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Introduction to the special issue

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Innovation Dynamics in the Age of Artificial Intelligence: Introduction to the Special Issue

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Abstract

In this paper, we discuss the impact of artificial intelligence (AI) on innovation dynamics and argue that AI has affected innovation dynamics in at least two distinct ways. First, innovation using AI has unique dynamics that are characterised by data playing a central role and the increasing importance of external collaboration; however, data security and privacy issues also present new risks to external collaboration. When innovating in AI, collaboration with customers and competitors is critical, yet there are considerable risks associated with data sharing. Second, unique organisational challenges

emerge during the diffusion of AI innovations, because adopting AI in an organisation not only results in the need for additional employee competencies but also challenges organisational power structures. We also discuss the merits of AI as a general purpose technology and argue that conclusions about AI in relation to innovation dynamics are likely to change when generative AI is widely adopted.

1. Introduction

Artificial intelligence (AI) is being rapidly and broadly adopted across industries and has profound impacts on organisations, even when compared to other technologies such as robotics (Furman and Seamans, 2019; Gjerding et al. 2020; Holm and Lorenz, 2022). AI is applied in a diverse range of processes within firms, and this suggests that AI is potentially a general-purpose technology (GPT) (Trajtenberg, 2018), particularly when generative AIs are also considered, such as the generative pretrained transformer series of large language models (LLM), including ChatGPT (Eloundou et al. 2023).[1] Rapid advancements in machine learning (ML) and deep learning (DL) have enabled AI to penetrate various industries and automate tasks that were once solely dependent on human intelligence and perceptual skills. Consequently, the impact of AI goes beyond merely automating discrete tasks; it also extends to the innovative alteration of existing processes and the introduction of

[1] The acronym 'GPT' is commonly used to represent both 'general-purpose technology' and 'generative pretrained transformer'. The latter refers to the neural network architecture developed by OpenAI in 2018 that powers the ChatGPT system. Variants of the third generation and GPT-4 are used in this system, which was released in late 2022 and has sparked widespread discussion about AI among both mainstream audiences and academia. In this paper, 'GPT' represents 'general-purpose technology'.

entirely new tasks. To understand the implications of AI for companies and industries, it is essential to examine its effects on fundamental concepts in the field of innovation studies.

1.1. Innovation dynamics with AI

The literature on innovation dynamics in the age of AI anticipates that there will be a significant impact. It is argued that the use of AI will 'challenge core axioms' (Füller et al. 2022), require new 'stylized facts' (Ciarli et al. 2021), change 'assumptions' (Johnson et al. 2022) and lead to a 'redesign' (Bahoo et al. 2023) of innovation dynamics or even entirely new methods for invention (Bianchini et al. 2022) and innovation (Cockburn et al. 2019). A large portion of the literature on AI and innovation dynamics consists of review articles that span different time periods and rely on different definitions and delimitations of AI (Bahoo et al. 2023; Borges et al. 2021; Hund et al. 2021; Mariani et al. 2023; Raisch and Krakowski, 2021). A recent complementary special issue (SI) in this journal also applied a broader approach and emphasised the larger set of digital technologies (Cefis et al. 2023). These review articles summarise the insights obtained when AI in innovation dynamics is viewed from a broad perspective and indicate avenues for further research, particularly on the impact of current AI technologies on innovation dynamics. However, the literature also highlights that the impact of AI is not limited to its effects on innovation dynamics when used as a tool in innovation. Rather, AI can also be an output of innovation dynamics. This AI output can translate into process innovations in other firms and thus affect a range of processes, such as process automation, data-driven decision-making, employee and customer management and the innovation process (Borges et al. 2021). Even within the innovation process, multiple subprocesses are affected by the use of AI: identification of opportunities, idea selection, concept testing and market launching (Füller et al. 2022). In terms of how AI contributes to innovation dynamics, the literature primarily emphasises that using AI speeds up selection processes in innovation dynamics; for example, AI systems can assist in selecting the most promising ideas (Cockburn et al. 2019; Raisch and Krakowski, 2021; Verganti et al. 2020). As indicated above, the various reviews and studies of AI in innovation dynamics generally position AI as a tool that can be used to enhance the innovation process. Despite this AI-as-a-tool perspective clearly dominating recent research, AI can also be considered a medium for collaboration or a counterpart (Anthony et al. 2023).

A wide range of economic activities are affected by AI as a consequence of the dual effects that AI asserts on providers and adopters (Ciarli et al. 2021; Varian, 2019). However, providers and adopters must work together more closely when undertaking innovation processes that involve AI. Whether developing ML algorithms or implementing the resulting AI in an organisation, there is a need for data that can be fed into the algorithms. Although the current paradigm is being challenged by the emergence of large generative pretrained transformer models, such as GPT-style language models, which do not necessarily depend on proprietary training data, organisations must still furnish these models with specific data to fine-tune them for particular tasks or, at minimum, during the inference stage upon deployment. Development of AI thus benefits from access to data that are the same as or similar to the data that the adopter will feed into it in practice, and this calls for close collaboration between providers and adopters during both AI development and implementation. However, there are new risks associated with data playing such a central role, namely around the ownership of, and access to, the data (Cillo and Verona, 2022; Varian, 2019).

