AI for Managing Open Innovation

Opportunities, Challenges, and a Research Agenda

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AI for managing open innovation: Opportunities, challenges, and a research agenda

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ABSTRACT

Artificial intelligence (AI) provides ample opportunities for enabling effective knowledge sharing among organizations seeking to foster open innovation. Past research often investigates the capability of AI to perform 'human' tasks in structured application fields. Yet, there is a lack of research that systematically analyzes when and how AI can be used for the more complex and unstructured tasks of open innovation (OI). We present a framework for leveraging AI-enabled applications to foster productive OI collaborations. Specifically, we create a 3x3 matrix by aligning the three OI stages (initiation, development, realization) with the three management functions of AI (mapping, coordinating, controlling). This matrix assists in identifying how various AI applications may augment or automate human intelligence, thereby helping to resolve prevailing OI challenges. It provides guidance on how organizations can use AI to establish, execute and govern exchanges across the OI stages. Finally, we lay out an agenda for future research.

1. Introduction

Rapid advancements in artificial intelligence (AI) technologies have created numerous opportunities for businesses to improve their operations, customer service, and data analytics, and, consequently, to gain a competitive advantage in their respective industries (Collins et al., 2021; Davenport & Ronanki, 2018). AI has the potential to transform the way businesses operate by automating routine tasks, augmenting human decision-making, and generating insights from vast amounts of internal and external data. McKinsey's Global Survey administered in 2022[1] found that AI adoption has doubled since 2017. Despite this growth and ever-increasing investments in AI technologies, including natural language processing, machine/deep learning, computer vision, robotics, as well as techniques like (genetic) algorithms, swarm intelligence, speech synthesis systems, and expert systems, many businesses are still unable to identify the potential business value of AI (Fountaine et al., 2019; Mikalef & Gupta, 2021). Firms struggle to realize the value-adding potential of AI since they cannot identify application fields where AI can help overcome business challenges (Duan et al., 2019; Enholm et al., 2022; Fabian et al., 2023). We address this challenge by delineating the business value that AI can provide for a specific application of high strategic importance, namely the management of open innovation (OI), which we define as the practice of leveraging external ideas, resources, and capabilities to improve innovation outcomes (Chesbrough & Bogers, 2014).

The literature has started to provide guidance on AI applications in various domains such as auditing (Kokina & Davenport, 2017), human resources (HR) (Vrontis et al., 2022), marketing (Davenport et al., 2020; Mustak et al., 2021; Vlačić et al., 2021), and supply chain management (Pournader et al., 2021; Toorajipour et al., 2021; Wehrle et al., 2022). Such studies typically consider AI's potential to perform "human" tasks in functional disciplines, focusing on more structured application fields. Some scholars further claim that AI has the potential to revolutionize less structured application fields, such as innovation management

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[1] https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2022-and-a-half-decade-in-review.

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(Füller et al., 2022; Haefner et al., 2021).

In this study, we focus on this more uncertain role of AI in managing OI. According to Chesbrough (2003), the key objective of OI is to overcome the silo mentality of relying solely on internal research and instead encourage companies to engage in external collaboration to drive innovation. For example, in 2009, Nestlé and General Mills started a joint venture to accelerate innovation research on breakfast cereal solutions using each other's technologies.[2] OI can be an effective response to uncertainty in the innovation process and an efficient way to develop new products and processes (West & Bogers, 2011). Despite its vast potential, initiating and managing OI involves complex processes which, by their very nature, often involve inefficiencies as well as intra- and interorganizational conflicts. Addressing or avoiding these conflicts can create substantial managerial challenges. Against this background of inherently uncertain and complex OI processes, leveraging AI's capacity to enhance human task performance could potentially deliver high business value. However, the role of AI in interorganizational processes such as OI have been largely overlooked in the techno-centric AI literature to date.

We propose that AI can play a vital role in enhancing OI by offering potential solutions to the various managerial challenges in OI. For instance, firms could use AI-powered technology transfer platforms like Patentplus[3] to facilitate searching for and linking with other organizations, apply natural language technologies like ChatGPT to analyze vast documentation of partner firms to identify avenues for OI, or use tools like Cicero to negotiate and manage alliances.[4] To provide a more comprehensive understanding of AI's potential to support OI, we conceptualize a framework of how and when AI can contribute to solving common OI management challenges and foster OI productivity.[5] As a starting point, we explore how firms currently leverage AI applications in the context of three main management functions, namely *mapping* (opportunity scanning in the problem space), *coordinating* (facilitating collaboration in the solution space), and *controlling* (fostering desired behaviors in the execution space). To advance our understanding of how and when AI applications can generate value in OI projects, we match the management functions that AI can perform with challenges across the OI stages of *initiation, development,* and *realization*. We use the resulting 3 × 3 AI-OI matrix to structure future research needs and demonstrate applications in managerial practice. Hence, the proposed AI-OI matrix is particularly useful for knowledge engineering. Based on a synthesis of this matrix, we also lay out an agenda for future research.

2. Artificial intelligence: Functions and business applications

2.1. Business value of AI

The proliferation of AI research has led to various definitions of AI (see Table 1). In a general sense, AI relates to something "artificial" that is produced by human beings, such as a technique, system, or machine, that can mimic human intelligence. In this sense, Wang et al. (2019, p. 2) broadly define AI as a "concept that captures the intelligent behavior of the machine." Such general definitions, however, lack the specificity needed to identify the potential business value of AI. Business studies have extended general definitions of AI to conceptualize the tasks or functions that AI applications can perform. For instance, Huang and Rust (2021) propose that AI can perform *mechanical* tasks such as documentation, *thinking* tasks including analysis and estimation, and *feeling* tasks like communication. Others, such as Rai et al. (2019), focus on human cognitive functions such as perceiving, reasoning, problem-solving, decision-making, and creativity.

TABLE 1
Sample definitions of AI.

Focus of AI	AI Definition	Authors
General	The general concept for computer systems able to perform tasks that usually need natural human intelligence, whether rule-based or not.	Afiouni (2019)
	A broad concept that captures the intelligent behavior of the machine.	Wang et al. (2019)
	A set of theories and techniques used to create machines capable of simulating intelligence.	Wamba-Taguimdje et al. (2020)
Cognitive tasks	Machines that mimic human intelligences computationally and digitally, designed to emulate (or surpass) capabilities inherent in humans, such as doing mechanical, thinking, and feeling tasks.	Huang & Rust (2022)
	The ability of a machine to perform cognitive functions that we associate with human minds, such as perceiving, reasoning, learning, interacting with the environment, problem solving, decision-making, and even demonstrating creativity.	Rai et al. (2019)
	Any machine that uses any kind of algorithm or statistical model to perform perceptual, cognitive, and conversational functions typical of the human mind.	Longoni et al. (2019)
Goal achievement	A system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation.	Kaplan & Haenlein (2019)
	The ability of a system to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals.	Mikalef & Gupta (2021)
Goal achievement via fulfillment of management functions	The ability of an AI system to identify, interpret, make inferences, and learn from data to foster open innovation productivity by performing the management functions of mapping, coordinating, and controlling.	Our study

