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Artificial intelligence and radical innovation: an opportunity for all companies?

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Abstract Artificial intelligence (AI) is often seen as a key technology for future economic growth. However, its concrete effects on the emergence of radical innovations and the associated socio-economic impacts, through increasing divergence between smaller and larger firms, have not yet been systematically researched. This paper addresses this by investigating the extent to which AI-related knowledge influences the emergence of radical innovations and differentiates between SMEs and large firms. Based on a unique dataset of European firms combining firm-level data with patent data, we find a nuanced influence from AI. While AI applications assert a positive influence, AI techniques negatively influence the emergence of radical innovations. Being an SME significantly moderates these effects. Larger firms gain from AI applications, whereas SMEs gain from AI techniques. Therefore, AI knowledge in itself is not a general answer to increase the likelihood of creating radical innovation. Instead, a more differentiated view on AI is needed.

Plain English Summary Possessing knowledge in AI techniques decreases the chance of creating radical knowledge in general, but SMEs benefit from such knowledge. Conversely, knowledge in AI applications is more beneficial for large firms.
Artificial intelligence (AI) is often seen as a key technology for future economic growth. However, some firms may have an advantage in utilizing AI knowledge to create radical innovation. This paper investigates the influence of AI-related knowledge in firms on the emergence of radical innovations with a specific focus on the differences between SMEs and large firms. We find that application-related AI knowledge increases the likelihood for radical innovations, while technique-related AI knowledge decreases it. Nevertheless, SMEs have an advantage in utilizing AI techniques to generate radical innovations. Thus, the principal implication of this study is that SMEs should focus on AI techniques, allowing them to capture unseen technological opportunities which cannot be obtained in a formalized R&D process within a large firm.

Keywords Radical innovations · Divergence · AI · Artificial intelligence · Firm level

JEL Classification L25; O31 · O32 · O33

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1 Introduction

Digitalisation is an ongoing transformative process, which drastically influences today's (modern) society (Alcácer et al., 2016; Andersen, 2006). One of the latest trends of this digitisation process is the technology of artificial intelligence (AI), which is often seen as a universal solution to many problems. Even though AI has an extensive history dating back to the 1950s, only recently can a surge in the interest of the effects of AI be observed. This acknowledgement of the potential effects is primarily attributable to advancements in machine and deep learning (Anyoha, 2017; Haenlein & Kaplan, 2019; Miyazaki and Sato, 2018). With the use of deep and machine learning, AI can now be used for different types of data in various thematic fields while simultaneously decreasing the cost of the needed adaptions to each field or datatype. Thus, it is approaching a general AI (Taddy, 2019; Yamakawa et al., 2016), which would allow for a pervasive use of AI on many different forms of data for various purposes. In light of these recent and impactful advancements, entrepreneurs, politicians as well as scientists see AI as a key technology for prospective technological and economic growth (Aghion et al., 2019; Craglia et al., 2018; Goralski & Tan, 2020).

Although there is a general consensus about the enormous socio-economic impacts of the ongoing and future developments of AI, the tangible direction of these changes is still debated (Hinks, 2019; Nam, 2019; Zhang & Dafoe, 2019). AI is also expected to have a substantial impact on innovation processes, for instance, by allowing to exploit (big) data for new applications and increasing the efficiency in the R&D process (Agrawal et al., 2019; Rammer et al., 2022). However, in spite of these expectations, the link to innovation is relatively under researched in the context of AI (Rammer et al., 2022), despite some important exceptions (e.g. Agrawal et al., 2019; Cockburn et al., 2019).[1] This holds particularly true for quantitative empirical analyses on the firm level (Raj & Seamans, 2019). We therefore contribute to this ongoing discussion by focussing on innovation. Thereby, we are interested in one particular kind of innovation, namely radical innovation. These innovations emerge from the recombination of former unconnected knowledge, which is accompanied by high uncertainty and risk (Fleming, 2001; Nerkar, 2003; Weitzman, 1998). However, if they are successful, they can lead to strong competitive advantages (e.g. Castaldi et al., 2015) as well as to the creation of entire new markets and industries (e.g. Henderson & Clark, 1990; Tushman & Anderson, 1986). Consequently, radical innovations have gained increased attention from policy makers (e.g. SprinD[2]) as well as researchers (e.g. Grashof et al., 2021; Hesse & Fornahl, 2020; Shkolnykova & Kudic, 2021). However, discovering these radical new ideas is anything but easy. Instead, as Agrawal et al. (2019) put it, it is like finding a needle in a haystack.

But AI technologies can eventually help to find these radical new ideas. AI has been identified as a general-purpose technology (GPT) and an invention of a method of inventing (IMI) (Cockburn et al., 2019).[3] Both concepts suggest that the use of AI knowledge drives (radical) innovation in firms: GPTs drive inventions in their application sectors as they enable innovation complementarities, which can promote the recombination of previously unconnected knowledge pieces, thereby enhancing the creation of radical innovations. IMIs increase research productivity, as they are new methods to generate inventions and therefore can act as a catalyst for new, rather radical, knowledge (Agrawal et al., 2019; Cockburn et al., 2019; Darby & Zucker, 2003; Griliches, 1957). Despite the high expectations about the potential of AI knowledge to promote rather disruptive innovation (e.g. Brynjolfsson et al., 2019; OECD, 2020), there are relatively few empirical studies that investigate the relationship between AI and (radical) innovation (e.g. Rammer et al., 2022). Consequently, it remains to be answered: To what extent does AI knowledge affect the emergence of radical innovations in firms?

[1] Some recent studies look at very specific technologies that are closely related to AI in order to examine the role of AI in innovation, e.g. robots (Liu et al., 2020) and big data (Niebel et al., 2019). However, these studies only, if at all, capture a fraction of the entire field of AI technologies and thus their influence on innovation.

[2] In 2019, the German government founded the national agency "Agentur für Sprunginnovationen" (SprinD). For more information, please see BMBF (2020).

[3] According to Cockburn et al. (2019), sensing and reacting robots such as autonomous cars can be seen as an example for the GPT side of AI, while statically coded algorithms such as the fMRI (functional magnetic resonance image) scans are an example for the IMI side of AI. It must be said that disentangling these two concepts on a technological level is not entirely possible as, e.g., advancements in deep learning could contain characteristics of both concepts.

In addition to examining the overall influence of AI, a previously neglected distinction is also made between the specific features of AI. In line with the conceptual framework of Cockburn et al. (2019), AI technologies can be differentiated according to their GPT and IMI characteristics. However, the influence of these features has not yet been empirically disentangled. While the former focuses on the impacts of the application of the technology (Bresnahan & Trajtenberg, 1995; David, 1990; Helpman & Trajtenberg, 1994), the latter concentrates on the methods that are used to generate new inventions and technological opportunities (Darby & Zucker, 2003; Griliches, 1957). Given these differences, we subdivide AI into GPT and IMI by its technological applications (as a proxy for its GPT characteristics) and its techniques and methods (as a proxy for its IMI characteristics) to achieve a better understanding of the relationship between AI knowledge and radical innovations.

