorithms are responsible for transforming data inputs into concrete decisions, such as patient treatment plans. These algorithms are combined together by private IT firms like IBM and, besides them, no organization or public stakeholder knows exactly how they work (Xie, 2017b). This lack of transparency is perceived as a major challenge; the AI technology represents as a “black box”, and its users have no power to understand its mechanisms, or modify them to tackle potential problems. Government policy-makers [5GOV01], [6GOV02] express their concerns about this issue:

> When it comes to AI, it is a black box. […] It is difficult for us to solve the problem […] once diagnosis error issues appear. […] It is not like carrying out experiments, where we can see the process. AI itself is under learning. We don’t know what is wrong if it [the AI system] has some problem. This is very dangerous! [5GOV01]

IT firm managers, however, minimize the challenge posited by the opacity of AI algorithms. They argue that there is no reason for AI users to have an attitude towards AI technology that is different from other popular technologies, of which the inner workings are similarly unknown to users. As stated by one of the top managers of IBM China:

> Doctors don't know the principles of machines such as CT [Computed Tomography] or MRI [Magnetic Resonance Imaging] either. But they are not afraid of them. It is not necessary for them [doctors or other users] to open the "black box" of AI. What is necessary is to make an evaluation standard of AI's performance. Then, they will feel safe. [2IBM02]

From the IT firm manager's perspective, algorithm opacity is not a problem, while the industry's lack of standards concerning AI performance evaluation is (see Section 5.4).

The other perceived technological challenge is related to the limitations of AI technology. Doctors report that the treatment recommendations made by Watson are in concordance with the ones made by human doctors about 80% of the times [1HP04]. However, while the Watson system is effective with structured data, the group of hospital managers/doctors highlights that it has difficulties working with unstructured data, such as medical imaging, which represent a large share of relevant data in healthcare. This means that the AI system still needs to be complemented with the experience of human doctors. As mentioned by one of the hospital managers/doctors: "When we use Watson, the input should be structured data. We need to read the [medical image] picture and then input the data. […] Watson itself cannot read medical image data directly" [1HP03]. There is also awareness of this from the government policy-maker side: "Medical image data is quite subjective, AI cannot make judgements, at least so far. […] It requires a doctor's experience" [5GOV01].

In the next section, we summarize and discuss our findings, and illustrate their implications for research and for practice.

6 DISCUSSION

6.1 Summary of findings

Mapping how the three groups of stakeholders (government policy-makers, hospital managers/doctors, and IT firm managers) frame the challenges of AI adoption in healthcare reveals several key findings. First, each group of stakeholders presents a bias in how they frame the challenges of AI adoption in the public healthcare sector. No single issue is shared across all the three groups of stakeholders. Instead, each stakeholder group has a distinct point of view for each of the seven dimensions of perceived challenges (see Table 4).

Second, stakeholder groups sometimes display contradictory views concerning AI. As one example, while government official policy documents stress the economic aspect of AI adoption in the public sector, the government policy-makers do not mention any economic challenges in the adoption of AI in healthcare. This paradox may be due to the generic nature of the policy formulations in official policy documents, as opposed to the specific case of IBM Watson adoption in a public hospital. Or it may be due to the deeper insights that stakeholder framings elicited through qualitative methods can give, as opposed to policy document analysis. As a second example, while IT firm managers elaborate at length about the social challenges introduced by AI, they minimize, or are silent about, the existence of any technological challenge. This finding contradicts the assumption that technology experts are the group most aware of technological challenges. Instead, technological challenges are largely focused on by government policy-makers. A possible explanation of this paradox could be that IT firm managers might be well aware of technological challenges but it’s not in their interest to voice them because they want to continue promoting the use of AI. Besides, technological challenges imply problems that IT managers need to fix – whereas social challenges are problems that users need to address. As a third example, hospital managers/doctors are the only group that mentions any economic challenge, and the only group that does not consider any social challenge to be relevant in the adoption of AI in healthcare. This may be because hospitals see AI as being at an initial stage of diffusion in healthcare, with high costs and low profits. Conversely, IT firms' lack of perceived economic challenges can be attributed to the fact that they have access to venture capital, and that the government aims at stimulating the diffusion of AI by providing financial support to AI developers in the form of project grants.