When assessing its capacity or performance, AI is often compared with human intelligence to evaluate if it can emulate or surpass human capabilities. In business contexts, however, AI is often assessed by its potential to assist (augment) or fully replace (automate) humans in performing relevant business activities. This potential is highly dependent on the complexity and nature of the tasks. At present, AI is capable of performing well-defined cognitive tasks with little or no human support, such as answering simple questions from customers, registering market transactions, and documenting new patents in a patent class and storing them in a database. In these cases, AI applications use standardized or rule-based logic in rule-based or predictable contexts (Huang & Rust, 2018). For these settings, *narrow* AI applications focus on solving well-defined (single) tasks. In contrast, *broad* AI applications are more versatile and involve general (human) intelligent actions that can address any task or problem in any domain, like analytical and intuitive thinking (Davenport & Ronanki, 2018) or empathetic feeling tasks (Huang & Rust, 2018). When taking on more complex tasks AI shifts toward context awareness (Ghahramani, 2015), allowing

[2] https://www.nestle.com/media/pressreleases/allpressreleases/cerealpartnersworldwide.
[3] https://www.patentplus.io/.
[4] https://ai.facebook.com/research/cicero/diplomacy/.
[5] We define OI productivity as the joint efficiency and effectiveness of OI efforts. It is the ratio of the value of innovation outputs (e.g., patent value, innovation quality, revenues, or market share) to the resources invested in innovation inputs.

machines to "learn how to learn" and ultimately extending their intelligence beyond the initial programming by humans (Davenport et al., 2020). However, it remains doubtful whether AI will be able to reliably address complex tasks, such as empathetic feeling, in the coming in the near future (Huang & Rust, 2018; Müller & Bostrom, 2016).

Instead of concentrating on different functions and task complexity, recent studies have addressed AI as a means to achieve certain organizational goals (Kaplan & Haenlein, 2019; Mikalef & Gupta, 2021). For example, Kaplan and Haenlein (2019) define AI as an enabler for firms to learn from existing data and flexibly adapt to the environment. By performing certain management functions, AI can help firms effectively achieve innovation (Haefner et al., 2021; Lundvall & Rikap, 2022) or societal goals (Mikalef & Gupta, 2021; Stahl, 2022). To highlight how AI can be used in the management of complex OI endeavors, we synthesize the extant research by discussing the three main management functions of AI.

2.2. Three main management functions of AI

To demonstrate the value-adding mechanisms of AI-based systems, we focus on performance or fulfillment of specific management functions (cf. Daugherty & Wilson, 2018).[6] As there are various perspectives on what constitutes essential management functions, our aim is not to comprehensively capture this research stream; instead, we present a conceptual anchor for defining central management functions in OI. Dating back to work by Fayol (1916), the management literature has highlighted multiple essential management functions: planning, organizing, commanding, coordinating, and controlling (Carroll & Gillen, 1987; Voxted, 2017). With regard to planning, we concentrate on sensing and scanning the organizational environment critical to OI, which is referred to as "mapping". We consider organizing, commanding, and coordinating as one broad management function that we term "coordinating" – the process of coordinating human efforts to jointly develop solutions. Finally, we view "controlling" as measuring and monitoring performance to ensure that goals are being achieved.

For the purpose of this study, which focuses on the management functions of AI in the OI context, we build on prior AI work (Huang & Rust, 2018; Mikalef & Gupta, 2021) and define AI as: *the ability of a system to identify, interpret, make inferences, and learn from data to foster OI productivity by performing the management functions of mapping, coordinating, and controlling.* Table 2 provides a list of references and examples.

First, AI can perform *mapping*, which is the sensing and scanning of a firm's internal and external environment by collecting and analyzing extensive datasets to solve organizational problems or seek new business opportunities. In this way, AI performs typically well-defined mechanical tasks such as analyzing large databases to find matches for a search problem. For instance, AI can help identify potential new clients in marketing (Paschen et al., 2020) or evaluate and select job candidates in recruitment. However, AI may also "learn" by combining data sources and engaging in analytical tasks that, for example, entail new business opportunities. Other examples include the use of AI to map different combinations of chemical compounds of proteins (Yang et al., 2022), develop new perfumes (Raisch & Krakowski, 2021), and support the drug discovery process (Lou & Wu, 2021). As AI has capabilities for handling, analyzing, and combining various data, it can enable the discovery of effective solutions that exceed the cognitive limitations of humans (Haefner et al., 2021).

Table 2
AI Functions.

AI function	Description	References	Examples
Mapping	Scanning an organization's internal and external environment to solve organizational problems or find business opportunities	Arts et al. (2018); Bouschery et al. (2023); Li et al. (1999); Lou & Wu (2021); Arul Murugan et al. (2022); Nguyen-Duc & Abrahamsson (2020); Paschen et al. (2020); Sharma et al. (2022); Tambe et al. (2019); Zhang & Tao (2021).	Employee selection: - Unilever - JPMorgan Invention discovery: - Symrise - Pfizer & IBM Watson
Coordinating	Integrating and linking different partners to accomplish a collective set of tasks	Alberola et al. (2016); Bouschery et al. (2023); Davenport & Ronanki (2018); Huang & Rust (2018); Kaplan & Haenlein (2019); Toorajipour et al. (2021); Webber et al. (2019).	Allocation of resources: - Walmart - Samsung - C3 AI Demand forecasting: Ikea Heineken Communication/ chatbots: - Starbucks - Domino's
Controlling	Influencing human behavior in desirable ways, including identifying anomalies and predicting undesirable outcomes in the future	Bardhan et al. (2020); Baryannis et al. (2018); Esteva et al. (2017); Baki Kocaballi et al. (2020); Lin et al. (2018); Luh et al. (2019); Kumar & Venkataram (1997); Varakantham (2017); Willis & Jarrahi (2019).	Disease detection: - Mayo clinic - Cleveland clinic - Nat. Univ. of Singapore HR performance measurement and compliance: - WorkCompass

Second, AI can be used for *coordinating*, which is integrating and linking different partners to accomplish a collective set of tasks (Briscoe & Rogan, 2015). AI can perform multiple tasks ranging from mechanical tasks that enable automating well-defined sub-processes to analytical and feeling tasks that facilitate integration between entities. In the field of operations, AI can improve the efficiency of resource allocation. For instance, manufacturing and retail firms like Samsung and Walmart increasingly rely on AI for supply chain coordination, while Ikea uses AI as an information tool to anticipate changes in demand forecasting. Finally, AI can assist in intra- and inter-organizational communications (Barbosa et al., 2020). In customer relationship management, AI-enabled communication systems, like the chatbots developed by Starbucks and Domino's, ensure effective communication between parties to align priorities and prevent communication breakdown.