Apart from addressing this research gap, we are additionally interested in one of the main challenges that may accompany the proliferation of AI, namely increasing divergence processes (Aghion et al., 2019). In fact, Andrews et al. (2019) found that between 2001 and 2013, manufacturing firms at the global productivity frontier experienced a growth rate of 2.8% per year, while laggard firms grew by just 0.6% per year. One popular explanation for this increasing gap is the heterogeneous diffusion patterns of new general-purpose technologies across firms (Andrews et al., 2019; Faggio et al., 2010). This suggests that not every sector, region and firm benefit equally from the emergence of a new general-purpose technology. Instead, following the resource-based view (e.g. Barney, 1991), firms differ in their ability to adopt new technologies, depending for instance on their financial abilities (e.g. Rogers, 2004), their absorptive capacities (e.g. Cohen & Levinthal, 1990) as well as their organizational structure (e.g. Goode & Stevens, 2000). In this context, the differences between firm size classes have been particularly emphasized (e.g.Acs & Audretsch, 1990; Antonelli & Scellato, 2015; Cohen & Klepper, 1996). For instance, the study by Rammer et al. (2020) about innovation activities of companies in Germany shows that there are significant differences in R&D spending and innovation success between small- and medium-sized enterprises (SMEs)[4] and large companies. While research on the relationship of firm size and innovation has a long history (e.g. Cohen, 2010), heterogeneous firm sizes have been largely ignored in the case of AI. And this is despite the fact that firms clearly differ in their capacities to realize and seize the potentials of AI. Particularly SMEs face greater disadvantages in the transformation, since they may for instance lack sufficient financial resources to bear the necessary capital expenses for implementing an AI system and/or are less prepared to valorize their data (Accenture, 2019; Bianchini & Michalkova, 2019; Daor et al., 2020; OECD, 2021). Consequently, AI has the potential to increase divergence between firms (Aghion et al., 2019). This holds particularly true if AI is also a driver of the emergence of radical innovations, creating the basis for a long-lasting competitive advantage and thereby economic growth (Ahuja & Lampert, 2001; Castaldi et al., 2015; Zhang et al., 2018). Then the fear that the already existing productivity gap grows further becomes more substantial (e.g. OECD, 2018). As such, it is important to consider the largely overlooked firm-specific differences and empirically investigate the extent to which the effect of AI on the emergence of radical innovations differs between SMEs and large firms. The third aim of this paper is therefore to contribute to closing this research gap by answering the following question: Which types of firms (large vs. SMEs) are particularly able to generate radical innovation through AI knowledge? Given the specific features of AI, we additionally focus on disentangling the influence of the different AI characteristics on different firm types.

In order to empirically analyse these three research gaps (the role of AI for the emergence of radical

[4] In line with previous studies (e.g. Forés & Camisón, 2016; Stavropoulos et al., 2020; Vaona & Pianta, 2008), we define a SME as a firm that has less than 250 employees. While the number of employees is indeed a commonly used measure in this regard (Perez-Alaniz et al., 2022), it only partially matches with the definition of the European Commission that additionally considers either turnover or balance sheet total (https://ec.europa.eu/growth/smes/sme-definition_en). As a first robustness check to our empirical results, we therefore also use the "Company size categories" provided by Bureau van Dijk, which are based on the number of employees, operating revenue and total assets (Bureau van Dijk, 2011). The corresponding empirical results remain robust and can be seen in Table 5 in the Appendix.

innovations, the moderating influence of firm size and the distinction between AI applications and AI techniques), we make use of two large data sources. For firm-level data, we employ the extensive firm database ORBIS offered by Bureau van Dijk (BvD), which offers information on various firm-specific characteristics (e.g. firm size). To identify the AI knowledge in firms, we use patent data from the patent database PATSTAT. There, we conduct a keyword search in the abstract and title of the patents as well as use the CPC and IPC codes. In order to account for the different effects of GPTs and IMIs, we divide AI patents into AI technique patents (as a proxy for its IMI characteristics) and AI applications patents (as a proxy for its GPT characteristics). Patents retrieved from PATSTAT are also used to identify radical innovations. In particular, we proxy the emergence of radical innovations by new technology combinations on a patent, which have not been combined before (since 1981). In total, based on the available information from the ORBIS database[5] enriched with PATSTAT information, our final dataset consists of active companies in the EU that filed patents (at least one) between 2011 and 2020.

By investigating these two research questions in a quantitative way and thereby additionally disentangling the influence of AI, our article expands previous research on AI and innovation (e.g. Rammer et al., 2022), particularly with regard to the emergence of rather radical innovations and potential firm-specific differences that eventually lead to an increasing divergence between firms. Besides contributing to the literature about AI and innovation, this paper has also rather practical ramifications for firms as well as policy makers. It not only provides evidence for significant differences in the influence of AI on the emergence of radical innovations across firm size classes, but also indicates contextual conditions necessary for SMEs to generate radical innovations through AI. Based on these findings, policy implications can be derived that aim to make the best use of existing AI potentials while considering possible divergence processes.

The remainder of the article is structured as follows: The second section lays the theoretical foundation, encompassing the concept of radical innovations and AI, the role of firm size as well as possible contextual drivers that may compensate for firm size. In the third section, the applied data and methods are presented. Afterwards the results of the empirical analysis are elucidated and discussed. Lastly, the paper closes with a conclusion about the main findings, highlighting research and policy implications.

[5] The ORBIS database only allows you to go back in time a maximum of 10 years.

2 Theoretical background: radical innovation, AI and firm size

2.1 AI and the emergence of radical innovation: a technological perspective

Technological innovation has been acknowledged as an important factor for firm productivity and economic growth (Romer, 1990; Rosenberg, 2004). Innovation is generally recognized to be the result of a cumulative process in which existing knowledge is combined in new ways (Arthur, 2007; Basalla, 1988). Weitzman (1998) defines the recombination of existing knowledge in a new fashion to form new artefacts as “recombinant innovation”.[6]

Nevertheless, the corresponding degree of novelty can be quite different (e.g. Suwala, 2017). While incremental innovations develop mostly alongside well-known trajectories and therefore only represent small improvements (Dosi, 1982), radical innovations[7] rely on the pioneering recombination of former unconnected knowledge pieces, which is accompanied by uncertainty and risk (Fleming, 2001; Nerkar, 2003). Self-driving cars are a vivid example of this. They recombine technologies related to the fields of automotive, sensor-based safety systems, communication and high-resolution mapping (Boschma, 2017;

[6] Similarly, also Schumpeter (1911) already conceptualizes innovation as new combinations (“Neue Kombinationen”).

[7] Similar to Castaldi et al. (2015), we use the terms “innovation” and “invention” interchangeably as the theoretical framework of recombinant innovation also uses the term “innovation”. Nevertheless, we highlight that our study focuses on technological achievements rather than successful commercialization.

Hesse & Fornahl, 2020).[8] Of course, these processes introducing novelty are rather uncertain and risky (Fleming, 2001; Strumsky & Lobo, 2015), but if they are successful, they can cause paradigm shifts (Dosi, 1982; Verhoeven et al., 2016) and can lead to the creation of entire new markets and industries (Henderson & Clark, 1990; Tushman & Anderson, 1986). Hence, radical innovations hold the potential for strong competitive advantages (Castaldi et al., 2015) and future sustainable economic growth (Ahuja & Lampert, 2001; Arthur, 2007). Since there is still no universal definition of radical innovations in the literature (Shkolnykova & Kudic, 2021), they have also been framed as "technological breakthroughs" (Castaldi et al., 2015), "disruptive innovations" (Tushman & Anderson, 1986) or "atypical innovations" (Uzzi et al., 2013). However, following recent approaches (e.g. Grashof et al., 2019; Rizzo et al., 2020), we use the term radical innovation if they introduce novel knowledge combinations. Due to the underlying conceptual differences, there are also various ways to measure radical innovations (Arts et al., 2013; Schoenmakers & Duysters, 2010; Verhoeven et al., 2016). In general, it can be differentiated between the emergence (or novelty) of radical innovations and the diffusion (or impact) of radical innovations (Arts et al., 2013; Hesse, 2020b; Verhoeven et al., 2016). In both cases, patent-based indicators are commonly used (e.g. Castaldi et al., 2015; Fleming, 2007).[9] To investigate the latter aspect, empirical studies have typically relied on forward citations (e.g. Ahuja & Lampert, 2001; Schoenmakers & Duysters, 2010). However, this ex post perspective has also been criticized for, among other things, introducing a success bias and not fully capturing the novelty of an invention since the approach does not allow to classify as novel those inventions that still have to receive the bulk of citations, thereby resulting in a biased recognition (Verhoeven et al., 2016). Apart from this criticism, in line with the original notion of the "recombinant innovation" approach (Weitzman, 1998), we are explicitly interested in the novelty aspect and therefore focus on the emergence of radical innovation, by searching for novel combinations of technological subclasses on patents (e.g. Fleming, 2007; Grashof et al., 2019; Verhoeven et al., 2016).[10]