The third finding is that the majority of challenges perceived by stakeholders involved in AI technology adoption is not technical in nature. Besides the observation that the AI technology at hand falls short of effectively processing unstructured data and the concerns about the opacity of its algorithms, the large majority of perceived challenges are non-technical. Most of the challenges are focused on political, legal, and policy-related issues, and data issues.

Fourth, the threat of AI replacing human workforce – a strongly debated aspect of the impact of AI in the public sector (see Section 2.2) – is mentioned as a challenge by both government policy-makers and IT managers. Paradoxically, the only group that does not mention this threat is the one that actually uses the AI system in its daily operations, i.e., the group of hospital managers/doctors.

6.2 Contributions to research

Our findings make a number of contributions to research on AI in the public sector. First, we provide an empirical basis for existing assumptions on the impacts and challenges of AI in the public sector. Empirical research literature on AI in the public sector is scarce, and consists largely of showcasing pilots of AI adoption, and providing some figures on the alleged impacts of such initiatives (e.g., Goldsmith & Crawford, 2014; Mitchell et al., 2016; Nuance Communications, 2016). Our study, by drawing on a systematic analysis of empirical data on the challenges of AI in the public sector, as perceived by different stakeholder groups, advances the nascent debate on impacts of AI in the public sector by providing a needed empirical basis. Studies on perceived challenges in other e-government areas have focused on social media adoption (Zheng, 2013), healthcare services (Andersen, Medaglia, & Henriksen, 2012), financial market information sharing (Sayogo, Pardo, & Bloniarz, 2014), open government data (Sieber & Johnson, 2015) but, to the best of our knowledge, no existing study empirically maps perceived challenges of AI adoption in the public sector.

Second, our study contributes to opening the "black box" of AI in the context of the public sector (K. C. Desouza, Krishnamurthy, & Dawson, 2017), by unpacking its perceived challenges. Currently, the very scope of AI is highly disputed. As computing technologies evolve, applications previously considered as examples of AI – such as optical character recognition or natural language processing – become routine and thus lead some to say that they are not examples of AI in the first place. This conundrum, known as the "AI effect" (McCorduck, 2004), has led to confusion in understanding exactly what we can expect from applications that are commonly referred to as AI technologies. By empirically mapping the perceived challenges of AI in the specific context of the public healthcare sector (as opposed to in abstract terms), we contribute to escaping this conundrum, and thus helping to open the "black box" of AI in the public sector. Moving beyond *a priori* speculation, we provided insights of what's inside the AI box by hearing from real stakeholders that use, diffuse, and regulate AI in the public sector.

Third, our findings on the framings of AI by its key stakeholders lay the foundations for a non-deterministic approach to the study of impacts of AI in the public sector. AI, as an Information Technology, is characterized by participants' uses and interpretations concurring to shape observable outcomes (Orlikowski & Scott, 2008). Our mapping of the challenges of AI adoption in the public sector – as framed by key stakeholders involved in its use, diffusion, and regulation – provides an empirical basis to the assumption that the introduction of AI technology in the public sector cannot be deterministically expected to result in a given set of outcomes. Instead, we advance the assumption that AI technologies are framed differently by different stakeholders, and therefore the impacts of AI in the public sector are always the outcome of contextualized interpretations.

6.3 Implications and recommendations for public managers

Based on our findings, we put forward four recommendations for the governance of AI adoption in the public sector.

6.3.1 Avoid "vision lock-in" in devising guidelines on AI

Findings from our study show how different stakeholder groups have different framings and different biases on the challenges of AI in the public sector. IT firm managers, for instance, do not perceive technology challenges in the adoption of AI, as much as hospital managers/doctors and government policy-makers do. Hospital managers/doctors feel pressure on costs, while IT firms don't. From a governance point of view, this diversity should prompt public managers to avoid espousing a single view on AI from just one of the stakeholder groups, since it would be inevitably one-sided. Similar to how governments are advised to avoid vendor lock-in when establishing partnerships with private IT firms (Scholl, 2006; Shaikh, 2016), policy-makers should thus avoid *vision lock-in*, and instead assemble holistic narratives and policy guidelines for AI in the public sector. The mapping of the different visions among different groups of stakeholders should be the first step towards a clear prioritization between different goals. Such prioritization is political in nature, and does not automatically ensue from the nature of the technology itself.