Third, AI contributes to *controlling*, which involves supporting and influencing human behaviors towards desirable outcomes. AI can be used to detect anomalies and predict future behaviors. It can be applied to broader problems and combine multiple tasks to provide holistic suggestions that guide human behavior in desired ways. In healthcare, AI has achieved promising results for disease recognition (Esteva et al., 2017), such as predicting patient reactions to immunotherapy and personalizing cancer treatment (Varakantham, 2017), and can be used to automate documentation to monitor patients undergoing radiation

[6] The three management functions are closely related to the double diamond framework introduced by Bouschery et al. (2023), who apply this framework to assess how transformer-based language models can contribute to innovation. Their model postulates that innovative organizations engage in tasks to explore a wide range of problems and opportunities in the problem space and then decide on adequate solutions to the given problem in the solution space. In both the problem space (problem articulation and selection) and solution space (concept generation, concept selection), innovation teams perform divergent (exploratory) and convergent (exploitative) tasks. Our research expands this framework by introducing a third space, the *execution* space, to explicate the commercialization phase of innovations in which the innovation is brought to the market.

(Luh et al., 2019). In cases where sensitive data need to be shared securely and/or the quality of information must be verifiable, AI can be coupled with blockchain technology. Blockchain technology provides an immutable ledger that, for instance, can be used to create a secure and transparent platform for sharing data that is subsequently analyzed by AI algorithms to generate insights or predictions (Muheidat & Tawalbeh, 2021). In the following section, we shift focus to the management of OI.

3. Managing oi with AI

3.1. Open innovation: stages and management challenges

The management functions outlined above are particularly salient in an OI context. The concept of OI has emerged as a contrast to traditional organization of innovation that relies almost exclusively on firms' own R&D, i.e., closed innovation (Chesbrough, 2003). Firms pursuing OI organize innovation activities as collaborative projects connecting their own R&D activities with those of external organizations such as universities (Fleming & Sorenson, 2004), suppliers (Dyer & Hatch, 2004), customers (Köhler et al., 2012), cross-industry partners (Enkel & Gassmann, 2010), startups (De Groote & Backmann, 2019), or competitors (Hamel et al., 1989). Firms collaborating on innovation benefit from pooling their knowledge and resources, efficiently dividing labor (Lawrence & Lorsch, 1967) and achieving a greater ability to tackle complex innovation problems (Knudsen & Srikanth, 2014). By combining internal knowledge with that of external partners, firms obtain richer opportunities for novel innovations than when drawing solely on their own knowledge pool (Rosenkopf & Nerkar, 2001). Collaborating with outside partners can also enhance experimentation to resolve inherent uncertainty associated with novel technologies and to arrive at promising solutions faster or with fewer resources (Fleming & Sorenson, 2004). Overall, OI strategies have been shown to improve firms' innovation performance across various settings and sectors (Grimpe & Sofka, 2009; Laursen & Salter, 2006).

Despite the great potential of OI, its management is challenging since it requires firms to manage resources, capabilities, and incentives across organizational boundaries (for a review, see Bogers et al., 2018; Laursen, 2012). Our focus is on synthesizing challenges resulting from information processing and decision-making patterns in OI management that could be resolved by AI applications. We structure the management of OI into three stages: initiation, development, and realization. This structure offers a useful framework for explicating distinct patterns while acknowledging that, in reality, these stages may overlap, be skipped or be redone, and affect each other dynamically (Grönlund et al., 2010; Huizingh, 2011). Table 3 describes the activities (the current section) and identifies challenges (see Section 3.2) for each OI stage.

The initiation stage precedes the search effort for desired innovations and entails screening available knowledge sources as well as determining the type and number of partners, and their extent of involvement (Laursen & Salter, 2006). Firms must anticipate partner availability and motivation, as well as assess the fit between the complexity of the innovation problem and the partners' knowledge base (Felin & Zenger, 2014). They also need to consider an appropriate governance form, such as technology licensing (Arora et al., 2001), setting up a collaboration agreement (Gambardella & Panico, 2014), or a strategic alliance (Kok et al., 2020). The initiation stage concludes with the choice of OI partners and mode of collaboration.

The development stage involves the core process of collaborative knowledge production. Partners conduct research within their sphere of expertise while remaining cognizant of the partial outcomes of their specialized sub-projects to be integrated within the larger collaborative innovation project (Knudsen & Srikanth, 2014). The diverse research outputs from the various partners need to be collected, transformed, and assimilated so they can be recombined and integrated as unified knowledge stock for exploitation (Lane et al., 2006; Todorova & Durisin, 2007). To ensure coordinated action, social and formal governance mechanisms are installed to monitor partners' research efforts and contributions (Dekker & van den Abbeele, 2010; Reuer et al., 2002). The development stage ends with an invention that can be commercialized.

Table 3
OI activities and challenges.

OI stages	Main activities	Main challenges
Initiation	● Selecting partners (availability, motivation, cooperativeness, knowledge) and identifying innovation opportunities ● Selecting collaboration mode	● Cognitive information processing constraints in the search process ● Human bias in selection of partner and collaboration mode ● Dealing with innovation-cost dilemma ● Predicting potential relational issues
Development	● Finding partner resource complementarity ● Knowledge collection, transformation, and assimilation for technological invention	● Efficient resource allocation ● Dealing with the "paradox of openness" ● Safeguarding against knowledge leakage and free-riding ● Overcoming internal resistance and the "not-invented-here" syndrome
Realization	● Commercialization of innovation ● Renegotiating ● Monitoring of (undesired) partner behaviors ● Termination or continuation decision	● Selecting promising innovation and business model ● Balancing joint value creation and firm value capture: managing value distribution tensions ● Terminating or renewing collaboration ● Breach detection and resolving disputes

The realization stage involves decision-making about how the invention is turned into an innovation with commercial value. Typical decisions include selecting realized inventions for commercialization (West & Bogers, 2014), choosing business models (Saebi & Foss, 2015), and using knowledge protection instruments such as patents to capture the created value (Somaya, 2012). The latter choice implies (re)negotiations about property rights, value distribution among partners, and conflict management (Adegbesan & Higgins, 2011; Oxley, 1997). Firms must not only monitor their partners' conduct to prevent opportunistic behavior, but also evaluate collaboration termination or renewal (Sampson, 2005).

3.2. Matching AI functions with OI challenges: the AI-OI matrix

In Fig. 1, we combine the three AI functions according to the three OI stages to formulate nine roles that AI can play. In the resulting AI-OI matrix, each cell describes how AI can perform a specific role and contribute to the management of OI challenges at the given stage. We discuss potential AI applications for each cell and then provide examples of use cases in which AI is already performing comparable tasks.