These radical new ideas, however, are anything but easy to find. Instead, as a result of an ever larger and more complex knowledge space, breakthrough ideas are simply becoming harder to find (Agrawal et al., 2019; Cowen, 2011; Gordon, 2016). In this context, Jones (2009) points to the increasing "burden of knowledge". With an expanding technological frontier, it becomes harder for researchers to know enough to find novel knowledge combinations that result in radical new ideas. This is shown by an enormous expansion in collective research efforts and extended doctoral duration, as ever-more specialized researchers need to combine their knowledge in order to produce these radical innovations (Agrawal et al., 2019; Jones, 2009). By referring to Moore's law,[11] recently Bloom et al. (2020) additionally show that the research effort is rising substantially, but the research productivity is decreasing sharply. The authors demonstrate that a doubling of the output side (constant exponential growth rate of 35 percent per year), as indicated by Moore's law, has only been

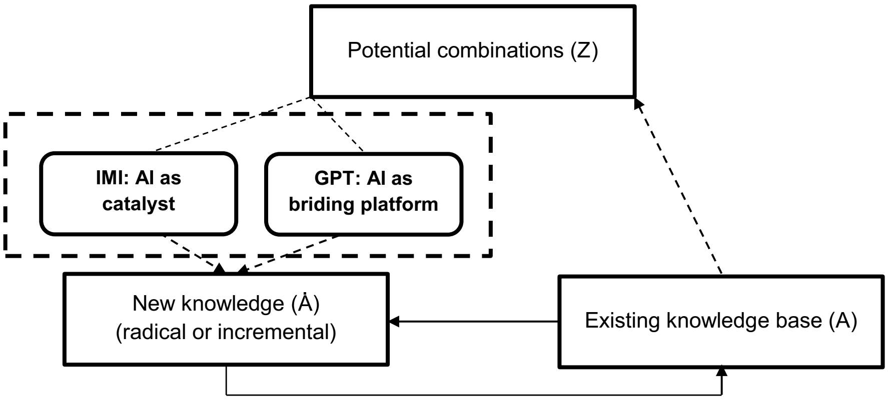
[8] An alternative example that is more related to patents, which we use to measure radical innovations (see Sect. 3.2.), is the well-known example of the "Oncomouse", which was the first patented, genetically modified animal (having a significantly higher susceptibility to cancer). It combined among others the International Patent Classification groups for "new breeds of animals" and "(…) DNA or RNA concerning genetic engineering (…)" for the first time (Verhoeven et al., 2016).

[9] However, there are also other approaches that rely on publication data (e.g. Uzzi et al., 2013), survey-based indicators (e.g. Hervás-Oliver, et al., 2018) or web scraping and data mining techniques (e.g. Kinne & Lenz, 2019). Since we are particularly interested in the technological nature of innovations and the underlying creation process of new (technological) knowledge, patents appear to be more suitable for the purpose of our study (Archibugi & Pianta,1996).

[10] An alternative measure for the emergence of radical innovations is backward citation, which capture references to prior art (e.g. Dahlin & Behrens, 2005). However, the chosen indicator is preferred because it fits better with the notion of the "recombinant innovation" approach (Weitzman, 1998), and it is more related to the actual knowledge creation process since it captures the actual recombination of technological knowledge, whereas backward citations only refer to prior art (Hesse, 2020b).

[11] Moore's law refers to the empirical observation that the number of transistors packed onto a computer chip doubles about every 2 years (Bloom et al., 2020; Moore et al., 1965).

Fig. 1 Extended combinatorial-based knowledge production function (stylized form)



achieved by a huge increase in the research efforts, which have been risen by a factor of 18 since 1971.

Nevertheless, AI technologies can eventually help in this context. Although there is no universal definition of AI (Obschonka & Audretsch, 2020), following Haenlein & Kaplan (2019), we define AI as "(…) a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Haenlein & Kaplan, 2019, p. 5). By conceptually developing a combinatorial-based knowledge production function, which is embedded in the classic Romer/Jones knowledge production, Agrawal et al. (2019) emphasize the importance of AI, or how they call it meta technologies, in overcoming the problem of finding new, rather radical, knowledge combinations out of an ever larger and more complex knowledge space. Furthermore, AI has been identified as a general-purpose technology (GPT)[12] and an invention of a method of inventing (IMI). Both concepts suggest that AI drives innovation in firms. Based on the IMI characteristics of AI, it is argued that the research productivity is increased, as they are new methods to generate inventions[13] (Agrawal et al., 2019; Cockburn et al., 2019; Darby & Zucker, 2003; Griliches, 1957). The GPT characteristics of AI rather suggest an enhancing influence on inventions by enabling innovation complementarities (Agrawal et al., 2019; Cockburn et al., 2019). In general, GPTs can drastically change methods and procedures. They are not final solutions in themselves but are an essential complement in the emergence of innovations and function as enablers of new opportunities, thus leading to rather radical innovations (Bresnahan & Trajtenberg, 1995; Ristuccia & Solomou, 2014). Consequently, the following hypothesis is proposed:

H1: The amount of AI knowledge in the knowledge base of firms has a positive influence on the emergence of radical innovations in firms.

Nevertheless, although AI technologies have particular features that allow for a differentiation between GPT and IMI characteristics (Cockburn et al., 2019), so far, the influence of AI has not been empirically disentangled. The further differentiation into GPT and IMI is, however, necessary for a better understanding of the relationship between AI knowledge and radical innovations. Based on the underlying idea of Cockburn et al. (2019), we therefore want to conceptually extent the combinatorial-based knowledge production function suggested by Agrawal et al. (2019), which also matches with the concept of "recombinant innovation", by explicitly investigating the two main mechanisms through which AI knowledge might influence the emergence of radical innovations in firms. Figure 1 presents a simplified, but extended, overview of the conceptual approach presented in Agrawal et al. (2019). While the solid lines capture the Romer/Jones function, indicating that new knowledge is a function of the existing knowledge stock of a researcher/firm and then

[12] At this point, we would like to emphasize that there are also concerns that it is too early to claim that AI is a GPT (e.g. Vannuccini & Prytkova, 2021). However, for the purpose of our paper, we particularly stress the bridging character of AI, which is somehow independent from the ongoing discussion about AI fulfilling all characteristics of a GPT technology.

[13] For example, Zhavoronkov et al. (2019) have used deep learning techniques to identify pharmaceuticals.

becomes part of the existing knowledge base, the dashed lines show the additional approach by Agrawal et al. (2019).

Firstly, the existing knowledge base of a researcher/firm determines the number of potential knowledge combinations. Following the idea of the "burden of knowledge" (Jones, 2009), the key assumption here is that this potential number increases exponentially with knowledge access (Agrawal et al., 2019). Of course, not all combinations also imply radical new knowledge (Mewes, 2019). Instead, searching for novel combinations among the massive amount of potential combinations is needed to discover new rather radical knowledge.

AI technologies, such as deep learning, can facilitate this discovery process by providing a way to search a larger part of the potential combinations and thereby increase the likelihood to identify rather radical knowledge combinations, particularly in environments where interaction among knowledge sources is often highly complex (Agrawal et al., 2019). Following the idea by Cockburn et al. (2019), in this last step, the actual discovery process, we extend the original framework of Agrawal et al. (2019) by specifying through which features AI might contribute to fishing out radical new combinations.