6.3.2 Use adaptive governance strategies to reconcile diverging views on AI

Emerging technologies call for new forms of governance of the participating stakeholders (Charalabidis, Lampathaki, Misuraca, & Osimo, 2012; Ojo & Mellouli, 2016). The presence of different, and sometimes conflicting, understandings of the challenges of AI adoption in the public sector illustrated by our findings requires governance strategies that can reconcile these differences, while maintaining the stability that is required in public action. The notion of *adaptive governance* has recently gained popularity due to its focus on combining flexibility in swiftly changing environments, with the requirements of stability and accountability that characterize public sector action (Janssen & van der Voort, 2016; Wang, Medaglia, & Zheng, 2018). Adaptive governance has been defined by featuring the characteristics of "decentralized bottom-up decision-making, efforts to mobilize internal and external capabilities, wider participation to spot and internalize developments, and continuous adjustments to deal with uncertainty" (Janssen & van der Voort, 2016, p. 4) and, as such, can reconcile diverse views concerning AI adoption challenges in the public sector.

A *decentralized bottom-up decision-making* strategy can be adopted by public managers to involve groups of stakeholders in formulating their views on AI, to be then incorporated into emerging AI policy guidelines. In our study, we found that different groups of stakeholders have different framings of AI adoption in healthcare. For example, hospital managers/doctors emphasized that in order for AI in healthcare to be effectively adopted, there is a need for integrated and continuous data nation-wide. From the government point of view, there is thus a need for decentralized bottom-up decision-making in devising a strategy that is conducive to data integration that involves organizations across the country.

Efforts to mobilize internal and external capabilities can be translated into government initiatives to not only rely on internal technical and managerial skills required to govern the introduction of AI, but also on external ones, to be identified in the market. As our findings show, the government has some understanding of the technological challenges that can hinder the effective adoption of AI in the public sector. This understanding needs to be matched with technical capabilities that are held outside the government, that is among IT firms. Government policy-makers are already partially aware of the need to adopt this approach. As one of the interviewed government policy-makers observed "[regarding data challenges,] if the government keeps the data and works on this issue, the efficiency will be too low. We [the government] need to involve the IT firms with managerial skills and professional technology to work together with us. We [the government] will take the responsibility of supervision" [5GOV01].

Wider participation to spot and internalize developments implies encouraging all stakeholders (i.e., not only IT firms, but also street-level public managers and service providers) to stay updated on the evolution of AI technology and its applications. For example, our findings show how government policy-makers and hospital managers/doctors alike highlighted the challenge of lack of trust towards AI-based decisions. Building trust in AI requires looking beyond just the three groups of stakeholders in our study, to also include patients, insurance companies, medical firms, and non-government organizations.

And finally, *continuous adjustments to deal with uncertainty* involves maintaining a set of core principles for governing AI adoption, but keeping room for flexibility in the face of e.g., failures of specific AI applications, changing standards of technology, or hype bubble bursts. As our findings show, AI adoption in healthcare is at a very early stage, as highlighted by IT firm managers and hospital managers/doctors. Public managers should avoid introducing very rigid standards that might hamper AI technology development and use.

6.3.3 *Prioritize the development of AI management guidelines and data integration, before focusing on AI applications.*

Our findings show that organizational and managerial challenges and data challenges are considered the prevalent ones by all the key stakeholders. Regarding the organizational and managerial challenges, public policy-makers should work towards devising shared definitions of AI as well as shared standards of AI use and performance evaluation. This nascent phase of AI diffusion in the public sector is characterized by both great dynamism and great confusion;

identifying shared definitions and standards can prevent the latter from taking over the former. Regarding the data challenges, our findings clearly show that the majority of stakeholders agree that AI applications are only as good as the data upon which they are built. If there is no data integration, no state-of-the-art AI technology can provide its promised added value. So before focusing on AI applications, public managers should first focus on establishing data quantity and quality, data integration, and data continuity.