3.2.1. AI applications to solve management challenges in the initiation stage of OI projects

To search for and identify the "right" OI partner(s), firms need to screen the business environment and map potential external sources of innovation (Laursen & Salter, 2006; Monteiro & Birkinshaw, 2017). Bounded by managers' information processing abilities and biases (Haefner et al., 2021), firms may miss out on valuable partners and opportunities, resulting in sub-optimal innovation solutions (Meulman et al., 2018). Even when firms can search extensively, they may fail to create complete maps of innovation opportunities and favor known partners. Further, firms face an innovation-cost dilemma where

OI stages		*AI functions*		
		Mapping	*Coordinating*	*Controlling*
	Initiation	**I – AI as scout** Exploratory search: partner and innovation opportunity identification	**II – AI as matchmaker** Reconnaissance of partners	**III – AI as forecaster** Foreseeing problems, opportunities, and aids
	Development	**IV– AI as cartographer** Mapping potential recombination of partners' diverse knowledge	**V – AI as conductor** Knowledge integration for innovation development	**VI – AI as whistleblower** Early warning and detection of opportunistic behavior
	Realization	**VII – AI as vanguard** Evaluation of new business opportunities	**VIII – AI as broker** Deploying joint resources for commercialization	**IX – AI as custodian** Guarding intellectual property and (re)allocation of value capture

Fig. 1. AI-OI matrix presenting the nine roles of AI in OI.

inclusion of more diverse partners can trigger innovation benefits via access to non-redundant information, but also lead to increased coordination costs (Cassiman & Valentini, 2016; Faems et al., 2010). Finally, firms must foresee potential relational challenges during partner selection (Faems et al., 2008), where differences in expectations or objectives could cause suboptimal OI solutions and early termination (Bogers et al., 2017).

In sum, the initiation stage of OI projects presents significant challenges, including the search for partners and assessment of potential relational and coordination challenges that create the need to process a considerable amount of relevant knowledge and sources. AI has the potential to alleviate human constraints in managing these diverse challenges.

I. AI as scout – Partner and innovation opportunity identification

A key management aspect of the initiation stage is the selection of useful knowledge and the external partners possessing it. AI may foster more radical innovation by identifying and evaluating distant knowledge and unfamiliar partners, thus helping to overcome cognitive information processing constraints in the search process to widen the search scope.

There are existing use cases in which firms rely on AI to improve their search scope — especially in the areas of talent acquisition and customer need identification. For instance, JPMorgan allows experienced HR managers to work closely with an AI-based solution to identify firm-specific predictors of candidates' future job performance. Similarly, Kanetix, an insurance company, uses AI to evaluate customers' purchasing data to identify untapped customer needs.

II AI as matchmaker – Partner reconnaissance

An important role of managers in the initiation stage of an OI project is to create an understanding of how diverse sets of specialized partners can work together. Managers must establish standards for communication and determine the modes of collaboration or contracting. AI can partially take over coordination tasks by analyzing and predicting information gaps between partners and interaction modes to address them.

The intelligence community Palentir offers a platform called Foundry aimed at improving partner reconnaissance. The platform is intended for large corporations that want to engage in Industry 4.0 with the onboarding process of their partners. To improve Foundry's ability to onboard partner firms, Palentir uses AI and machine learning to continuously analyze user decisions and feedback. Foundry can detect missing knowledge and provide training and/or prepare firms on how to share data. Hence, Foundry supports detecting specific innovation opportunities regarding Industry 4.0.

III AI as forecaster – Conflict foresight

OI projects in the initiation stage benefit from managerial consideration of potential risks and barriers. Envisioning alternative outcome scenarios is often challenging because risks and conflicts may emerge from various sources (e.g., technology, competition) and are too complex for anticipation/forecasting or interfere with managers' career incentives, e.g., by emphasizing worst-case scenarios. Given these conditions, AI can support proactive, analysis-driven simulation processes to identify possible futures, pinpointing potential hurdles (imposed by partners or market developments) that may impact collaborations during the development or realization stages.

Existing AI use cases often deal with legal risks and intellectual property rights. Origenis[7] provides an AI platform for analyzing chemical structures in patent applications that can help pharmaceutical firms uncover research strategies and support due diligence processes for future patent needs and ownership. The platform also helps partners detect overlap with existing patents. AI simulations can also consider environmental, technological, competitor, and supply chain information to help predict and prevent conflicts.

[7] https://www.origenis.de/ai-innovation-platform.

3.2.2. AI applications to solve management challenges in the development stage of OI projects

To develop OI projects, firms must be willing to engage with a broad set of partners to exchange knowledge (Almirall & Casadesus-Masanell, 2017; Dahlander & Gann, 2010; Zobel & Hagedoorn, 2020). Such openness can, however, produce tension, i.e., the "paradox of openness" (Arora et al., 2016; Laursen & Salter, 2014). Firms thus require knowledge protection mechanisms that prevent knowledge leakage without impeding the processes that support joint knowledge creation (Wadhwa et al., 2017). Consequently, managers must judge the need for knowledge combinations from different partners (Teece, 2018), especially in cases involving remote operations or conflicting self-interests (Das & Teng, 2016). OI management, therefore, requires (in)formal control mechanisms that encourage reciprocity while discouraging knowledge hoarding, free-riding, or defection from (in)formal agreements (West & Bogers, 2014).

Further, new R&D management approaches are required when OI projects compete for innovation budgets (Bogers et al., 2017) or face resistance due to "not-invented-here" (NIH) syndrome (de Faria et al., 2020; Hannen et al., 2019). OI requires R&D employees to change their work practices to incorporate engagement with external parties (Salter et al., 2014) and thus benefits from managers who can overcome internal resistance by convincingly communicating the benefits of OI (Gimenez-Fernandez et al., 2020).

In sum, managers perform crucial coordination tasks during the development stage of OI that involve sharing of information and integration amongst partners, all of which can benefit from AI.

IV AI as cartographer – Knowledge recombination

The development of complementarity between partner knowledge is crucial for the success of OI. However, complementarity cannot be fully anticipated ex-ante and is best recognized after the formation of the collaboration through mutual, in-depth reconnaissance (Deken et al., 2018). As a result, identifying and re-assessing opportunities for knowledge recombination is a challenging task.

AI can identify existing and prospective knowledge complementarity by analyzing partners' knowledge stocks. With the potential of developing knowledge complementarity and underutilized opportunities for recombination, AI can help partnering firms overcome internal resistance or NIH syndrome by mapping and visualizing the potential of OI. In other words, AI can help reveal the potential benefits of OI that would otherwise be ambiguous to partnering firms and their employees. As such, AI can be used to stimulate reciprocity by mapping the mutual benefits that derive from the complementarity of partners.

For example, Pfizer uses AI for drug discovery and development by analyzing vast numbers of chemical compounds to identify suitable combinations to treat specific diseases. Notably, to aid development of a COVID-19 vaccine, Pfizer used IBM Watson to analyze 25 million medicine abstracts, more than 1 million full-text medical journal articles, and 4 million patents.

V AI as conductor – Knowledge integration

OI partners must integrate their diverse knowledge inputs to create new inventions. While such integration is integral to collaborative knowledge production within OI, it is difficult to coordinate and managers may discover too late that individual outputs are incompatible with the wider goals of the OI project. Ideally, OI management creates conditions under which partners are willing to share knowledge in compatible formats without constraining the creative process or triggering resistance. AI can help create such conditions.

Spacemaker, an AUTODESK design software product, exemplifies how AI can aid knowledge integration. This collaborative platform enables early-stage real estate designs to be uploaded as 3D models to geo-positioned sites, providing designers with a testing ground to investigate how designs are impacted by various contingencies. AI systems can also act as evaluators of the novelty of an idea (Maher & Fisher, 2012), intervening, moderating, and providing input when needed (Strohmann et al., 2018) while remaining a neutral arbiter to facilitate trusting collaborations (Hofeditz et al., 2022). Finally, AI can enable extensive analytic data sharing through methods like AMDEX.[8] These methods allow partners to share data while encrypting the original source of knowledge, enabling feedback to participants without compromising control over their data. This approach encourages free information exchange while safeguarding intellectual property.