In accordance with the GPT framework (Bresnahan & Trajtenberg, 1995; David, 1990), GPTs act as "engines of growth" throughout the whole economy. They are commonly characterized by the following three criteria: pervasiveness, an innovation spawning effect and a scope for improvement (Cockburn et al., 2019; Helpman & Trajtenberg, 1994). Pervasiveness means that GPTs are vital to and widely applied in different sectors (Cockburn, et al., 2019; Youtie et al., 2008). Furthermore, GPTs spawn innovation in every sector in which they are applied, as they offer new technological opportunities. They generate innovation complementarities, leading to productivity growth in the applied sector. Advances in the GPT lead to advances in the application sector, which then lead to feedback loops that result in innovations and improvements in the GPT itself and thus to further impacts in all application sectors. Accordingly, GPTs additionally need a scope for improvement in order to enable these complementarities and feedback loops, thereby increasing the rate of innovation across all sectors (Bresnahan & Trajtenberg, 1995; David, 1990; Helpman & Trajtenberg, 1994). In light of these characteristics, it is here argued that GPTs can act as a bridging platform that connects different technologies by being an essential complement in the emergence of innovations and enabling new opportunities (Bresnahan & Trajtenberg, 1995; Ristuccia & Solomou, 2014). This bridging platform can therefore essentially promote the recombination of previously unconnected knowledge pieces and thereby enhance the creation of radical innovations. AI application technologies like sensing and reacting robots include the described GPT characteristics. They can be used in logistics or production processes in many different sectors and furthermore are implemented technologies in various products. Therefore, we proxy the GPT characteristics of AI through AI application technologies (Cockburn et al., 2019), and we therefore propose the following hypothesis:

H1a: The amount of knowledge about AI applications in the knowledge base of firms has a positive influence on the emergence of radical innovations in firms.

The IMI concept was initially introduced by Griliches (1957) by referring to the discovery of double-cross hybridization. His example of hybrid corn showed that IMIs are new research tools that do not just create new or improve existing products (creating a new corn variety), but they represent a whole new way of creating and/or updating products, with a much broader application (creating a widely used method for breeding various new varieties) (Cockburn et al., 2019; Griliches, 1957). An IMI can thus initiate different waves of invention. They create new technological opportunity and appropriability across a wide range of potential products (Darby & Zucker, 2003). As already indicated, AI methods and techniques[14] can also be identified as IMIs (Cockburn et al., 2019). One example for this is the fMRA (functional magnetic resonance image) technique—an algorithm that "transformed our understanding of the human brain" (Cockburn et al., 2019, p. 126) and heavily influenced protocols and paradigms in brain

[14] For the sake of clarity, we will only refer to AI techniques in the following.

research. As such, AI techniques can be regarded as a catalyst and method for generating new, rather radical, knowledge. Consequently, the following hypothesis is proposed:

H1b: The amount of knowledge about AI techniques in the knowledge base of firms has a positive influence on the emergence of radical innovations in firms.

2.2 AI and the emergence of radical innovation: a firm-specific perspective

While previous research has already indicated that firm size is a significant driver for firms' innovativeness in general (e.g. Acs & Audretsch, 1990; Cohen & Klepper, 1996), in the case of AI, it still remains unclear whether its influence on (radical) innovations varies with firm size. Since particularly radical innovations can lead to long-lasting competitive advantages (e.g. Castaldi et al., 2015), firm-specific differences would ultimately also imply consequences for the increasing productivity divergence across firms worldwide (e.g. Andrews et al., 2019; Berlingieri et al., 2017; Faggio et al., 2010). In previous research, different explanations have been offered for the rising divergence processes (Andrews et al., 2019; Cette et al., 2018). One popular explanation refers to the heterogeneous diffusion patterns of new general-purpose technologies across firms (Andrews et al., 2019; Faggio et al., 2010). For instance, based on a large longitudinal sample of 25 technologies in 139 countries, Comin & Mestieri (2018) show that the adoption lags for new technologies across countries have declined, while the divergence in the intensity of use of these technologies has increased. In other words, new technologies diffuse at an increasing rate between countries but only at an increasingly slowly rate between all firms within an economy (Andrews et al., 2015; Bahar, 2018). This suggests that not every sector, region and firm benefit equally from the emergence of a new general-purpose technology. This is also in line with the resource-based view (RBV),[15] being one of the most well-known theoretical perspectives in the research field of strategic management (Newbert, 2007; Šarić, 2012; Steffen, 2012). The RBV is based on the assumption that resources are immobile and unequally distributed among firms, leading to different resource endowments and their persistency over time. From this asymmetry ultimately arises the possibility of achieving a resource-based competitive advantage. The core idea of the RBV therefore deals with the firm's internal resource base[16] and how firms can make use of these resources in order to gain a competitive advantage (Barney, 1991; Newbert, 2007; Steffen, 2012). As such, in general, firms also differ in their ability to adopt new technologies, depending for instance on their financial abilities (e.g. Rogers, 2004), their absorptive capacities (e.g. Cohen & Levinthal, 1990) as well as their organizational structure (e.g. Goode & Stevens, 2000).

Clearly, firms also differ in their capacities to realize and seize the potentials of AI (OECD, 2021). Particularly small- and medium-sized enterprises (SMEs) face greater disadvantages in this technological transformation (Daor et al., 2020; OECD, 2021). Building and maintaining an AI system requires costly investment (e.g. in the data infrastructure). Often, realizing potential benefits of AI also requires large intangible investments (e.g. human capital). However, SMEs may lack sufficient financial resources to bear these capital expenses, especially since calculating the cost of developing an AI system and its potential benefits are often challenging. Indeed, the implementation of AI technologies may not result in immediate benefits and productivity gains, which raises sunk costs for SMEs before a growth path could be achieved (Accenture, 2019; Brynjolfsson et al., 2021; OECD, 2021). Moreover, SMEs are less well prepared to valorize their data. Although SMEs produce and handle a great volume and variety of data, they often lack the ability to collate, manage and protect them. Moreover, compared with larger firms, the data collected and stored may not be of adequate quantity and/or

[15] Originally emerged from the contributions of Penrose (1959), Rubin (1973) and Wernerfelt (1984), the RBV has since then continuously been advanced, highlighting, for example, the importance of dynamic capabilities to actually utilize the available resource bundles (Teece et al., 1997) as well as focusing on specific resources such as knowledge (Grant, 1996).

[16] In line with previous studies (e.g. Grashof, 2021), the widely used definition by Barney (1991) is used, where resources are defined as "(…) all assets, capabilities, organizational processes, firm attributes, information, knowledge, etc. controlled by a firm that enable the firm to conceive of and implement strategies that improve its efficiency and effectiveness" (Barney, 1991, p. 101).

quality to derive meaningful insights. Larger firms have in this context a larger potential (Bianchini & Michalkova, 2019; Cockburn et al., 2019; OECD, 2021). These disadvantages of SMEs can also be observed in the very recent study by Rammer et al. (2022), finding significant difference in the usage and economic relevance of AI depending on firm size.[17] Consequently, the following hypothesis is proposed:

H2: The influence of the amount of AI knowledge in the knowledge base of firms on the emergence of radical innovations is significantly more pronounced for large firms.

The previously described firm-specific differences are also likely to be reflected in a different influence of AI techniques and applications on the emergence of radical innovations. In the case of AI applications, it is assumed that particular large firms can gain, in terms of generating radical innovations. As already indicated, through the application of a GPT, innovation complementarities are generated (Bresnahan & Trajtenberg, 1995), which allow to connect previously unconnected, but already established knowledge domains within firms. However, this requires an already diverse knowledge base within the firm, which is more likely to be the case in large firms (e.g. Pomfret & Shapiro, 1980). Furthermore, through its bridging nature, the application of AI can also potentially help to avoid, or at least minimize, the risk of a cognitive lock-in situation that comes with increasing company size (Forés & Camisón, 2016; Levinthal & March, 1993; Nooteboom et al., 2007). As such, it is assumed that knowledge about AI applications can particularly help large firms to maximize the benefits of their internal knowledge base and thereby increase the potential for generating radical innovations. Consequently, the following hypothesis is proposed:

H2a: The influence of the amount of knowledge about AI applications in the knowledge base of firms on the emergence of radical innovations is significantly more pronounced for large firms.