Innovation dynamics are also impacted by AI because when firms adopt AI, they tend to be more involved in basic research and a new element emerges: the human–algorithm interaction. This means that social actors have a greater role in the innovation process and that the innovation process is not confined to the research and development department. Arguably, this necessitates the adoption of a new framework for understanding innovation dynamics that must also involve the management level of the organisation (Cillo and Verona, 2022; Hund et al. 2021; Verganti et al. 2020). In fact, this situation may occur not only in firms that provide AI technologies but also in those that adopt AI technologies; in both cases, internal research must take into account the technological and organisational changes and challenges faced by the whole organisation (Füller et al. 2022; Kinkel et al. 2022). Such studies conducted at the adopter level should shed light on the human–algorithm interaction, success factors for AI adoption and requirements for skills and collaboration.

The papers in the SI further our knowledge in several of these areas. They variously present analyses of the difficulties associated with data access and collaboration when developing new AI solutions (Woolley, 2023); the full process of developing, providing, adopting and adapting when co-producing new AI solutions (Lepratte and Yoguel, 2023); the organisational changes and challenges faced by adopters (Taherizadeh and Beaudry, 2023); and the unique facets of collaboration for innovation when the outcome is new AI technology (Petruzzelli et al. 2023).

The remainder of this peditorial is structured as follows. In Section 2, we introduce the papers included in this SI and their contributions to the abovementioned discussions in the innovation literature. Each of these discussions is then furthered in the following three sections. Section 3 discusses the definition of AI and its potential to be a GPT. Delimiting AI and discussing its relationship to other concepts (e.g. ML and DL) is necessary for a consistent discussion of AI in innovation dynamics. In Sections 4 and 5, we discuss two themes in innovation dynamics that are affected by AI and analysed in the papers in this SI. Section 4 addresses how AI affects open innovation when firms' proprietary data become a necessary and valuable resource for innovation. In Section 5, we focus on AI adoption and the new requirements that emerge for firms that adopt AI, either in their production process or innovation process. Section 6 summarises the contributions that this SI makes to the literature on innovation dynamics in the age of AI.

2. The papers in this special issue

The papers in this SI (Lepratte and Yoguel, 2023; Petruzzelli et al. 2023; Taherizadeh and Beaudry, 2023; Woolley, 2023) focus on various aspects of the innovation process. Figure 1 depicts a simple generic innovation process. The initial research stage involves both basic and applied research and results in an invention. The second stage, the development stage, involves testing, prototyping and investing and transforming an invention into an innovation. The following diffusion stage focuses on commercialisation and adoption by customers. Note that the innovation process is not necessarily a linear and unidirectional process and that innovation processes typically involve collaborating and sourcing across organisational boundaries.

Figure 1 about here

Woolley (2023) discusses how AI coupled with blockchain technology systems can be used to facilitate collaboration for innovation between competitors. Two case studies in the pharmaceutical and medical imaging fields are presented in which AI is also used as a tool in research and development. In this scenario, individual organisations must pool proprietary data without giving their competitors access to the data. The proposed solution is the implementation of federated machine learning (FML), which leads to reflecting on the governance of innovation processes across organisational boundaries.

Lepratte and Yoguel (2023) analyse the complete innovation process in a case where AI is an output of the process and the customer participates in the entire process. The innovation in the case study is the application of AI in medical imaging scanners. This specific AI innovation emerged from a co-production process that involved the customer and the supplier. The analysis also covers the final adoption by the customer, the necessary organisational adaptations and the commercialisation of the innovation.

Petruzzelli et al. (2023) focus specifically on the collaboration that occurs during the research stage of innovation processes that generate AI as an output. The authors present a quantitative study in which the dependent variable was the quality of the patent. It was found that the quality of the patent was more or less independent of the collaboration type, except when the collaboration was between a firm and a university or research institute. In such cases, the quality of the patent tended to be relatively low. It is argued that AI technology has unique features that set it apart from other GPTs, with implications for collaboration patterns. In particular, AI technology inventions benefit particularly from applied knowledge, making university–industry collaborations less useful.

Taherizadeh and Beaudry (2023) studied AI as a process innovation in small and medium sized manufacturing enterprises by conducting 28 interviews at 16 firms and five ‘AI-focused events’. Using grounded theory, they describe AI adoption as an AI-driven digital transformation where the main emphasis is on the development stage of the innovation process. This development, or transformation, involves five distinct dimensions with different implications and requirements for organisational change, employees' skills and management.

These four papers reveal different roles that AI plays in the innovation process. In Taherizadeh and Beaudry (2023), AI is a technology that firms can adopt as **a process innovation**. In such cases, firms often do not undertake research but rather invest in and develop an AI asset for use in the firm. The role of AI is different in the analyses presented in Woolley (2023). Here, AI is a **tool in the innovation process** used in the research and development stages to write code, simulate virtual prototypes and so on. Finally, both Lepratte and Yoguel (2023) and Petruzzelli et al. (2023) present studies in which AI is a **product innovation**. This involves delivering algorithms to customers, who then feed the AI with proprietary data. In the ensuing sections of this editorial, we approach and discuss three themes that are prominent in recent research on AI and innovation and that span the four papers: 1) AI as a GPT, 2) the central role that data plays when AI is employed and 3) the organisational challenges and adaptations associated with AI use.