VI AI as whistleblower – Early warning system

To enable control during the development stage, AI can potentially act as whistleblower by detecting and reporting potential violations, fraud, or unethical behaviors of collaboration partners. Early awareness allows for timely countermeasures and helps reduce opportunistic behaviors and potential partner conflicts, preventing emergence or escalation.

An exemplary use case is the platform Wheesbee[9], which uses AI-based techniques to connect European SMEs and analyze public data on SME knowledge, projects, and technologies. Wheesbee enables analysis of strategic considerations and dynamic changes when, for example, certain partners acquire major new customers who are competitors to other partners. In the same vein, the insurance industry has started to deploy AI-based tools to analyze patterns in insurance claims that indicate possible fraud. Similar linguistic analyses can produce red flags when partners communicate with each other following opportunistic patterns. Additionally, sentiment analysis can analyze inter-partner communication or negative customer feedback to detect negative sentiments (Bouschery et al., 2023; Stahl, 2022).

3.2.3. AI applications to solve management challenges in the realization stage of OI projects

During the realization stage of OI projects, management faces several challenges such as identifying valuable innovations for commercialization and selecting a suitable business model (Saebi & Foss, 2015; West & Bogers, 2014). The tension between joint value creation and individual firm value capture is another challenge that partners must address, requiring decisions about how much value each partner receives based on past and anticipated future contributions (Gnyawali & Ryan Charleton, 2018). Tasks include contractually assigning ownership of property rights among partners, exclusivity, non-disclosure agreements, (joint) patents, copyrights, trademarks, design rights, or trade secrets (Adegbesan & Higgins, 2011; Hagedoorn & Zobel, 2015; Oxley, 1997). Similarly, decisions are needed about project termination or renewal (Sampson, 2005). To sustain cooperation, it is essential that OI partners live up to their promises, which requires a management control structure that detects possible breaches and resolves disputes (Das & Teng, 2016). AI can assist managers with these tasks during the realization stage.

VII AI as vanguard – Business opportunity evaluation

In the realization stage of OI, management task shifts from developing solutions to choosing attractive opportunities for commercialization. However, managers might lack the capacity or motivation to consider a broad set of potential business models. As a result, they are likely to rely on a narrow set of business models with which they have positive experience and could constitute the least common denominator for all project partners. As this approach may underestimate the potential range of business models, AI can offer useful tools for comprehensively exploring business model opportunities.

ITONICS[10], a company specializing in trend watching, provides an illustrative use case of this AI role. This company uses specialized AI bots to perform environmental, technological, and competitor simulations that help its clients identify business opportunities within their partner portfolio.

[8] AMdEX (https://amdex.eu/) is an initiative that promotes trusted and secure market exchange with data sovereignty.

[9] https://www.wheesbee.eu/.

[10] https://www.itonics-innovation.com/.

VIII AI as broker – Resource deployment

OI managers must secure and deploy resources to commercialize the selected innovations and business models. However, as the complex operations associated with implementing business models reliant on partner interdependencies are taxing, managers are constrained by information processing capacity and attention (Min, 2010; Sharma et al., 2022). As a result, resource deployment may not reach optimal efficiency and effectiveness, providing an area where AI could contribute.

AI can support supply chain management by assisting firms in effectively allocating resources. One notable example is Heineken, which has utilized Blue Yonder's machine learning technology to mitigate the impact of external disruptions, such as the COVID-19 pandemic, on its supply chain. This tool enabled Heineken to optimize inventory management and anticipate consumer behavior by leveraging historical data. Similarly, the healthcare industry utilizes machine learning models that leverage patients' electronic health records to analyze data and aid managers to efficiently allocate limited resources across the healthcare system.

IX AI as custodian – Guarding knowledge

The successful realization of OI depends on the individual rewards that partners receive for their efforts and contributions. Managers make use of intellectual property tools to create boundaries that help define a fair distribution of jointly created value. However, initial agreements are typically incomplete and require renegotiation. AI-based systems that preserve the interests of all partners could facilitate this process. Furthermore, AI can help detect intellectual property violations and offer objective remedies that managers can hardly accomplish. Hence, AI can serve as an effective mediator, arbitrator, or mediator (Larson, 2010; Siemon, 2022).

An example of the role of AI in flexibly managing IP rights comes from the SIOPE DIPG Network, which works with AMdEX to manage a registry of data collection provided by network members. Using AI tools from AMdEX, this registry shows how collaboration agreements between network members can be automatically enforced.

3.3. Using the AI-OI matrix in practice

Our AI-OI matrix can raise awareness about the potential of AI for OI and facilitate the development of effective AI implementation strategies. Firms can benefit by using this matrix to guide the complex task of developing and using AI tools for OI. Specifically, the matrix allows managers to identify problem areas in their OI projects and compare them against the readiness of AI solutions to pinpoint opportunity areas. In this way, managers can use the AI-OI matrix as a heatmap to locate areas of current OI projects with the most severe challenges, thereby highlighting the potential value of AI. At the same time, another heatmap can be developed to identify the readiness of AI tools across the different OI stages and reveal technology-driven opportunity areas. For example, AI tools may function well as a scout (cell I), but perform poorly as a custodian (cell IX) due to regulatory or technological issues. After matching the severity of OI challenges with the readiness of AI applications within the AI-OI matrix, managers can identify and compare problem areas with opportunity areas and initiate three response strategies: (1) implementing AI applications with high readiness in problem areas that allow for strong improvements (i.e., severe problem area/strong opportunity area); (2) closely monitoring the readiness of AI in problem areas where current AI solutions lack readiness (i.e., severe problem area/no opportunity area); and (3) evaluating whether AI solutions with high readiness can provide benefits in areas not considered to be particularly problematic (i.e., no problem area/strong opportunity area). Fig. 2 illustrates how the AI-OI matrix can be used as a heatmap to identify problem areas (left) and opportunity areas (right), as well as the three corresponding response strategies that can be derived from comparing problem areas with opportunity areas.

4. Implications for research and practice

In closing, we zoom out and translate the insights gained from this study into opportunities for future research and practice. Our aim is to provide a research agenda with great potential to provide actionable insights for management practice based on the identified OI challenges. As a guiding principle, we distinguish between three driving factors for research opportunities on AI in OI emerging from (a) current technological limitations of AI and potential future applications, (b) organizational aspects of AI adoption, and (c) various AI-induced outcomes. Accordingly, we structure our conclusions into research questions linked to (a) the technological pace of AI in the OI context (see Table 4), (b) challenges associated with AI adoption in OI (see Table 5), and (c) OI consequences after AI implementation (see Table 6).