In the case of AI techniques, it is assumed that knowledge in AI techniques enhances the emergence of radical innovations particularly in SMEs. While larger firms rather use AI in order to maximize the benefits of their internal knowledge base and to optimize their production lines (referring to AI applications), small firms and entrepreneurs are able to use AI in a less formalized production environment. Instead, they use it more as a tool to open up new markets and generate new products (Chalmers et al., 2021). This reflects the IMI properties of AI techniques (Cockburn et al., 2019). Although SMEs might lack a sufficiently diversified internal knowledge base (Pomfret & Shapiro, 1980), they are more flexible, agile and also appear to be more risk-taking (Damanpour & Wischnevsky, 2006; Nooteboom et al., 2007). As such, we assume that SMEs are more likely to use knowledge in new AI-related methods of inventing (AI techniques) in order to create radical innovations, as they are more flexible in terms of their organizational and cognitive structure (e.g. Nooteboom et al., 2007; Tornatzky & Fleischer, 1990). Consequently, the following hypothesis is proposed:

H2b: The influence of the amount of knowledge about AI techniques in the knowledge base of firms on the emergence of radical innovations is significantly more pronounced for SMEs.

However, not every SME is also identical in terms of its resources and its existing knowledge base (Schulze-Krogh, 2018; Wapshott & Mallett, 2018). As such, some SMEs may be more capable of using AI to create rather radical innovations than others. A related technological knowledge base to AI appears to be promising in this context. In general, it has been shown that firms are able to only develop technologies to which they share some related knowledge base (Breschi et al., 2003). For the effective implementation of an AI system, it is also likely that a related technological knowledge base matters, e.g. in cloud computing and data storage (OECD, 2021). Although on the regional level, Xiao and Boschma (2021) find evidence that a regional knowledge base in Information and Communication Technologies (ICTs), which is strongly related to AI, enables regions to diversify into AI technologies, particularly in catching-up regions. We assume that these recent results also hold true on the firm level. However, in line with our previ-

[17] Our study differentiates from Rammer et al. (2022) in terms of the geographic coverage (European firms), time coverage (from 2011 to 2020), the overall focus on rather radical innovation and of the differentiated view on AI (separating between applications and functions). As such, we are partially in line with the calls for future research highlighted by Rammer et al. (2022).

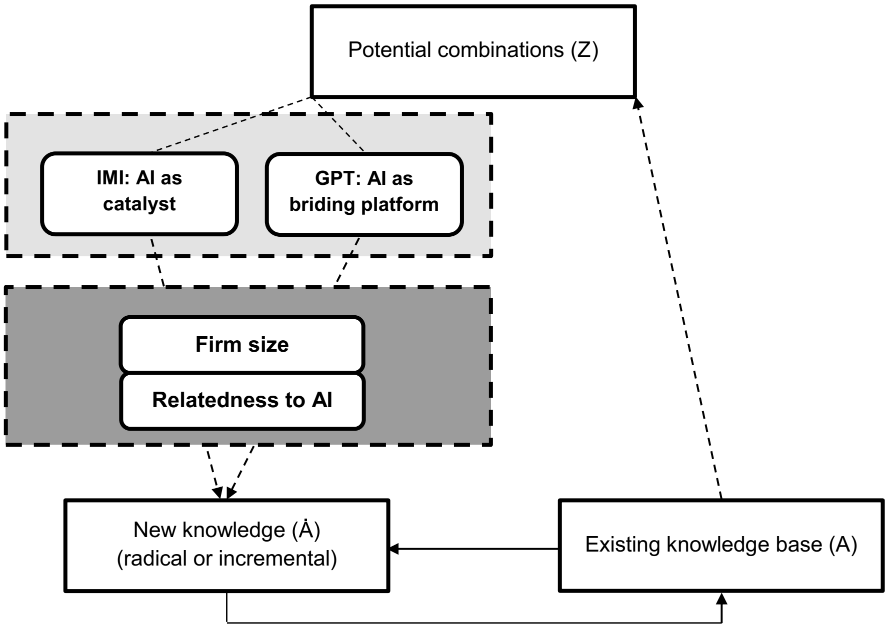


Fig. 2 Theoretical framework (stylized form)

ous expectations on the different role of AI applications and AI techniques (see for instance H2a and H2b), we suppose that this is also reflected in the moderating influence of the related technological knowledge base of firms on the emergence of radical innovations. As already indicated, the GPT features of AI act as bridging platform to connect previously unconnected knowledge domains (Bresnahan & Trajtenberg, 1995; Ristuccia & Solomou, 2014), but this requires an already diverse internal knowledge base, which is more likely to be the case in large firms (e.g. Pomfret & Shapiro, 1980). As such, it is reasonable to assume that particular for large firms, it is beneficial to have a broad knowledge base that is related to AI applications. Thus, the following hypothesis is proposed:

H3a: The influence of a related knowledge base to AI applications on the emergence of radical innovations is significantly more pronounced for large firms than SMEs.

For SMEs, it is instead assumed that a high degree of relatedness to AI techniques in particular favours the emergence of radical innovations. Since SMEs are more flexible, agile and more risk-taking (Damanpour & Wischnevsky, 2006; Nooteboom et al., 2007), they are more likely to use the IMI properties of AI techniques to open up new markets and generate new products (Chalmers et al., 2021; Cockburn et al., 2019). Therefore, it is probable that particularly those SMEs that own a highly related knowledge base to AI techniques are also more capable to come up with radical innovations. Consequently, the following hypothesis is proposed:

H3b: The influence of a related knowledge base to AI techniques on the emergence of radical innovations is significantly more pronounced for SMEs than large firms.

Figure 2 illustratively summarizes our theoretical framework. The first part of our theoretical framework has already been described in detail in Sect. 2.1. Based on the idea by Cockburn et al. (2019), we extend the combinatorial-based knowledge production function suggested by Agrawal et al. (2019), by concretising through which features AI (GPT characteristics vs. IMI characteristics) might influence the creation of (radical) new knowledge combinations. While the first part of our theoretical framework deals more with the technological level, the second part deals with the firm level. In line with the RBV (e.g. Barney, 1991; Newbert, 2007), firms are argued to also differ in their capacities to realize and seize the potentials of AI (OECD, 2021).

Apart from the technological level, it is therefore necessary to additionally consider the firm-specific differences. In our study, we thereby particularly focus on firm size and the relatedness of firms' internal knowledge base to AI (applications and techniques). The combination of the technological and firm level makes it possible to understand the emergence of radical innovations through AI knowledge in companies in a more nuanced way.

3 Data and methodological approach

3.1 Data

In order to empirically analyse the derived hypotheses, we make use of two large data sources. In terms of firm-level data, we employ the extensive firm database ORBIS offered by Bureau van Dijk (BvD), which offers information on various firm-specific characteristics (e.g. firm size). In this work, we are particularly interested in firm-specific characteristics that help in facilitating radical innovations. For this, we use firm data of all firms based in the EU that has information on either the number of employees or their revenue within the last 10 years, which is the maximum lookback period in the ORBIS database, which offers us a dataset of 67.477 firms. The second large data source we use is PATSTAT, which we use to identify radical as well as AI patents between 2011 and 2020.

In line with our conceptual focus on the emergence (or novelty) of radical innovations (see Sect. 2.1), we proxy the emergence of radical innovations by new technology combinations on a patent, which have not been combined before (based on a reference dataset) following previous studies (e.g. Arant et al., 2019; Grashof et al., 2019; Verhoeven et al., 2016). The reference dataset is based on all of PATSTAT patents that are localized via its applicant address within the EU since 1981,[18] following other studies that use similar timeframes (e.g. Grashof et al., 2019; Hesse & Fornahl, 2020; Verhoeven et al., 2016). The reference dataset consists of 3,795,924 docdb patent families, while the observation period (2011–2020) entails 1,094,051 docdb patent families. In total 16,200 patent families were attributed as radical patents.[19]

This approach is based on the argument that formerly unconnected knowledge domains generate radical innovations (Fleming, 2001). These knowledge domains are measured by the 4-digit CPC codes,[20] which in line with previous studies (e.g. Hesse & Fornahl, 2020; Mewes & Broekel, 2020) are argued to be the best trade-off between a maximum number of technologies and a sufficiently large number of patents in each of these classes. Additionally, we used 1981 as a cut-off for the references based on the argument that there is a trade-off between the maximum number of patents as well as including different innovation regimes (e.g. since 1979, 267 new full digit IPC groups were introduced (Verhoeven et al., 2016)). Going further into the past may introduce problems with measuring patent combinations that are not important for current research advancements due to the change of technological trajectory within the CPC 4-digit group.