6.3.4 Focus on the governance of *AI, instead of governance* by *AI*

As the AI research community overwhelmingly agrees upon, the rise of machines capable of carrying out tasks that require high levels of innovation, planning, and empathetic behaviour (the "strong AI") is yet merely the subject of speculation, and not to be expected in the immediate future (Russell & Norvig, 2016). Key aspects of public decision-making – such as issues of ethical trade-offs, innovation, and individual and group identity – are inherently political in nature. They require capabilities of contextualized, creative, and empathetic behaviour in dealing with humans, which AI technology in its current "weak" form cannot provide (Andersson, Grönlund, & Åström, 2012). Algorithmic governance in the public sector is at best envisioned as concerning mundane tasks only (Janssen & Kuk, 2016). Yet, the current public debate on AI in the public sector often confuses the two separate issues of governance *by* AI (i.e., the use of AI as a tool to automate policy making) and governance *of* AI, and tends to focus on the former at the expense of the latter.

AI in the public sector is often depicted with the technocratic image of politicians being replaced by robots (Davis, 2017), and algorithms replacing political deliberation. Instead, as findings from our study show, the issue of the type of governance *of* AI needed to tackle its challenges is the most pressing one at this stage. None of the stakeholders investigated in our study mentioned governance *by* AI, since they all believe that AI cannot fully replace human agents so far. However, as AI technology in the public sector is starting to replicate the boom it has already experienced in commercial applications, stakeholders are already taking their own uncoordinated initiatives, and developing diverse and autonomous visions of the technology and its uses. This calls for not only public managers, but also experts and researchers, to focus on advancing our understanding of the governance of AI, and reduce the attention given to speculative (at least for now) accounts of replacing politicians with machines.

6.4 Limitations

This study has some limitations. The first concerns the generalizability of the findings. We have chosen the public healthcare sector as the object of our study because healthcare is one of the public sectors in which AI is being most rapidly adopted, and with the most promising applications (e.g., medical records mining, diagnoses, treatments, and drug creation). However, our findings may not be reflective of other sectors. For example, our finding regarding the challenge of the medical tradition of a country may not apply to other contexts. Future research could adopt the approach of this study to investigate and compare the challenges of AI in other public sector areas.

The second limitation concerns the geographic location of our study. We have chosen public healthcare in China for our study because China provides an ideal setting to investigate healthcare as a sector of government action – that is a public sector. Different from other contexts such as the U.S., healthcare services in China are strongly dominated by public sector intervention, in terms of regulation, strategy, and financing (Hu et al., 2008). Nevertheless, we are aware that not all conclusions from our analysis in the Chinese settings might be applicable to other countries, even among those that feature a national healthcare system. In particular, some of the findings in legal challenges we highlighted in our case (such as the absence in China of a regulatory framework that allows an AI system to sign for a treatment plan along with humans) are less significant in other national contexts. Future research could compare the findings from our study with results from different geographical contexts.

The third limitation concerns the data analysis. The classification of different categories of challenges we present can be partly affected by subjective bias in the interpretation of the empirical data. While we adopted a well-consolidated protocol for coding the interview data and the documents we analysed (Strauss & Corbin, 1998), drawing on the concept of technological framing (Cornelissen & Werner, 2014), we acknowledge that the categorization of the data might partly reflect the subjective bias of the authors.

Finally, we did not include patients as our stakeholders. We acknowledge the need for a patient-centric view in modern public healthcare, and of the consequent need to include patients' perspectives in healthcare research. However, because in our study we focused on the challenges of *adoption* of AI in the public sector, we had to focus on the stakeholders that use, regulate, and diffuse AI in the public healthcare sector (i.e., government policy-makers, doctors/hospital managers, and IT firm managers). For example, while patients are the *beneficiaries* of Watson in hospitals, its *users* are the doctors, not the patients. In addition, access to patient data was hindered by practical considerations: first, hospital managers denied access to patient data on the ground of privacy concerns; second, since our case dealt with AI use in cancer treatment, a number of patients deceased during the course of the study data collection.