4.1. Technological pace of AI for OI

Here, we focus on management considerations for the use of AI for OI rather than technological considerations. However, an essential technological aspect relevant to AI's applications in OI management is the pace at which AI capabilities are expected to develop. Although current applications are subject to important limitations, such as in analysis of unstructured data, these limitations are likely to disappear with improved algorithms and increased processing power. Consequently, the evolving technological dynamics of AI will require researchers to reevaluate its usefulness for specific OI functions and the resulting managerial implications. Future research should consider the pace of technological advancements in AI, particularly in areas related to knowledge search, knowledge assimilation, and relationship management within OI. We briefly elaborate on these research opportunities in the following sections.

4.1.1. Knowledge search

AI has made progress for overcoming information processing constraints in search processes and limiting human biases in partner selection (Huang & Rust, 2021). AI tools can automate tedious tasks, support managers to efficiently find appropriate contractual forms, and match employees based on traits, experience, and motives. One of the greatest obstacles in unlocking opportunities is the limited availability of structured data to train AI models. Further, the applicability and usefulness of various AI search types (e.g., supervised, random forest, support vector machine, neural networks) (Kirubarajan et al., 2020) for specific tasks remain unclear.

Identifying and matching partners' complementarity of knowledge is a challenge for OI managers. AI can facilitate the process of identifying complementary resources for recombination among partners. While patent descriptions provide limited insights, machine learning and natural language techniques can inductively determine knowledge complementarity based on internal documentation and research proposals (Faems, 2020; Lundvall & Rikap, 2022). In conjunction with topic modeling, these approaches can help establish phenomenon-based constructs and conceptual relationships (Hannigan et al., 2019). However, applying these AI techniques across different knowledge domains is challenging. Additionally, the shift from sharing one-to-one or one-to-few to sharing one-to-all, along with sharing relevant firm data upfront, requires significant organizational changes and increases misappropriation risks. Nevertheless, AI can help overcome the paradox of openness by encouraging firms to become more indiscriminately open.

4.1.2. Knowledge assimilation

The coordinating function involves development of the innovation itself. Existing AI tools likely lack the relevant capabilities for this task, as there is a strong need for creativity and emotional connections between individuals. Humans are social creatures that excel at understanding feelings and can merely be empowered by AI tools for this function (especially in supportive stages prior to and after

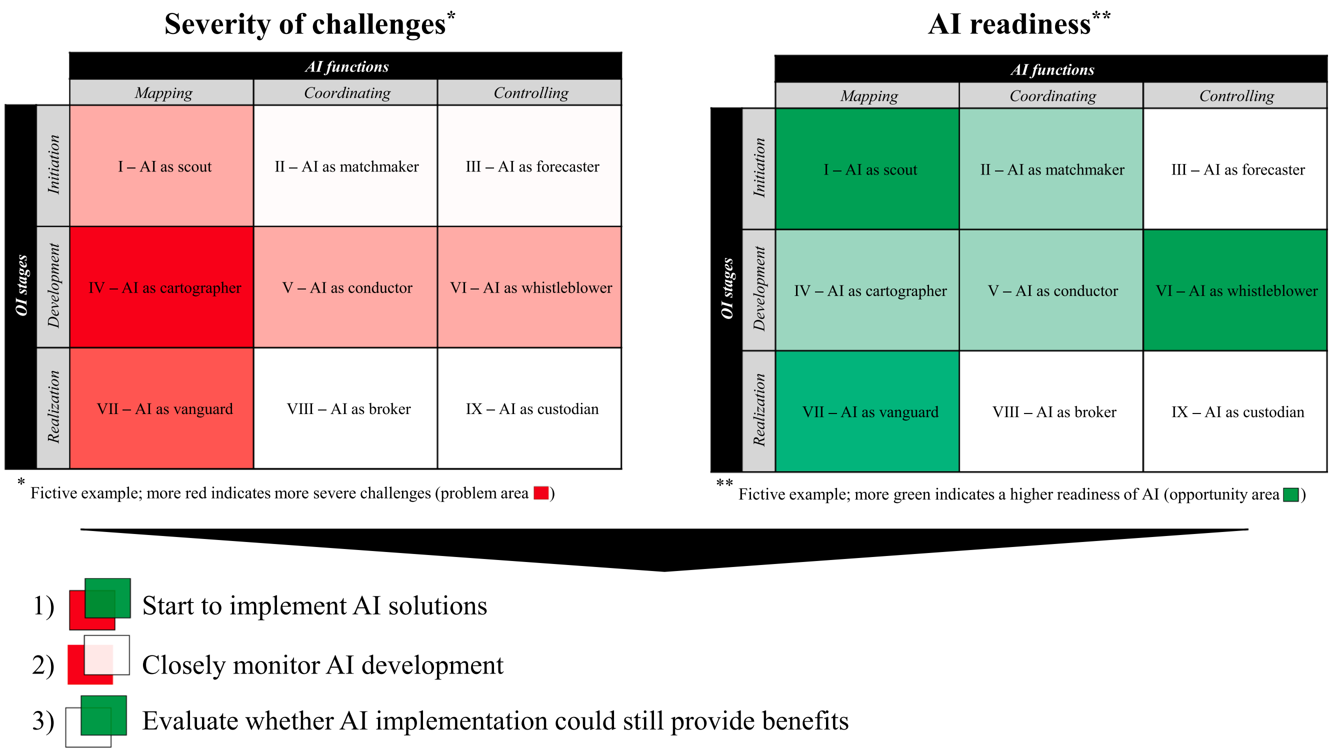

Fig. 2. Illustrative uses of the AI-OI matrix in practice.

development). As a result, managers will likely continue to play an essential role in coordination by asking the right questions, imagining and developing creative solutions, dealing with uncertainty and uncharted areas, prototyping, and selecting promising ideas for realization. Nevertheless, narrow AI solutions could help free up managerial attention to focus on these inherently human tasks.

A separate aspect is that AI remains ill-equipped to help firms overcome internal resistance and NIH syndrome. Future research could investigate how AI can address these human emotions and limitations and build AI applications aligned with their needs and values or provide sufficient levels of trust and transparency for humans to accept, internalize, and work with the suggestions made by recommender systems.

4.1.3. *Relationship management*

Given the current limitations of AI's empathetic capacity, its role in OI mainly focuses on the preparation stage, helping avoid conflicts by better matching project members based on their traits, experiences, or motives, rather than acting as a mediator. AI can be utilized to provide inputs, such as summarized information, contract reviews, and legal expertise, to resolve disputes. However, AI's ability to manage and contain behavioral conflicts between individuals is currently limited. Consequently, AI has rarely been employed as an independent (robotic) judge. To use AI as an active conflict management tool, partners must agree on the algorithms programmed into the AI system beforehand, as the power no longer lies in the hands of a judge but in the hands of the programmer (Barnett & Treleaven, 2018; Ermakova & Frolova, 2022).

As the above-described limitations of AI are unlikely to persist, research revisiting opportunities to use AI for OI will be needed. Table 4 presents a set of salient research questions that seek to understand the technological dynamics of knowledge search, knowledge assimilation, and relationship management.

4.2. *Adoption of AI for OI*

The adoption of AI to support OI is an important area for future research that deals mostly with organizational responses to AI opportunities and OI needs. Conceptually, three mechanisms explain organizational adoption of AI for OI: (a) the functionality that AI can offer at the project level, (b) the patterns by which AI practices diffuse within organizations, and (c) the degree to which AI practices become institutionalized in and across industries. We explore each aspect below.