To identify the AI patents in firms, we conduct a keyword search in the abstract and title of the patents as well as use the CPC and IPC codes based on the search algorithm of the WIPO (2019). In order to account for the different effects of GPTs and IMIs, we divide AI patents into AI techniques and AI applications patents. The differentiation between AI techniques and AI applications acts as a proxy for the different characteristics of AI, namely being an IMI and a GPT. AI techniques in this regard act as a proxy for the IMI features. It focuses on patents that are related to technical methods and techniques of AI. AI applications, in turn, entail the application fields of AI (e.g. robotics) and are, therefore, in our view, a suitable proxy for the GPT characteristics of AI. In total 85,662 docdb patent families are considered AI patents since 2000, with 65,984 attributed as techniques and 23,246 attributed as applications.[21] Giczy et al.

[18] There are a number of ways to localize patents. In our case, we used the applicant address, instead of, e.g., the patent office (EPO), as the focus of our analysis is on the knowledge base of firms within the EU. Since there is the possibility of "foreign" patent applications at national patent offices as well as the European patent office, there is an argument for a distortion of this European knowledge base through patents of non-European firms. Additionally, our approach only leads to a negligible amount of missing data as we only focus on the country of the applicant and therefore do not need a full address. This stands in contrast to the data availability for the inventor address, which is often missing.

[19] With a share of about 1.5%, radical patents occur similarly rarely as in other studies focusing on a different research context (e.g. 5% in Rizzo et al. (2020) and about 7% in Verhoeven et al. (2016)).

[20] Other approaches also use 8-digit codes of the classification (e.g. Verhoeven et al., 2016).

[21] Note that being attributed as AI technique or AI application is not mutually exclusive. Nevertheless, the overlap between those two attributes is very small. Furthermore, one of these patent families identified as AI is also identified as a radical patent and thus omitted in the analysis.

Table 1 Descriptive statistics

Variable	Obs	Mean	Std. Dev	Min	Max	
AI	54,970	0.048	0.568	0	63	PATSTAT based on WIPO (2019) search string
Techniques	54,970	0.042	0.506	0	58	See above
Applications	54,970	0.007	0.130	0	11	See above
Firm size	38,410	0.645	0.478	0	1	ORBIS
RelDens techniques	54,970	1.513	4.232	0	50.33	PATSTAT
RelDens applications	54,970	1.023	3.888	0	66.120	PATSTAT
Radical	54,970	0.160	1.109	0	64	PATSTAT
Patents	54,970	9.161	57.598	0	2792	PATSTAT

(2021) are giving an extensive overview over different ways of identifying AI patents, as well as developing their own machine learning-based approach. We favour the WIPO's (2019) over their approach because of (a) its higher precision (Giczy et al., 2021), (b) the proposed method of Giczy et al. (2021) that only entails classifiers for a part of AI, which the WIPO (2019) search string classifies as "techniques" and thus does not allow for the differentiation between AI application and technique patents and (c) the dataset constructed by Giczy et al. (2021) which is based on USPTO patents, while our analysis is focused on EU-based patent applications as well as EU-based firms.

We then combined these two databases via the information provided by ORBIS IP, where each firm is linked with its respective patent. From ORBIS IP, we used the BvD id as well as the application number to link both ORBIS' firm database and PATSTAT, which lead to 625,107 patent families linked to 107,574 unique firms. These two datasets combined generate a final database consisting of an unbalanced panel of firms that are located in the EU and applied for any patent within the timeframe of 2011 to 2020 entailing patent information as well as firm-specific information.

3.2 Operationalization

In this section, the methodological approach is presented, which we applied to operationalize the above presented hypotheses. The centre of our interest is the amount of the radical knowledge in firms. To measure this, we count the number of radical patents in each firm based on DOCDB patent family ids. Thus, patents from the same patent family are not counted twice per firm. If a radical patent is attributed to more than one firm, we assume that the knowledge of this patent is not exclusive and thus attribute a full patent to all applicant firms. Therefore, radical knowledge is proxied by the number of radical patents in each firm (*radical*).[22] Furthermore, the amount of AI-specific knowledge is also measured by the number of AI patents in each firm (*AI*). Here, we also divide these patents into AI methods (*methods*) as a proxy for the IMI characteristics and AI applications (*applications*) as a proxy for GPT characteristics based on the search algorithm of the WIPO (2019). Since our second research question deals with the firm-specific differences between SMEs and larger firms, we additionally consider a dummy variable indicating whether a firm is a SME or not, which is based on the frequently used measure of the number of employees of each firm (Perez-Alaniz et al., 2022). In line with previous studies (e.g.Forés & Camisón, 2016; Stavropoulos et al., 2020; Vaona & Pianta, 2008), we thereby attribute a firm to being a SME if its number of employees is below 250 (*SME*). Nevertheless, since it only partially matches with the definition of the European Commission that additionally considers either turnover or balance sheet total, as already indicated in footnote 2, we also use the BvD size classes as a further robustness check. The corresponding results

[22] Given the relatively low number of radical patents (see also Table 1), we have decided against calculating the share of radical patents in all patents at this point, since this relative measure has only limited informative value in our research context. However, in line with previous studies (e.g. Damioli et al., 2021), we control for the number of (non-radical) patents. Moreover, we also conducted a propensity score matching to account for a potential size effect (see Sect. 3.3).

remain stable and can be found in the appendix (see Table 5 in the Appendix).[23]

We furthermore expect that the relatedness of firms to AI technologies positively influences the impact of AI on radical knowledge generation. For this, we calculate the relatedness density (Boschma et al. 2014, 2015; Balland et al., 2019) of firms to both AI techniques (*RelDens techniques*) and AI applications (*RelDens applications*). We use the technological relatedness of all 4-digit CPCs based on the co-occurrence of these classifications on patents. The sum of the co-occurrence of each pair of 4-digit CPCs based on patent families is considered (Balland & Rigby, 2017; Boschma et al. 2015; Rigby, 2015). The co-occurrence matrix of technological CPCs is standardized based on the cosine distance function (Klavans & Boyack, 2006; van Eck & Waltman, 2009), cumulating in a relatedness matrix of all CPCs to each other. The relatedness is calculated using a moving window of 5 years over the 10-year period of the dataset, starting in 2011 and considering the previous 4 years of the patent data of all EU patents. Afterwards, the relative technological advantage is calculated for each firm, which is a binary indicator showing whether a firm has a comparative advantage in a specific technological class or not. Finally, the relatedness density is computed by dividing the technological relatedness of one technology to all other technologies in which a firm has a regional technological advantage with the sum of the relatedness of the technology to all other technologies (Boschma et al., 2014; Hidalgo et al., 2007).

Lastly, the technological diversity of a firm is assumed to have a positive influence on the emergence of radical innovations, because it helps to search for complementarities and novel combinations (Hesse, 2020a; Quintana-García & Benavides-Velasco, 2008). To measure a firms' technological diversity, we use the Herfindahl–Hirschman Index based on CPC 4-digit codes of all patents a firm has applied (e.g. Garcia-Vega, 2006; Leten et al., 2007). As the Herfindahl–Hirschman Index is a concentration measurement, we are using the inverse of the index to approximate a firms' knowledge diversity. Thus, a firm with a more diverse CPC space will also have a higher technological diversity. The Herfindahl–Hirschman Index is measured by counting the individual patents of each 4-digit CPC in each firm with a 5-year moving window (year of observation and 4 previous years) and calculating the share of each 4-digit CPCs. Then these shares are squared and added up to generate the Herfindahl–Hirschman Index which is then inversed (*HHI-1*).