3. Artificial intelligence defined

While AI is ubiquitous, it is also ambiguous. This is a consequence of the definition of 'intelligence' being similarly ambiguous and subject to change. Thus, when considering how to define 'AI', it may be beneficial to stress the automated learning capacity rather than their intelligence, as in Dibiaggio et al. (2022). However, AI is traditionally defined as a technology that replicates human intelligence, and this is the definition associated with the original Turing Test, an experiment that examines whether a machine can imitate a human (Turing, 1950). This is a very broad definition which, in principle, does not even require the technology to be digital. A much narrower definition specifies that AI consists of automated learning methods for creating algorithms. The resulting algorithms are highly specialised prediction tools that typically perform a narrowly defined task better than humans. Thus, they are rarely mistaken for human intelligence. A third definition of AI is the technique of substituting humans with software. This software may be created through automated learning, which results in a large overlap between this definition and the former definition of AI. However, such software can also include hard-coded algorithms, which are sometimes referred to as good old-fashioned AI (GOFAI). Finally, a fourth definition posits that AI is a system of software algorithms that performs autonomous learning using data supplied by human and/or machine sensors and actions and activities that are affected by the algorithms' predictions (Dibiaggio et al. 2022).

The papers in this SI vary in terms of the degree to which AI is explicitly defined; however, they all employ a broad definition of AI that goes beyond narrowly equating AI with automated learning. Petruzzelli et al.'s (2023) definition of AI includes a range of digital and interconnected technologies. Woolley (2023) and Lepratte and Yoguel (2023) define AI as a branch of computer science, while Woolley (2023) also emphasises as part of the definition the ability of AI to replace humans. Taherizadeh and Beaudry (2023) do not define AI explicitly, but it is clear from their interviews that the studied technologies replace humans in tasks and the human experience across the firms. These definitions are relatively similar and thus the studies are complementary. The definition of AI used by Petruzzelli et al. (2023) may appear to be narrower than those used by the other authors, but, as mentioned earlier, Petruzzelli et al. focus on the early part of the innovation process in which patents are created from research. While the definitions in the remaining three papers focus on AI as a technique that involves algorithms replacing humans, in practice, the studies approach AI from a broader perspective and emphasise the consequences for organisations, including for corporate governance, internal work organisation and interorganisational collaboration.

Despite the varying definitions of AI in the literature on AI and innovation, a sizeable share of published works label AI as a GPT without much argument (Anthony et al. 2023; Bahoo et al. 2023; Borges et al. 2021; Füller et al. 2022; Johnson et al. 2022). Although, there have been some in-depth discussions on the degree to which AI qualifies as a GPT and to what extent this depends on the definition of AI (Cockburn et al. 2019). The papers in this SI advance this debate. The general finding that AI has broad implications for organisations' learning capabilities, collaboration patterns and innovation processes is consistent with AI being a GPT. Nevertheless, debates about categorising AI as a GPT are more productive when working with a precise definition of AI. Consequently, when discussing AI as a GPT, the focus is generally on AI as an automated learning method and the use of the resulting prediction tools (Dibiaggio et al. 2022). Thus, this discussion focuses on recent developments in ML. These developments enable algorithms to 'encode' knowledge that has been considered tacit and thus allow the automation of tasks that depend on perceptual and pattern recognition skills, leading to progress in AI in terms of replication of human intelligence more broadly. None of the four papers in this SI contradict the notion that AI is a GPT. Petruzzelli et al. (2023) argue in detail that AI should be considered a GPT, while Woolley (2023) and Taherizadeh and Beaudry (2023) cite other researchers who have attached this label to AI. If the narrow definition of AI as an ML-based prediction technology is accepted, then AI could be considered a GPT in the sense that prediction technology is widely applicable across different sectors and activities. Yet, ML algorithms are usually trained to perform very specific tasks, which limits the possibility of applying the same algorithm to different domains or for different tasks. This distinguishes AI from GPTs such as electricity or the internet, which are common infrastructures utilised for diverse activities and by a range of sectors. The key point is that, given the wide potential use of prediction, AI does have GPT-like characteristics and could have a major impact on the whole economy.

The three characteristics of GPTs are pervasiveness, the ability to further innovation in adopting sectors and continuous improvement in the technology itself (Bresnahan and Trajtenberg, 1995; Cockburn et al. 2019; Petruzzelli et al. 2023). Despite the pervasive use of AI supporting the argument that AI is a GPT, it could be concluded that until the introduction and broad diffusion of generative AI models, AI differed from other historical GPTs (e.g. the steam engine, electricity and information and communication technology). This is because automated learning tends to be highly specialised to a domain of activity, such that an AI trained for one type of application will not, as a rule, be easily transferred to another (Brynjolfsson and Mitchell, 2017). Brynjolfsson and Mitchell (2017) argued that a condition for automating a task with AI is that the task is routinised and repeated frequently and that each instance of executing the task is similar to the others. This appears to distinguish AI from infrastructural GPTs such as electricity and the steam engine, which do not change in terms of their operating principles from one type of application to another.