4.2.1. *Functionality*

As AI features become particularly desirable at the OI project level, AI adoption becomes particularly salient. For instance, the degree to which AI can automate OI activities (versus augmenting humans) may depend on how well the OI problem is understood, its objectives (e.g., exploratory or exploitative), the number and nature of potential partners, and broader OI project governance (e.g., incentives for data sharing, safeguarding mechanisms, and contractual agreements). The experiences of OI project partners with AI applications may further drive adoption across OI stages (e.g., creating awareness of potential applications, the ability to share and protect sensitive information). When considering how AI can address OI challenges in specific projects, it is imperative to understand synergies (or complementarity) between functionalities, such as when enhanced coordination through AI by knowledge integration (cell V in Fig. 1) is supported by tighter control through AI over shared information and early warning of undesired partner behavior by whistleblowers (cell VI in Fig. 1).

4.2.2. *Practice diffusion*

Firms considering AI adoption must consider how AI practices should diffuse across all OI projects. Experience managing multiple OI projects can improve an organization's understanding of introducing, applying, and managing AI. Participating in multiple OI projects could influence applications within and across projects (e.g., repeated use of features, enabling deeper investments, and experience building). Experience with AI in other business applications, such as personnel selection and supply chain management, can help identify potential uses and facilitate AI implementation in OI projects. Organizations' digital maturity and literacy are likely drivers of adoption as they provide fertile infrastructure (structured IT and data environments) and tendency to develop and

Table 4
Future research opportunities: technological pace of AI for OI.

Research trajectory	Conceptual focus	Research questions
Improvements in AI technological capabilities for OI	Knowledge search	- How can organizations structure their data to train AI models more efficiently? - How can AI search types (supervised, random forest, support vector machine, neural network) be optimized for particular search tasks? - What are the risks and benefits of shifting from sharing one-to-one or one-to-few to one-to-all openness? - How can AI help overcome the paradox of openness? - How can AI help overcome the challenges of identifying, describing, and matching partners' complementarity of knowledge? - How can AI tools improve the transparency of knowledge search and selection processes?
	Knowledge assimilation	- In what ways can AI be used to empower humans in the coordination function of innovation development and manage knowledge integration processes? - How can AI help organizations find the most complementary partners for their OI projects? - What knowledge integration processes can be improved by AI tools? - How can AI tools be developed to overcome internal resistance and the NIH syndrome to internalize knowledge? - What AI tools can help organizations develop creative solutions for OI problems? - How can AI applications be designed to address human emotions and limitations while aligning with their needs and values?
	Relationship management	- How can AI be used to adequately match OI project members to avoid conflicts? - What AI tools can effectively identify and prevent potential sources of conflict between OI partners? - How can AI help organizations detect and penalize opportunistic partner behavior? - How can AI conflict management tools be set up to be perceived as unbiased by OI partners?

implement new AI applications. Furthermore, an organization's digitalization strategy may determine its orientation towards AI use, i.e., whether it focuses on automating technology to enhance task efficiency or differentiating itself by augmenting human skills in innovation activities.

4.2.3. Institutionalization

As AI approaches for OI become widely adopted, important research questions arise at the industry level. The institutionalization of AI in OI may be influenced by the level of digitalization in partner industries. Firms may face varying pressures to adopt AI and develop capabilities due to competition or institutional pressure to imitate "best practices." Industry dynamics are likely to evolve, making the ability to benefit from AI features in OI a core part of a firm's technological capital. This will affect a firm's attractiveness as an OI partner within its industry and beyond.

For OI researchers, the multilevel nature of adoption mechanisms has implications for the theoretical framework used to study adoption. Combining theoretical frameworks related to rational decision-making, organizational capabilities, learning, governance and control, institutional pressures, and behavioral biases shows promise for developing a comprehensive understanding of the role, use, and consequences of AI in OI. Table 5 provides a summary of relevant questions yet to be addressed.

Table 5
Future research opportunities: challenges associated with the adoption of AI for OI.

Research trajectory	Conceptual focus	Research questions
Technological Pace of AI for OI	Functionality	- Which OI tasks can be automated or augmented with the help of AI? How will technological advancements change this automation-augmentation division? - What specific AI functionalities are desirable for OI projects, and how do they vary with problem characteristics, objectives, potential partners, and project governance mechanisms? - How do AI functions interrelate and when do they complement each other? - How and when does the use of AI influence innovation and project performance?
	Practice diffusion	- How do organizations become aware, motivated, and capable of considering AI solutions to address OI challenges? - How does experience in managing and governing multiple OI projects influence AI adoption and diffusion across projects? - How do organizations foresee and trade off expected benefits and costs of AI solutions? - What facilitators or enablers (e.g., technological advancements, data exchange developments, digital maturity and strategy) support the adoption of AI for OI? - What strategies or processes do firms adopt to integrate (emerging) AI solutions?
	Institutionalization	- How do firms implement and use AI functions in OI? - What drives the extent and nature of AI applications in OI? - How does the extent of digitalization in OI partners' industries affect AI adoption and capability development? - How do firms develop capabilities for productive AI use to address OI challenges? - How does AI adoption and success affect organizations' attractiveness as OI partner within their industry and beyond? - Under what conditions do firms abandon AI in OI?

Table 6
Future research opportunities: consequences for OI after AI implementation.

Research trajectory	Conceptual focus	Research questions
Implications of using AI solutions in OI	Greater openness	- How can AI tools govern relationships when critical information must be shared among multiple OI partners? - What measures help organizations trust that AI solutions play an impartial role between OI partners? - What is the role of transparency or explainability of AI or in combination with social factors regarding the willingness to share information with AI tools? - How are security issues of AI tools managed? - How can intermediaries ensure the independence and security of AI solutions?
	Reduced transaction costs	- How do firms adapt the selection process when using AI-related partner search? - How do increased partnering opportunities associated with the use of AI affect competition across and within industries? - Do decreased transaction costs in OI affect the diversification strategies of firms? - Does reliance on AI functions limit the distinctiveness of OI partner networks? - Do transactional forms of collaboration become increasingly dominant?
	Organizational change	- How do firms manage organizational tensions when AI solutions alter routines and hierarchies? - What implementation strategies minimize the unintended effects of increased reliance on AI? - How can managers decide on the degree of AI reliance? - How does the use of AI solutions shape a firm's organizational design, and what organizational designs are suited for AI integration in OI projects? - How does reliance on AI affect the development and maintenance of valuable tacit knowledge in OI and how does this reliance impact knowledge development?
	Behavioral and psychological responses	- What features of human–AI interactions help mitigate biased responses from employees (e.g., aversion or over-reliance)? - How do humans manage trade-offs between intuition and AI reliance and what are the associated socio-psychological effects? - How do technostress or negative emotions evolve due to increased human–AI interactions in the OI context and what are the consequences of and means to mitigate these effects?