7 CONCLUSION AND FUTURE RESEARCH

The diffusion of AI in the public sector is in its nascent stage, and so is the body of research on the phenomenon. In this study, we mapped how key stakeholders in the public healthcare sector frame the challenges of AI adoption. The study aims at providing a foundation for a needed stream of research focusing on the wide variety of aspects involved in the phenomenon of AI adoption in the public sector. The findings from our study in this emerging research field open up new avenues for future research on the impacts of AI in the public sector. In particular, our findings call for future studies to focus on 1) explanatory factors for, 2) consequences of, and 3) the process of emergence of different views on the challenges of AI adoption in the public sector.

First, there is a need for future research to investigate the *factors* that can explain why the various stakeholder groups perceive the challenges differently. Research questions focusing on determining factors of framing differences include: how does the understanding of other technologies adopted in the public sector influence the framing of challenges? How does the IT literacy of different stakeholders influence their framing of challenges? How does the organizational culture of different stakeholders influence their framing of challenges?

Second, future studies can investigate the *consequences* of stakeholder groups framing the challenges differently. Information Systems (IS) literature on technological frames of reference (TFR) has already begun to investigate effects of e.g., congruences and incongruences between technological framings at the organizational, meso-level of analysis. Studies have focused on how different groups of stakeholders see the adoption of a wide range of technologies, including office groupware (Orlikowski & Gash, 1994), sales force automation (Young et al., 2016), and mobile technologies (Mazmanian, 2013) but, to the best of our knowledge, not AI technologies. Existing research shows that incongruences between these framings can either result in technology project failures (Davidson, 2006; Davidson & Pai, 2004) or motivate organization members to negotiate shared frames (Azad & Faraj, 2008; Yeow & Sia, 2008). In a similar fashion, we call for future studies to investigate the consequences of differences in framing the challenges of AI in the public sector in a wide variety of terms, including efficiency, effectiveness, and political legitimacy. Research questions driving future empirical studies should thus include: how do differences between government agencies and IT firms in the framings of the technological challenges of AI adoption affect project failure rates? How do differences in framings of ethical challenges of AI adoption affect government legitimacy as perceived by citizens? How do differences in framings of economic challenges between government agencies and IT vendors affect project economic sustainability? How do governments respond to diverse framings of AI?

Third, we call for future studies to investigate the *process* whereby different views on challenges of AI in the public sector emerge. Our current understanding of how different stakeholders frame AI technology is still opaque: i.e., black-boxed. In general terms, the negotiation of meaning of a specific technology has the characteristics of a political process, where power plays an important role (Olesen, 2014; Yeow & Sia, 2008). AI technology, in particular, can be expected to raise concerns that are political in nature. These include, for instance, the impacts of AI on the workforce, with its threats of not only augmentation, but also replacement of skilled workers (Eggers et al., 2017). Therefore, research questions related to the process of emergence of different views on the challenges of AI in the public sector should include: how are stakeholders' expectations of AI technologies affected by imbalances of power between different stakeholders? What are different stages of development of views on the challenges of AI in the public sector?

The increasing diffusion of AI in the public sector can be expected to bring about a number of relevant transformations. By mapping the framings of the challenges that emerge within the phenomenon of AI adoption in the public sector, we aimed at providing a first step towards a more systematic investigation of its complex implications.

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Appendix A. List of interview questions

- What is your role? What are you responsible for?
- What are the challenges in the use of Watson?
- What are the challenges in the introduction of Watson in hospitals?
- What do you think Watson can do in healthcare?
- In your opinion, what is the motivation for hospitals to use Watson?
- Which values do you think Watson brings to healthcare?
- How do you use Watson in your everyday work?
- Do you think the use of Watson requires support (e.g., from colleagues or through training)?
- Are you satisfied with the current use of Watson?
- Are there any regulations that support the development/adoption of AI in healthcare?
- What are the impacts of existing regulations on the use of Watson?