3.3 Method

To analyse the proposed hypotheses, we conduct a panel regression analysis on the firm level of EU-based firms. Our dataset has a panel structure consisting of firm data ranging from 2011 to 2020. The dependent variable is the radical patent count of each firm in each year (*radical*). Thus, we use a quasi-Poisson fixed effects generalized linear model to account for the count data structure of the dependent variable (Berge, 2018) as well as overdispersion. The fixed effects are (a) the country of a firm to account for the institutional context, (b) the year to control for unobserved heterogeneity across time and (c) a dummy variable indicating whether the corresponding firm is independent and does not belong to a corporate structure. In line with previous studies (e.g. Grashof, 2021), this dummy is based on the BvD corporate independence indicator measured by the number of shareholders and the percentage of their individual and collective holdings.[24]

[23] Even though using a categorical variable to assess the size of firms eases interpretation of interaction terms, we nevertheless checked the results for a continuous scale (number of employees in 1000), and they did not change in their interpretation. These results can be provided upon request.

[24] In line with previous research (e.g. Biga-Diambeidou et al., 2021; Hsu et al., 2021), we do not use firm fixed effects here, since our main variables of interest AI patents and its division in techniques and applications change relatively little over time for a given firm and may be highly correlated with individual effects. The inclusion of firm fixed effects would therefore basically absorb any effect of our main variables of interest, and as such, we would fail to detect a relationship in the data even if it actually exists (Hall et al., 2005; Hsu et al., 2021; Zhou, 2001). Moreover, we additionally argue that conducting a propensity score matching approach, thereby identifying statistical twins that are statistically similar in terms of their firm-specific characteristics (e.g. firm size), and then including firm fixed effect in our panel regression would be in a way duplicative. As a further robustness check, we, however, also conducted a panel regression with firm and year fixed effects only (with standard errors clustered at the firm level). The corresponding results, which can be provided upon request, tend to confirm our previous argumentation, because all variables, even the control variables (e.g. number of patents), lose a great deal of significance. Nevertheless, in general they are still in line with our main results presented in Table 3 (despite the coefficients for *techniques/applications* and their interaction terms with *SME* becoming slightly insignificant as well as the coefficient of *RelDens applications* turning negative).

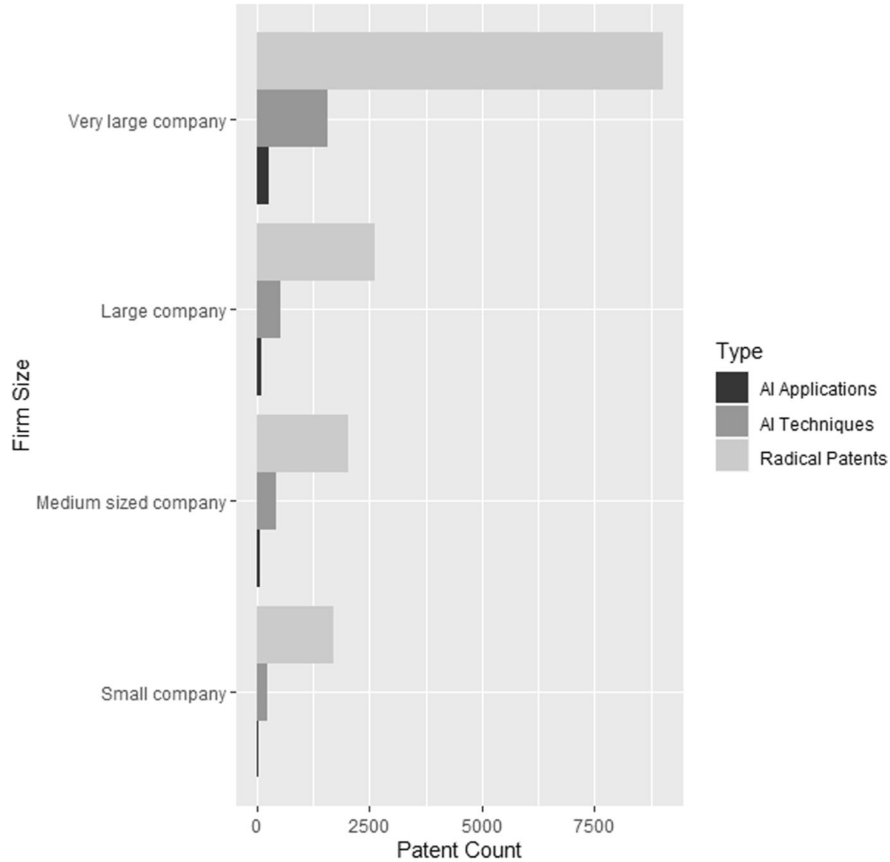


Fig. 3 Firm sizes of AI and radical patent applicants

However, to account for possible endogeneity problems, we first conducted a propensity score matching based on the nearest neighbour algorithm (Abadie & Imbens, 2016; Rosenbaum & Rubin, 1983) as there are potentially selectivity biases. For instance, Fig. 3 shows that a size effect can be observed that follows the presumed path of general patent activity across different firm sizes. To address this issue, similar to Shkolnykova & Kudic (2021), we identified statistical twins that are very similar, in a statistical sense, to firms with AI patents, but do not have AI patents themselves. In more concrete terms, we matched each firm that had at least one AI patent in a specific year with one other non-AI patenting firm, starting with the year 2011, where a firm is matched if it has its first AI patent in the dataset 1 year later (2012 in this instance). Thus, the matching is conducted based on a dummy variable indicating whether a firm has an AI patent in the following year or not (treatment variable).[25] The binomial regression for the matching contains the following independent variables (matching variables): the patent count of a firm in year i, the HHI-1 diversity index in year i, the firm size dummy, the country of the firm and its independence score. In total, we matched 5497 firms within our dataset, and thus our final dataset consists of 54,970 datapoints with a timeframe of 10 years.

Additionally, we checked the overlap between radical and AI patents. However, no overlap was found. We furthermore implemented a 1-year leading lag for our dependent

[25] At this point, it is important to point out that it is more complex to establish a before/after picture with regard to the emergence of AI patents than in studies evaluating for instance the treatment effect of a specific policy intervention, where you clearly can differentiate between a pre-treatment and a post-treatment phase. This has to do with the time-sensitive nature of patent applications as well as the tacitness of knowledge creation (Shkolnykova & Kudic, 2021).

Table 2 Correlation matrix

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
Radical	1	0.11	0.11	0.07	0.15	0.15	0.42
AI	0.11	1	0.94	0.41	0.26	0.26	0.24
AI applications	0.11	0.94	1	1.15	0.24	0.24	0.23
AI techniques	0.07	0.41	1.15	1	0.12	0.12	0.1
RelDens techniques	0.15	0.26	0.24	0.12	1	0.98	0.54
RelDens applications	0.15	0.26	0.24	0.12	0.98	1	0.53
Patents	0.42	0.24	0.23	0.1	0.54	0.53	1

variable. As a robustness check, we further conducted the analysis with various lags ranging from 0 to 3 years with no significant change in results (see Table 4 in the Appendix).

Table 1 shows the descriptive variables of our final dataset, while Table 2 shows the correlation matrix which indicates no problems with multicollinearity. Note that the difference in numbers of observation stems from missing values regarding the number of employees based on the ORBIS database.

Our final regression analysis takes the following stylized form:

$$\widehat{Y_{it}} = \alpha + \beta_1 AI_{it} + \beta_2 SME_{it} + \beta_3\, AI\ x\ SME_{it} + \beta_4 Pat_{it} + \pi_i + \omega_i + \tau_t + \in_{it} \quad (1)$$

$$\widehat{Y_{it}} = \alpha + \beta_1\, AItechniques_{it} + \beta_2\, AIapplications_{it} + \beta_3 SME_{it} + \beta_4\, AItechniquexSME_{it} + \beta_5\, AIapplicationsxSME_{it} + \beta_6 Pat_{it} + \pi_i + \omega_i + \tau_t + \in_{it} \quad (2)$$

$$\widehat{Y_{it}} = \alpha + \beta_1\, AItechniques_{it} + \beta_2\, AIapplications_{it} + \beta_3\, SME_{it} + \beta_4\, RelDens\ techniques_{it} + \beta_5\, RelDens\ applications_{it} + \beta_6\, RelDens\ technique\ x\ SME_{it} + \beta_7 RelDens\ applications\ x\ SME_{it} + \beta_8 Pat_{it} + \pi_i + \omega_i + \tau_t + \in_{it} \quad (3)$$

As mentioned above, all estimations include fixed effects for the country of a firm (ω_i), the corporate structure of a firm (π_i) and the corresponding year (τ_t) in order to account for unobserved time-invariant heterogeneity.