This high degree of application specificity aligns with the findings of Petruzzelli et al. (2023), who determined that industrial firms display an advantage over universities and research institutes in developing high-impact patents for AI because of their superior access to the specialised data needed for training ML models and their superior domain-specific knowledge. The arguments presented by Taherizadeh and Beaudry (2023) can also be interpreted as supporting the idea that AI is specific, even though the authors do not directly address this issue, as their analysis demonstrates the specificity of organisational adaptation when adopting AI. Despite this continuing to be the prevalent AI application paradigm within organisations in 2023, instruction-tuned generative AI models are gradually reshaping the landscape. The architecture and magnitude of these models, such as GPT-4, enable their general use across diverse tasks and applications, the use of consistent operating principles in large models and relatively straightforward fine-tuning of smaller, computationally economical models for specific tasks. Consequently, it can be posited that AI is on a positive trajectory towards being considered a genuine GPT.

4. The value of data and the challenges associated with collaboration

When AI is used in the innovation process, data plays a central role (Cillo and Verona, 2022; Varian, 2019). If AI is equated with ML and is used as an input or a tool in the innovation process, then data and AI are complementary inputs or assets. Instead, if AI is an output of an innovation process, then data is a complementary good. If AI is defined as a system, then data and the processes involving data (e.g. data collection and cleaning) are part of the AI system.

Including data in the innovation process creates new tasks and concerns about topics such as bias, ethics, the economic value of data and data sharing for open innovation. The four papers in this SI address different aspects of these concerns. For example, Taherizadeh and Beaudry (2023) have analysed the increasing importance of data within the firm when adopting AI, as well as the new routines needed, for example, the collecting and cleaning of data. Such new routines have also been analysed by Lepratte and Yoguel (2023), who further discuss how routines are affected both in firms using AI for innovation and in firms adopting AI innovations. The central role of data, its value and the incentives and practical problems associated with guarding data and sharing data in open innovation are also discussed in the papers of this SI. Petruzzelli et al. (2023) discuss the problems that arise when collaborating for invention, especially the difficulties that occur when collaborating parties have different aims and traditions in terms of data sharing. While Petruzzelli et al. focus on inventions in AI (i.e. new patents), they also make clear that the further transformation of these inventions into innovations and viable business models hinges on the availability of data of sufficient quantity and quality. Woolley (2023) describes the data security and privacy issues that lead to concerns about data sovereignty and goes beyond these issues to discuss how FML and blockchain technology can provide a solution for data sharing problems.

Each of the papers in this SI discuss the role that interfirm collaboration plays in promoting innovation. Both Petruzzelli et al. (2023) and Woolley (2023) support the idea that collaborators are motivated by gaining access to complementary assets that their firm lacks (Teece, 1992). The complementary asset that appears to be lacking is not knowledge as such but rather data in an area in which the partner has considerable applied expertise. This is a central point made by Petruzzelli et al. (2023), and they connect this motivation to gain data to the firm's choice of partners. This is consistent with the findings of Woolley (2023), who reports that firms engage in collaboration not to gain access to scarce scientific or technical knowledge needed for training ML algorithms, but to gain access to the benefits that come from using larger volumes of high-quality data for training domain-specific ML algorithms. Lepratte and Yoguel (2023) focus on a case study in which a business enterprise can only develop an innovation via collaboration (co-production) with a customer—a hospital—that has considerable practical experience in using magnetic resonance images for diagnosing and treating patients with multiple sclerosis. Thus, their findings support the idea that collaboration is motivated by accessing the data of a partner with experience and expertise in a particular applied domain. Taherizadeh and Beaudry (2023) do not address the issue of interfirm collaboration directly but do observe that firms work with external partners and stakeholders when adopting AI technology.

Thus, the applied nature of developing AI is still evident, and the innovation process of adopting AI tends to begin with a small pilot project, which is then scaled up. The findings of the papers presented in this SI are consistent with the idea that AI is developed and applied through a learning-by-doing process. Woolley (2023) shows how AI with FML can help transform interfirm collaboration for innovation to the extent that FML allows firms to collaborate on the development of an ML model without sharing their data on a centralised platform, which would otherwise be necessary. Hence, AI and FML are transformative with respect to intellectual property rights related constraints on collaboration. While it was argued in earlier papers that the data requirements of AI will have effects on intra-organisational processes (Cillo and Verona, 2022) and that the economic value of data will have implications for, inter alia, collaboration for innovation (Varian, 2019), the studies discussed here are among the first to analyse these issues empirically. In particular, the findings of Lepratte and Yoguel (2023), Taherizadeh and Beaudry (2023) and Woolley (2023) empirically show that the changes to collaboration for innovation caused by the new role of data in the innovation process are indeed real and take different forms for the different agents involved in the innovation process.

5. AI and organisational change

When a new technology such as AI is adopted, current internal and external organisational routines and configurations are challenged. Internally, the use of AI in the innovation process entails the entire organisation being involved in the innovation process and not just a specialised department (Cillo and Verona, 2022; Hund et al. 2021, Verganti et al. 2020). The case study presented by Lepratte and Yoguel (2023) confirms that the consequences of using AI are not confined to people and departments directly using AI. For instance, changes can be observed in organisations' marketing routines, research routines and other processes. Notably, these changes do not manifest immediately but are rather revealed as AI use is integrated into the organisation and complementary innovations are introduced. This is particularly evident in the case studies by Taherizadeh and Beaudry (2023) and confirms the arguments of Füller et al. (2022) and Kinkel et al. (2022). Interestingly, AI is introduced to automate tasks (Agrawal et al. 2019) that are often repetitive and tedious, but new repetitive tasks are also created by AI technology, such as data preparation and cleaning or auditing of underlying algorithms (Lepratte and Yoguel, 2023). As the new task portfolio evolves, a new division of labour manifests and new coordination tasks emerge (Petruzzelli et al. 2023). This is also seen when there is collaboration for invention in AI, where the traditional problems of cognitive distance and differing goals and incentives have novel implications (Petruzzelli et al. 2023). Woolley (2023) notes that while the use of AI might render relational governance redundant, it accentuates the importance of transactional governance in areas like cybersecurity.