Appendix B. List of policy documents (coded by policy area)

Policy area	*Policy document*
a) General healthcare	Guidance Opinions of the General Office of the State Council on Promoting the Construction and Development of Medical Consortiums (General Office of the State Council of the P.R.C., 2017b)

Policy area	*Policy document*
	State Council on the Issuance of 2017 Key Tasks in Deepening the Reform of the Medical and Health System (General Office of the State Council of the P.R.C., 2017c)
	The State Council's General Office's Opinions on Supporting Social Forces to Provide Multi-level and Diversified Medical Services (General Office of the State Council of the P.R.C., 2017a)
	Circular of the State Council on the Issuance of the Plan for Deepening the Reform of the Medical and Health System during the 13th Five-Year Plan (State Council of the P.R.C., 2016)
	Guidance Opinions of the General Office of the State Council on Promoting the Construction of a Classification and Treatment System (General Office of the State Council of the P.R.C., 2015a)
	Suggestions of the CPC Central Committee on Formulating the 13th Five-Year Plan for National Economic and Social Development (Central Committee of the Communist Party of China, 2015)
	Notice on Launching the Pilot Work of Establishing a Wholly Foreign-owned Hospital (National Health and Family Planning Commission of the P.R.C. & Ministry of Commerce of the P.R.C., 2014)
	Several Opinions of the State Council on Promoting the Development of Health Service Industry (State Council of the P.R.C., 2013a)
	Guidance Opinions of the State Council on the Establishment of a General Practitioner System (State Council of the P.R.C., 2011)

Policy area	*Policy document*
	The General Office of the State Council Forwards the Notice of the Ministry of Health and other Departments of the Development and Reform Commission on Further Encouraging and Guiding Social Capital to Organize Medical Institutions (General Office of the State Council of the P.R.C., 2010)
b) Emerging technologies	Notice of the Ministry of Science and Technology on the Issuance of the 13th Five-year Special Plan for Science and Technology Innovation in the Field of Advanced Manufacturing Technology (Ministry of Science and Technology of the P.R.C., 2017)
	Opinions of the State Council on Implementing the Division in Key Work Departments of the "Government Work Report" (State Council of the P.R.C., 2017a)
	Notice of the Ministry of Industry and Information Technology on Issuing the Plan for the Integration of Information Technology and Industrialization (2016-2020) (Ministry of Industry and Information Technology of the P.R.C., 2016)
	Several Opinions of the General Office of the State Council on Enhancing Service and Regulation of Market Players (General Office of the State Council of the P.R.C., 2015b)
	Notice of the State Council on Issuing the Action Plan for the Promotion of Big Data Development (State Council of the P.R.C., 2015b)
	Opinions of the State Council on Promoting the Innovation and Development of Cloud Computing and Cultivating New Formats for the Information Industry (State Council of the P.R.C., 2015a)

Policy area	*Policy document*
	Guidance Opinions of the State Council on Promoting the Orderly and Healthy Development of the Internet of Things (State Council of the P.R.C., 2013c)
	Several Opinions of the State Council on Promoting Information Consumption to Expand Domestic Demand (State Council of the P.R.C., 2013b)
c) Emerging technologies in the healthcare sector	Guidance Opinions of the General Office of the State Council on Promoting and Regulating the Development of Medical Big Data Applications (General Office of the State Council of the P.R.C., 2016)
	Notice of the National Health Commission on the Issuance of the 13th Five-Year Plan for the Development of National Population Health Information (National Health and Family Planning Commission of the P.R.C., 2017)
d) Artificial Intelligence	Notice of the State Council on the Issuance of a New Generation of Artificial Intelligence Development Plan (State Council of the P.R.C., 2017b)
	Notice on the Issuance of the Three-Year Action Plan for "Internet + Artificial Intelligence" (National Development and Reform Commission of the P.R.C., 2016)

Appendix C. Overview of additional secondary data sources

Organization	*Source*
IBM China	Online media interview (Xie, 2017c)
	Conference paper (Xie, 2017a)
	Academic presentation at Peking University (Xie, 2017b)
	Presentation at the Global Big Data Conference (Liu, 2017)
	Online media interview (Liu, 2016)

Organization	*Source*
	Online media interview (Liu, 2010)
CognitiveCare	Conference presentation (Hua, 2017)