4.3. Consequences of using AI in OI

A logical next step for AI in OI is to examine its multifaceted consequences. The introduction of AI as a new actor in the stages of OI presents new challenges, such as socio-organizational issues during AI integration or changes in the nature of OI projects. To comprehensively understand these consequences, OI researchers may need to expand current theories and incorporate information systems perspectives. The following discussion delves into the significant implications of using AI solutions and identifies emerging challenges that warrant attention from OI researchers and practitioners.

4.3.1. Greater openness

The use of AI solutions in OI projects presents a paradoxical consequence: On one hand, AI can enhance knowledge protection (e.g., cells VI and IX in Fig. 1), but, on the other hand, it raises concerns about protecting knowledge. This is particularly relevant when AI is used for knowledge recombination (e.g., cell V in Fig. 1) or partner identification (cell I in Fig. 1), as it requires multiple partners to share R&D-related information with AI tools upfront. Governing AI tools that handle critical information is thus crucial for OI research and practice. The success of AI solutions in gaining partner acceptance relies on their ability to maintain an impartial role that safeguards the interests of all parties. Achieving this impartial role may be challenging and could lead to the emergence of new intermediaries, such as AI brokers that govern AI solutions in collaborations. While intermediaries could mitigate knowledge protection issues in OI projects, they also introduce new concerns related to trust and competition (Brockman et al., 2018).

4.3.2. Reduced transaction costs

As AI solutions are increasingly accepted in OI projects, previous patterns of partner selection may start to dissolve. Decreasing transaction costs of OI projects, which partly resolve the innovation-cost dilemma, can provide further innovation opportunities for a broad range of organizations. Future research could explore how both aspects may unleash new competitive dynamics. For example, new ventures could identify collaborators more easily, thus accelerating competition in less dynamic environments. However, this might also benefit incumbents and newly created digital organizations with large data pools that can be used by AI to identify wider partnering opportunities and, consequently, strengthen their joint market power. Decreased transaction costs for managing OI projects could also make it easier for organizations to expand in scope and scale, thus having implications for corporate strategy. Finally, use of AI in OI projects may not only create interesting dynamics for research on industry networks or strategic management, but also highlight the need for attention from supervisory bodies and antitrust researchers when, for example, big data moguls like Meta, Microsoft, and Alphabet use AI to gain further market power. In this regard, expensive AI solutions requiring specialized expertise could pose an entry barrier to smaller enterprises, locking them out of specific OI projects.[11]

4.3.3. Organizational change

In addition to its consequences for partnerships and the competitive landscape, the use of AI may change existing routines, structures, and the relevance of certain skillsets within organizations. For instance, OI projects may require increased centralization to effectively use AI in coordination tasks and alter internal structuring following AI-based team composition and task allocation. Such changes may impact powerful, highly skilled employees who currently oversee critical OI tasks, such as partner selection (cell I in Fig. 1) or coordination in the development stage (cell V in Fig. 1). These effects could trigger deskilling or displacement of certain groups while making others (such as AI operators and managers) indispensable (Benbya et al., 2021). A more

[11] Possible negative consequences of AI go beyond antitrust issues. In March 2023, an open letter signed by more than 1,000 notable signatories warned of the potential negative consequences of AI systems and called for "all AI labs to immediately pause for at least 6 months the training of AI systems more powerful than GPT-4.".

objective composition of teams and task allocation may increase participation of out-group members but also introduce the risk of systematic discrimination (Ferrer et al., 2021). Power struggles could arise, necessitating effective management when firms rely heavily on AI solutions.

To address these dynamics, OI researchers and practitioners can draw upon technological dominance theory (e.g., Arnold & Sutton, 1998; Sutton et al., 2023) to examine what designs could balance the (dis)advantages of using AI. They should also consider how reliance on AI impacts the development and preservation of valuable tacit knowledge in OI, as well as the long-term consequences of these effects. Additionally, theories of the firm can provide insights into how AI solutions shape organizational design, while theories of change can help understand how organizations prevent organizational turmoil.

4.3.4. Behavioral and psychological responses

Finally, the use of AI in OI projects involves close interactions with humans, which elicits various cognitive and emotional responses. While AI can help overcome cognitive biases, it also introduces new ones arising from human-AI interactions. Biases may emerge due to issues like excessive attention demands or dysfunctional attention allocation, hindering effective decision-making. While it may be possible to resolve such issues with AI, it is important to understand the organizational design features and implementation strategies that help in this regard. Field studies experimenting with different AI designs and implementation strategies can shed light on the conditions under which humans work more effectively with AI. Finding a balance between being overly averse or insufficiently critical of AI advice is another challenge (Commerford et al., 2022). While prior studies hint that algorithmic aversion may be particularly strong due to task subjectivity and the human nature of OI (Castelo et al., 2019), research could investigate the drivers of individuals' aversion or appreciation of AI solutions to understand their use in the OI context.

Increasing use of AI in OI projects may also lead to elevated employee stress and anxiety. Technostress (stress from working with technologies [Ayyagari et al., 2011]) and technological anxiety (Firk et al., 2023) related to AI diffusion thus become relevant in the OI context. Additionally, AI's continuous monitoring of worker output may create pressure, limit autonomy, and impede learning by preventing mistakes. Research could explore what conditions enhance innovation productivity while promoting employee well-being and learning. Table 6 presents potential research questions regarding how AI affects employee attitudes, behaviors, and learning in the OI context.

4.4. Implications for practice

The AI-OI matrix provides a useful tool for managers to match various existing and emerging AI applications to address specific AI-related management problems. Instead of focusing on technology and required technological infrastructure, this study underscores the significance of the human-side of AI, highlighting the value-adding mechanisms of AI to address inherent OI management challenges.

Our matrix can assist managers by increasing awareness of the potential of AI in OI and providing guidance for developing effective AI implementation strategies. Managers can use the matrix as a heatmap to identify both opportunity areas and problem areas in OI projects. By comparing the severity of challenges in OI projects against the readiness of AI solutions, managers can pinpoint areas that require improvement, target organizational investments and training programs, and highlight areas where AI can quickly generate business value.

As a new paradigm, OI has imposed new strategic imperatives for firms to develop responsive organizational structures and (cross-functional) teams, cultivate collaborative and open cultures, expand internal and external knowledge flows, and manage value protection and knowledge sharing risks. However, the advent of powerful new AI-enabled search queries for partnering firms creates pressure to proactively open up and share information *ex ante* with a wider population to become a coveted partner. This will place even greater emphasis on openness, transparency, and reputation. At the same time, AI increases the need to protect intellectual property as data sharing is facilitated – both intended and unintended. To reduce unintended loss of sensitive data, managers should educate their employees about data management, install or enhance cyber security measures, and adopt techniques that enable data sharing without compromising data control.

CRediT authorship contribution statement

Thijs Broekhuizen: Conceptualization, Writing – original draft, Writing – review & editing. **Henri Dekker:** Conceptualization, Writing – original draft, Writing – review & editing. **Pedro de Faria:** Conceptualization, Writing – original draft, Writing – review & editing. **Sebastian Firk:** Conceptualization, Visualization, Writing – original draft, Writing – review & editing. **Dinh Khoi Nguyen:** Conceptualization, Writing – original draft, Writing – review & editing. **Wolfgang Sofka:** Conceptualization, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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