Petruzzelli et al. (2023) and Lepratte and Yoguel (2023) highlight the organisational adaptations or changes that are needed when integrating AI. This theme was discussed in the literature published throughout the 1990s and early 2000s that explored the relationship between information technology (IT)and the internal organisation of the firm (e.g. Bresnahan et al. 1999). It could be argued that the vast increase in the volume of information available for decision-making due to IT resulted in an information bottleneck at the top of the organisational hierarchy. To bypass this bottleneck, businesses adopted more decentralised forms of organisation, with decision-making rights delegated to the level that was best able to make use of the increased information. Firms had an interest in investing in the skills of their line workers and this is aligned with the literature on skill-biased technical change (Caroli and Van Reenen, 2001; Piva et al. 2005). This is an under-addressed issue in research focusing on the impacts of AI. AI can be implemented as a technology that gives orders and replaces skilled employees or as a technology that leverages employees' skills (Agrawal et al. 2019; Holm and Lorenz, 2022). The link between information processing and a decentralised organisational design is crucial when using AI to enhance employees' skills; however, most research on AI focuses on AI as a technology that replaces skilled employees. While information processing remains of paramount importance to the firm, there is no longer an emphasis on investing in the skills of the decentralised worker or team to process information. Rather, the focus is on how to implement AI to make decisions that are currently made by employees who use their experience-based knowledge. Hence, the key issue is now the collection and cleaning of the data needed for running AI systems.

This requires investments in hardware (e.g. sensors, networks that connect machines and workstations), data labelling and training of algorithms.

On a related note, the impact of using AI in this manner on the skills of employees at different levels of the hierarchy remains ambiguous in the literature on AI. Holm and Lorenz (2022) suggested that the impact may depend on how AI is used within work activities. For example, if AI is used as an input to further decision-making, then AI will tend to complement workers' skills. According to Lepratte and Yoguel (2023), this would appear to be the case for radiologists who use AI to interpret magnetic resonance images. Similar to the study conducted by Lepratte and Yoguel, Woolley's (2023) analysis focused on innovation in the health care industry. Findings from health care-based studies often provide a reminder that the choice to use AI in place of people is not always simple, even if the AI is capable of performing a prediction task at a level that makes any subsequent decision task redundant. The issue is that tasks connected to decision-making cannot be automated or even separated from the decision itself. Therefore, decision-making generally remains decentralised, and AI is instead deployed as a tool at the various decision points. This could occur in a scenario where the action that follows the decision is, for example, 'treat the case' or 'inform the patient of the diagnosis'. Even if an AI could, in principle, be used to automate the decision task, the legitimacy requirements of the downstream tasks dictate that a doctor or other health care professional must be involved in the decision task. In addition, Woolley (2023) has demonstrated that decision-making and hierarchy issues are not restricted to inside firms but also arise externally (i.e. outside the firm's boundaries). The need to share data when collaborating for innovation can challenge prevailing notions of governance mechanisms and organisational boundaries; however, implementing a combination of

FML and blockchain has emerged as a strategy for ensuring accountability and transparency and decentralising authority while maintaining organisational boundaries and autonomy.

In addition to being intertwined with internal and external reorganisation, the adoption of AI as a predictive tool challenges the organisational truce. Automating prediction entails moving from a regime based on experience and intuition to a regime based on data (Taherizadeh and Beaudry, 2023) as AI codifies experience (Lepratte and Yoguel, 2023). This regime change challenges the legitimacy of specific employees and thus the distribution of power within the organisation. It potentially acts as a source of friction, which can lead to a reluctance to adopt the new technology (Lepratte and Yoguel, 2023; Taherizadeh and Beaudry, 2023). As emphasised by Taherizadeh and Beaudry (2023), in such cases, the management's willingness to commit to organisational change becomes central to the success of AI adoption.

6. Outlook and promising avenues for future research

The studies presented in this SI were conducted to investigate the changes occurring in innovation dynamics in the age of AI without any preconceived notions of such changes. A large proportion of the existing literature on AI and innovation consists of review articles (Bahoo et al. 2023; Borges et al. 2021; Hund et al. 2021; Mariani et al. 2023; Raisch and Krakowski, 2021). Within this literature, the expected effects of the use of AI on innovation dynamics have been outlined; however, findings have been based on studies that are decades old, have highly disparate definitions of AI and have analysed the broad category of digital technologies. Nevertheless, the findings that emerged from the studies described in this SI confirm and qualify the arguments and expectations outlined in previous studies.