Figure 1 – A Venn diagram of policy areas affecting AI adoption in healthcare

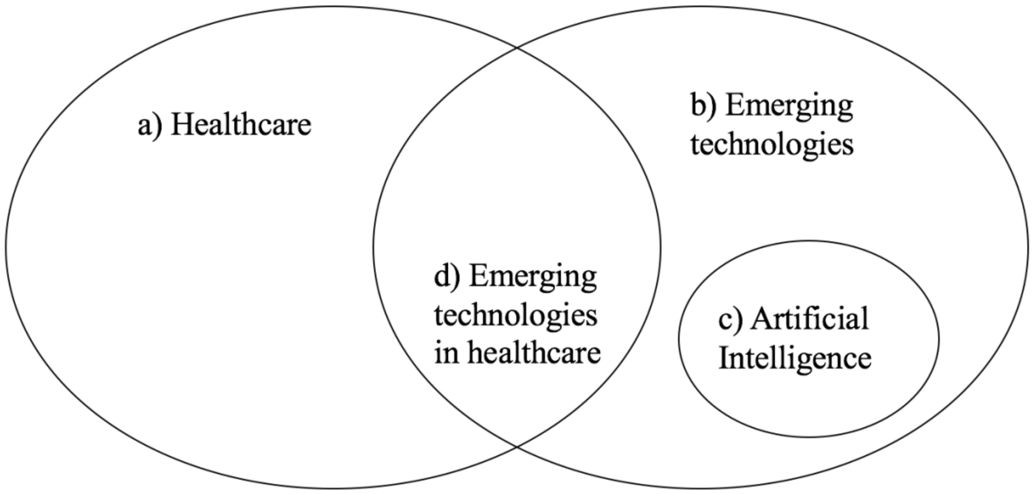

Table 1 –Stakeholder groups

Stakeholder group	*Stakeholder organization*	*Description*
Hospital managers/doctors	ZP-TCM Hospital	ZP-TCM Hospital is the first hospital that adopted Watson in China.
IT firm managers	IBM China	IBM China provides fundamental technology support for the use of Watson in China.
	Hangzhou CognitiveCare	Hangzhou CognitiveCare is the partner company of IBM China that services hospitals using Watson across the country. CognitiveCare works with EWELL to adapt Watson to the Chinese context.
	EWELL	EWELL is a high-tech company focusing on R&D in the healthcare industry. EWELL provides technical support and training to the ZP-TCM Hospital.
Government policy-makers	Ministry of Science and technology of the People's Republic of China (MOST)	Policy-makers involved in formulating policies regarding healthcare and emerging IT (including AI) to facilitate social, economic, and technology development in China.
	National Development and Reform Commission of the People's Republic of China (NDRC)	

Table 2 – Overview of interview data sources

Organization	*Position*	*Informant code*	*Interview mins*	*Interview N*
1 – ZP-TCM Hospital	Vice director, medical doctor	1HP01	70	1
	Department head, medical doctor	1HP02	80	1
	Department head, medical doctor	1HP03	40	1
	Department head, medical doctor	1HP04	30	1
	Employee, medical doctor	1HP05	30	1
2 – IBM China	Director	2IBM01	70	1
	Director	2IBM02	80	1

Organization	*Position*	*Informant code*	*Interview mins*	*Interview N*
3 – Hangzhou CognitiveCare	CEO	3IT01	30	1
	Department head	3IT02	80	1
	Department head	3IT03	70	1
	Department head	3IT04	90	1
	Employee	3IT05	40	2
4 – EWELL	Vice CEO	4IT01	90	1
	Department head	4IT02	45	1
5 –MOST	Department head	5GOV01	77	1
	Department manager	5GOV02	50	1
6 –NDRC	Department manager	6GOV01	45	1
	Department manager	6GOV02	40	1
TOTAL			*1097*	*19*