The papers presented in this SI focus on two key topics. First, the changing nature of collaboration for innovation is discussed. With data playing a central role in the training of AI, collaboration becomes both necessary and difficult, as data owners seek to protect the economic value of their data and simultaneously consider privacy concerns. The other key topic is the internal organisational impact that results from the use of AI. Important concerns arise when a firm is adopting AI or attempting to diffuse a novel AI innovation. These concerns centre on the potential of AI use to challenge legitimacy and power and its tendency to decentralise decision-making as a consequence of standardised and automated decisions.

Several scholars have argued for the expectation that the use of AI in innovation and innovation in AI results in internal organisational changes for both adopters and developers (Cillo and Verona, 2022; Füller et al. 2022; Hund et al. 2021; Kinkel et al. 2022; Varian, 2019; Verganti et al. 2020). Woolley (2023) has demonstrated some of these changes and calls attention to how organisational boundaries and the governance of innovation collaboration are challenged by the role that data plays in AI innovation. Petruzzelli et al. (2023) have demonstrated that the collaboration for invention process changes when using AI, and they theorise that the changes are related to the changing importance of goals, incentives and cognitive distance. Together, Woolley (2023) and Petruzzelli et al. (2023) indicate that there is a need for further research on how the collaboration that occurs during the innovation process changes when AI is involved. Further research is also needed on how incentives shape such collaboration, as data sharing makes collaboration both tantamount and risky. One solution is the implementation of the new governance mechanisms proposed by Woolley (2023); however, the generalisability of this solution must be explored.

The analyses performed by Lepratte and Yoguel (2023) and Taherizadeh and Beaudry (2023) identify the internal organisational challenges experienced when innovating with AI. Previous literature has stressed how these internal challenges arise because social actors must be considered explicitly in the innovation process (Hund et al. 2021) and the management must be actively involved (Cillo and Verona, 2022). The use of AI also challenges the legitimacy of individuals, as AI can be used to assist in decision-making (Borges et al. 2021; Cockburn et al. 2019), which has historically been based on skills developed through experience (Lepratte and Yoguel, 2023). This evolution from a culture of experience to a culture of data implies that the management has a critical role in managing the willingness to commit and adapt to changes, and thus avoid friction and resistance (Taherizadeh and Beaudry, 2023). As argued by Lepratte and Yoguel (2023), this means that the introduction of AI may not only result in the automation and the augmentation of tasks but also in a coevolution of routines within the organisation. While these insights are illuminating, the scope of their application is currently unknown. For example, some organisational arrangements may be more suitable than others for the adoption and application of AI, with less friction and resistance generated. Research on this topic would be valuable to progress innovation management in the age of AI.

6.1. Generative AI

The timing of this SI can be considered both a limitation and an opportunity for stimulating further research on generative AI. The papers featured in this SI were written between 2021 and 2023, a period of rapid technological change within the field of AI. As a result, many of the current mechanisms through which AI is expected to influence industry dynamics may indeed change in the near future. Of particular note, generative AI has diffused at a very high rate, and this has led to a surge in interest in, and the development of, LLMs (e.g. ChatGPT). Generative AI systems are not only novel in terms of their output (new text or images) but also in terms of how they are trained (Eloundou et al. 2023). The rapid development of generative AI expands the applications of AI and makes the discussion about innovation dynamics in the age of AI even more pressing. Furthermore, many recent working papers have analysed its impact and are providing a glimpse of how this change might manifest (e.g. Bubeck et al. 2023; Eloundou, 2023; Felten et al. 2023; Noy and Zhang, 2023). Studies have already linked the applications of generative AI to the human ability to assess which occupations are likely to be affected by this technology (Eloundou, 2023; Felten et al. 2023).

In contrast, this paper and those in this SI focus on predictive AI and the associated paradigm; this type of AI utilises algorithms fed with proprietary data to produce predictive software with a relatively narrow scope of application. This has been the dominant paradigm for some time but will potentially be challenged soon. Developments in transfer learning (i.e. retraining of a model to perform a new task based on insights from previously solving a related task) and LLMs that allow models to effectively perform a variety of tasks that they have not been explicitly trained to perform might alter the abovementioned paradigm in the near future. Consequently, it could be asserted that due to the rapid technological changes that AI is undergoing, it may soon be classified as a true GPT.

LLMs and transfer learning are reshaping the ML data landscape and potentially reducing the volume of proprietary data that firms need to collect and manage. Earlier, the vast quantity of data required for training, along with the cleaning and preparation processes, posed significant hurdles for AI adoption in firms. However, the advent of LLMs and transfer learning, which enable the adaptation of pre-existing models to new tasks using smaller, domain-specific datasets, can alleviate these issues

(Howard and Ruder, 2018; Ruder, 2019). In addition, recently developed techniques such as SetFit (Tunstall et al. 2022) that apply the 'few-shot' approach facilitate the training of well-performing models for language classification tasks using as few as eight examples per category. Nevertheless, even with such advancements, data management challenges, such as data bias, privacy and security, remain crucial issues in the AI application process.

The adoption of generative AI is likely to result in a shift in innovation dynamics that is potentially very different from the changes brought about by the adoption of predictive AI. This is an avenue for future research and possibly a future SI when findings from empirical studies on generative AI emerge.

However, predictive AI is likely to remain the dominant paradigm for many industry applications in the near future. There are currently numerous tasks that involve processing tabular and numerical data, such as predictive maintenance, logistic optimisation and customer churn prediction, that may be supported by a level of automation.