Table 3 – Example of the interview data coding procedure

Empirical data	*First-order coding*	*Second-order coding*
"The characteristics of diseases in China have many differences with North America. […] *people's attitude towards diseases is different."* [2IBM01]	Country-specific medical practices	Social challenge
"At the beginning [of introducing Watson in the hospital], *we wanted Watson to be able to bring profits. But so far, we did not see any profits from Watson.*" [1HP03]	High costs but no profits for hospitals	Economic challenge
"They [the patients] *have no idea about Watson. They will think: why do I need a machine to look at* [my problem]*? I prefer an expert doctor."* [1HP04]	Lack of trust in AI-based decisions	Ethical challenge
"With regulation support we will feel safe. […] *Without standards and regulations, they* [the hospitals who use AI] *will worry if it* [Watson] *can be used in this way."* [3IT01]	Lack of official industry standards for AI use and performance evaluation	Political, legal, and policy challenges

Empirical data	*First-order coding*	*Second-order coding*
"The data is in the hospital. [IT firms] *cannot get the data.* […] *For example, Alibaba is entering the health industry. But hospitals only allow Alibaba to access data of outpatients, not data of inpatients. They* [the IT firms] *cannot get the core data* [continuous data of inpatients] *from hospitals."* [5GOV01]	Organizational resistance to sharing data	Organizational and managerial challenges
"Most of the IT personnel should have a PhD degree, and the same with medical personnel. It is really hard to find this kind of talent [in the local market]*."* [3IT04]	Lack of in-house AI talent	
"At each point, it can be seen as big data. But what about when we look at the whole experience? [It does not qualify as big data] *So far, China doesn't have such good patient data from diagnosis, treatment, and observation."* [1HP05]	Lack of integrated and continuous data	Data challenge
"When it comes to AI, there is a black box. […] *It is difficult for us to solve the problem* […] *once diagnosis error issues appear.* […] *It is not like carrying out experiments, where we can see the process. AI itself is under learning. We don't know what is wrong if it* [the AI system] *has some problem. This is very dangerous!"* [5GOV01]	Algorithm opacity	Technological challenge

Table 4 – Stakeholders' framing of challenges in the adoption of AI in public healthcare

Challenges / *Stakeholders*	*Social challenges*	*Economic challenges*	*Ethical challenges*	*Political, legal, and policy challenges*	*Organizational and managerial challenges*	*Data challenges*	*Technological challenges*
Government policy-makers	Country-specific patient disease profiles		Lack of trust towards AI-based decisions	National security threats from foreign-owned companies collecting sensible data	Organizational resistance to data sharing	Insufficient size of available data pool	Algorithm opacity
				Lack of rules of accountability in the use of AI	Lack of in-house AI talent		Lack of ability to read unstructured data
					Threat of replacement of human workforce		
Hospital managers/doctors		High treatment costs for patients	Lack of trust towards AI-based decisions	National security threats from foreign-owned companies collecting sensible data		Lack of data integration and continuity	Lack of ability to read unstructured data
		High costs but no profits for hospitals		Costly human resources still legally required to account for AI-based decisions		Lack of standards of data collection, format, and quality	

IT firm managers	Insufficient innovation social driving forces		Unethical use of shared data	Lack of an official industry definition of AI	Lack of strategy plans for AI development	Lack of data integration and continuity	
	Unrealistic expectations towards AI technology			Lack of official industry standards of AI use and performance evaluation	Lack of AI interdisciplinary talent	Lack of standards for data collection, format, and quality	
	Country-specific medical practices			Country-specific legal drug standards	Threat of replacement of human workforce		
	Insufficient knowledge on values and advantages of AI technology						

About the authors

Tara Qian Sun is a PhD fellow at the Department of Digitalization of the Copenhagen Business School in Copenhagen, Denmark, and at the Sino-Danish College of the University of the Chinese Academy of Sciences in Beijing, China. Her research interest lies in digital innovation, social innovation, and science and technology policy. Her PhD project focuses on the adoption of Artificial Intelligence in healthcare from the perspectives of policy, technology, and management. [e-mail: qs.digi@cbs.dk]

Rony Medaglia is an Associate Professor at the Department of Digitalization of the Copenhagen Business School in Copenhagen, Denmark. His research focus is on digital transformations in the public sector. He has authored publications in several international journals, including *Journal of Information Technology, Government Information Quarterly, Information, Communication and Society, the International Journal of Public Administration,* and the *Communications of the Association for Information Systems*. [e-mail: rony@cbs.dk]