Therefore, the papers in this SI provide 1) insight into how firms' innovation processes are currently affected by AI and 2) a solid foundation for understanding how future waves of technological change in AI will further alter such processes.

Disclosure statement

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References

Agrawal, A., J. S. Gans, and A. Goldfarb. 2019. "Artificial Intelligence." *The Journal of Economic Perspectives* 33 (2): 31–50. doi:10.1257/jep.33.2.31.

Anthony, C., B. A. Bechky, and A. Fayard. 2023. ""Collaborating" with AI: Taking a System View to Explore the Future of Work." *Organisation Science.* doi:10.1287/orsc.2022.1651.

Bahoo, S., M. Cucculelli, and D. Qamar. 2023. "Artificial Intelligence and Corporate Innovation: A Review and Research Agenda." *Technological Forecasting & Social Change* 188: 122264. doi:10.1016/j.techfore.2022.122264.

Bianchini, S., M. Müller, and P. Pelletier. 2022. "Artificial Intelligence in Science: An Emerging General Method of Invention." *Research Policy* 51 (10): 104604.

Borges, A. F. S., F. J. B. Laurindo, M. M. Spínola, R. F. Gonçalves, and C. A. Mattos. 2021. "The Strategic Use of Artificial Intelligence in the Digital Era: Systematic Literature Review and Future Research Directions." *International Journal of Information Management* 57: 102225. doi:10.1016/j.ijinfomgt.2020.102225.

Bresnahan, T. F., E. Brynjolfsson, and L. Hitt. 1999. "Information Technology and Recent Changes in Work Organisation Increase the Demand For Skilled Labor." In *The New Relationship: Human Capital in the American Corporation*, edited by M. M. Blair and T. A. Kochan. Washington, DC, USA: Brookings Institution Press.

Bresnahan, T. F., and M. Trajtenberg. 1995. "General Purpose Technologies 'Engines of Growth'?" *Journal of Econometrics* 65 (1): 83–108. doi:10.1016/0304-4076(94)01598-T.

Brynjolfsson, E., and T. Mitchell. 2017. "What Can Machine Learning Do? Workforce Implications." *Science* 358 (6370): 1530–1534. doi:10.1126/science.aap8062.

Caroli, E., and J. Van Reenen. 2001. “Skill-biased Organisational Change? Evidence From A Panel of British and French Establishments.” *The Quarterly Journal of Economics* 116 (4): 1449–1492. doi:10.1162/003355301753265624.

Cefis, E., R. Leoncini, L. Marengo, and S. Montresor. 2023. “Firms and Innovation in the New Industrial Paradigm of the Digital Transformation.” *Industry and Innovation* 30 (1): 1–16. doi:10.1080/13662716.2022.2161875.

Ciarli, T., M. Kenney, S. Massini, and L. Piscitello. 2021. “Editorial: Digital Technologies, Innovation, and Skills: Emerging Trajectories and Challenges.” *Research Policy* 50 (7): 1-10. doi:10.1016/j.respol.2021.104289.

Cillo, P., and G. Verona. 2022. “The Strategic Organisation of Innovation: State of the Art and Emerging Challenges.” *Strategic Organisation* 20 (4): 743–756. doi:10.1177/14761270221119113.

Cockburn, I., R. Henderson, and S. Stern. 2019. “The Impact of Artificial Intelligence on Innovation: An Exploratory Analysis.” In *The Economics of Artificial Intelligence: An Agenda*, edited by A. Agrawal, J. Gans, and A. Goldfarb, 115–146. University of Chicago Press, Chicago, USA.

Dibiaggio, L., M. Keita, and L. Nesta. 2022. *Artificial Intelligence: Technologies and Key Players*. Sophia Antipolis, France: OTESIA Reports, SKEMA Business School.

Eloundou, T., S. Manning, P. Mishkin, and D. Rock. 2023. “GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models.” *arXiv preprint arXiv:2303.10130.* doi:10.48550/arxiv.2303.10130.

Felten, E., M. Raj, and R. Seamans. 2023. “How Will Language Modelers Like ChatGPT Affect Occupations and Industries?” *arXiv preprint arXiv:2303.01157.* doi:10.48550/arxiv.2303.01157.

Füller, J., K. Hutter, J. Wahl, V. Bilgram, and Z. Tekic. 2022. "How AI Revolutionizes Innovation Management – Perceptions and Implementation Preferences of AI-based Innovators." *Technological Forecasting & Social Change* 178: 121598. doi:10.1016/j.techfore.2022.121598.

Furman, J., and R. Seamans. 2019. "AI and the Economy." *Innovation Policy and the Economy* 19 (1): 161–191.

Gjerding, A. N., J. R. Holm, E. Lorenz, and J. Stamhus. 2020. "Ready, But Challenged: Diffusion and Use of Artificial Intelligence and Robotics in Danish Firms." *Journal of Business Models* 1 (1): 1-54.

Holm, J. R., and E. Lorenz. 2022. "The Impact of Artificial Intelligence on Skills at Work in Denmark." *New Technology, Work, and Employment* 37 (1): 79–101. doi:10.1111/ntwe.12215.

Howard, J., and S. Ruder. 2018. "Universal Language Model Fine-tuning For Text Classification." *arXiv preprint arXiv:1801.06146.* doi:10.48550/arXiv.1801.06146.

Hund, A., H. Wagner, D. Beimborn, and T. Weitzel. 2021. "Digital Innovation: Review and Novel Perspective." *The Journal of Strategic Information Systems* 30 (4): 101695. doi:10.1016/j.jsis.2021.101695.

Johnson, P. C., C. Laurell, M. Ots, and C. Sandström. 2022. "Digital Innovation and the Effects of Artificial Intelligence on Firms' Research and Development – Automation or Augmentation, Exploration or Exploitation?" *Technological Forecasting & Social Change* 179: 121636. doi:10.1016/j.techfore.2022.121636.

Kinkel, S., M. Baumgartner, and E. Cherubini. 2022. "Prerequisites For the Adoption of AI Technologies in Manufacturing – Evidence From a Worldwide Sample of Manufacturing Companies." *Technovation* 110: 102375. doi:10.1016/j.technovation.2021.102375.

Lepratte, L., and G. Yoguel. 2023. “Artefacts, Routines, and Co-production: A Pioneering Case of Artificial Intelligence-based Health Services in Argentina.” *Industry and Innovation* 1–23. doi:10.1080/13662716.2023.2194241.

Mariani, M. M., I. Machado, V. Magrelli, and Y. K. Dwivedi. 2023. “Artificial Intelligence in Innovation Research: A Systematic Review, Conceptual Framework, and Future Research Directions.” *Technovation* 122: 102623. doi:10.1016/j.technovation.2022.102623.

Noy, S., and W. Zhang. 2023. “Experimental Evidence on the Productivity Effects of Generative Artificial Intelligence.” *Science* 381 (6654): 187–192. doi:10.1126/science.adh2586.

Petruzzelli, A. M., G. Murgia, and A. Parmentola. 2023. “Opening the Black Box of Artificial Intelligence Technologies: Unveiling the Influence Exerted By Type of Organisations and Collaborative Dynamics.” *Industry and Innovation* 1–31. doi:10.1080/13662716.2023.2213182.

Piva, M., E. Santarelli, and M. Vivarelli. 2005. “The Skill Bias Effect of Technological and Organisational Change: Evidence and Policy Implications.” *Research Policy* 34 (2): 141–157. doi:10.1016/j.respol.2004.11.005.

Raisch, S., and S. Krakowski. 2021. “Artificial Intelligence and Management: The Automation–Augmentation Paradox.” *The Academy of Management Review* 46 (1): 192–210. doi:10.5465/amr.2018.0072.

Rammer, C., G. P. Fernández, and D. Czarnitzki. 2022. “Artificial Intelligence and Industrial Innovation: Evidence From German Firm-level Data.” *Research Policy* 51 (7): 104555. doi:10.1016/j.respol.2022.104555.

Ruder, S. 2019. *Neural transfer learning for natural language processing.* PhD thesis, National University of Ireland, Galway. Retrieved from http://hdl.handle.net/10379/15463

Taherizadeh, A., and C. Beaudry. 2023. "An Emergent Grounded Theory of AI-driven Digital Transformation: Canadian SMEs' Perspectives." *Industry and Innovation* 1–30. doi:10.1080/13662716.2023.2242285.

Teece, D. J. 1992. "Competition, Cooperation, and Innovation: Organisational Arrangements For Regimes of Rapid Technological Progress." *Journal of Economic Behavior & Organisation* 18 (1): 1–25. doi:10.1016/0167-2681(92)90050-L.

Trajtenberg, M. 2018. *AI as the Next GPT: A Political-Economy Perspective.* (No. w24245). Cambridge, Mass, USA: National Bureau of Economic Research. doi:10.3386/w24245.

Tunstall, L., N. Reimers, U. E. S. Jo, L. Bates, D. Korat, M. Wasserblat, and O. Pereg. 2022. "Efficient Few-Shot Learning Without Prompts." *arXiv preprint arXiv:2209.11055.* doi:10.48550/ARXIV.2209.11055.

Turing, A. M. 1950. "Computing Machinery and Intelligence." *Mind* 59: 433–460.

Varian, H. 2019. "Artificial Intelligence, Economics, and Industrial Organisation." In *The Economics of Artificial Intelligence: An Agenda*, edited by A. Agrawal, J. Gans, and A. Goldfarb, 399–419. University of Chicago Press, Chicago, USA.

Verganti, R., L. Vendraminelli, and M. Iansiti. 2020. "Innovation and Design in the Age of Artificial Intelligence." *The Journal of Product Innovation Management* 37 (3): 212–227. doi:10.1111/jpim.12523.

Woolley, J. L. 2023. "Getting Along With Frenemies: Enhancing Multi-competitor Coopetition Governance Through Artificial Intelligence and Blockchain." *Industry and Innovation* 1–34. doi:10.1080/13662716.2023.2168519.

Figure 1

	1	2	3
Phase:	Research	Development	Diffusion
Result:	Invention	Innovation	Sales
Papers in the SI and their focus			
Taherizadeh and Beaudry (2023)		X	X
Woolley (2023)	X	X	
Lepratte and Yoguel (2023)	X	X	X
Petruzzelli et al. (2023)	X		

Figure 1: An outline of a simple generic innovation process and the focus of the papers in the SI