4 Results and discussion

In this section, the results of our analysis will be presented and discussed (see Table 3). For this we calculated in total six regression models with the following structure. The first model acts as a baseline model to be able to make a general assumption on the influence of AI patents on the radical patent count of firms (1). The second model includes the firm size dummy and its interaction with the variable *AI patents* (2). The third model incorporates the differentiation between AI application patents and AI technique patents (3). In the fourth model, we expand the analysis on to the firm size and incorporated the interaction effects between the firm size and the division of the AI patent count into AI applications and functions (4). The fifth and sixth models are including the relatedness density to both AI application and AI technique patents (5) and their respective interaction effect with the firm size (6).

In the first step of the analysis, the general impact of AI together with our control variables is considered. The model (1) shows this baseline model of our analysis. Here we can observe a significant and positive influence of the overall non-radical patent count, showing the path dependence and cumulativeness of knowledge accumulation. Furthermore, we can show that there is no significant statistical influence of the AI patent count on the radical patent count of firms. This result is contrary to our hypothesis (**H1**) and could be explained by the amount of human capital that is needed to implement AI (Brynjolfsson et al., 2019) and thus is bound and cannot work on other (radical) inventions. Thus, it could be that most firms that innovate in AI overall tend to not focus on additional knowledge creation but on the application of AI.

To account for the second hypothesis (**H2**), an interaction effect between the SME dummy variable

Table 3 Regression results

	Dependent variable: number of radical patents t+1					
	(1)	(2)	(3)	(4)	(5)	(6)
AI patents	−0.45 (0.030)	−0.072 (0.056)				
Techniques			−0.078* (0.038)	−0.079 (0.065)	−0.052 (0.051)	0.023 (0.147)
Applications			0.187. (0.100)	0.021 (0.127)	−0.021 (0.146)	−0.055 (0.050)
SME		−1.56*** (0.153)		−1.60*** (0.145)	−1.53*** (0.162)	−1.75*** (0.150)
AI X SME		0.175** (0.064)				
RelDens techniques					0.011 (0.029)	−0.005 (0.025)
RelDens applications					0.007. (0.003)	0.006* (0.003)
Techniques X SME				0.446*** (0.095)		
Applications X SME				−1.23*** (0.217)		
RelDens techniques X firm size						0.088*** (0.014)
RelDens applications X firm size						0.016 (0.014)
Patents	0.003*** (0.0002)	0.002*** (0.0002)	0.003*** (0.0001)	0.002*** (0.0001)	0.002*** (0.0004)	0.002*** (0.0004)
Fixed-effects						
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
BvD independence FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
S.E. clustered	Year and country	Year and country	Year and country	Year and country	Year and country	Year and country
Observations	54,970	38,410	54,970	38,410	38,410	38,410
Squared Corr	0.38	0.46	0.39	0.48	0.44	0.47
Pseudo R2	0.32	0.38	0.32	0.39	0.38	0.39
BIC	44,084.9	31,210.7	44,014.9	31,108.5	31,347.6	30,881.6

Clustered standard errors in parentheses; $p<0.1$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

and the number of AI patents is included in the second model (2). Here we observe that the AI patent count has a significant higher statistical influence on the radical patent count for SMEs in comparison to large firms. The main effect of AI in this model is still not significant indicating that there is no impact of AI on the radical innovative output in large firms (SME = 0). Concluding that we cannot reject hypotheses H2. Additionally, being a SME generally has a significant negative impact on the radical patent count. Large firms are more likely to innovate radically, which is also in line with previous research (e.g. Grashof et al., 2021). Since larger firms can benefit from a larger amount of internal R&D resources while smaller firms are less likely to engage in formal R&D (Ortega-Argilés et al., 2009; Rammer & Schubert, 2016), it is not surprising that, all other things being equal, larger firms tend to produce more radical innovations. This coefficient stays robust over all models.

To further deepen the understanding of the ongoing processes, we split the variable AI into AI application patents and AI technique patents in the third model (3). Here we observe an interesting behaviour. Deviating from our results in the first model, AI techniques have a significant and negative impact on the emergence of radical innovations. AI applications, on the other hand, have a significant positive influence on the radical patent count of firms. This further strengthens our assumption on the difference between the aim of using AI on an application base or using it as a technique where new innovations can be built upon. To sum these findings up, hypotheses 1 cannot be fully rejected, as AI applications do indeed have a positive impact on radical knowledge generation.

After this, we further expand our models to incorporate the firm size, to account for hypothesis 2a and b. We can observe an interesting interaction effect of being a SME with AI knowledge (4). In the case of AI applications, being a SME has a negative moderating effect, meaning that large firms experience a more positive impact of AI applications on radical knowledge generation than SMEs (on the 10% significance level). Given the GPT characteristics of AI applications, we assume that larger firms, that generate knowledge in the area of AI applications, are able to benefit of the connecting properties of GPTs. Through the application of a GPT, innovation complementarities are generated (Bresnahan & Trajtenberg, 1995). Thus, previously unconnected but already established knowledge areas within the firm are getting connected through AI applications. Therefore, we assume that a learning-by-using/learning-by-doing effect is at place leading to internal knowledge creation through the application of AI which is a more informal form of knowledge creation. This has the requirement that an already diverse knowledge base is at place in the firm which is more likely the case in larger firms (e.g. Pomfret & Shapiro, 1980).

In the case of AI techniques, on the other hand, there is an opposing effect; in the case of SMEs, AI technique patents have a positive statistical influence on the radical patent count. This could be explained by the fact that SMEs are able to use AI in a less formalized production environment, but more so as a tool to open up new markets and generate new products (Chalmers et al., 2021), while larger firms use it as a method to optimize production lines. These underline the IMI properties of AI techniques (Cockburn et al., 2019) as smaller firms are more agile and can thus benefit from the implementation of new methods and generate new ideas and products from these. Given these results, we can summarize that firm size is indeed a significant moderator of the relationship between the amount of AI knowledge and the creation of radical innovation. However, taken a more differentiated look, we find more nuanced patterns indicating that large firms particularly gain from AI applications (capturing GPT characteristics of AI), while SMEs particularly gain from AI techniques (capturing IMI characteristics of AI).

To account for hypothesis 3, we further include the relatedness density to both AI techniques and AI applications. In model five, only the direct effects are considered, and the result further strengthen the argument of Cockburn et al. (2019) that AI is not only a GPT but also an IMI. We propose that these two theoretical concepts can be separated within the AI framework. The results show that the relatedness density of a firm to AI techniques has a significant (on the 10% significance level) positive impact, thus implying that firms that are in their knowledge base closer to AI as a method are able to generate more radical innovations. In the case of the relatedness to AI applications, we, however, do not find evidence for such an influence, thereby underlying again the need for differentiated view on AI (5). In the following model, the interaction effects between the relatedness density to both AI types and the firm size are included. Here we can observe a significant positive moderating statistical effect of being a SME on the impact of the relatedness density to techniques on radical patent generation (6). In the end, our results of this part are showing that not only is there a difference between the two types of AI and being a small firm on the impact on radical knowledge but also that the firms' relatedness is an important factor in this context. Having prior knowledge that is close to AI techniques enables smaller and thus more flexible firms to venture into new and unknown knowledge creation and open up new technological paths. Thus, for the case of relatedness density to AI techniques, there is no evidence to reject hypothesis 3.

Summing up, AI does have an impact on the radical knowledge generation, but the different types of AI have to be considered, as AI techniques have a positive and AI applications a negative influence on radical knowledge generation. Therefore, firms as well policy makers have to develop a clear goal of the implementation and/or research on AI, whether to use it as a means to improve efficiency or to improve innovativeness.

5 Conclusion

The aim of this paper was to contribute to the literature on AI and its effect on innovativeness with a particular interest in radical knowledge generation. We found that AI in general has a (marginally) significant and negative effect on radical knowledge generation measured through a radical patent count. However, given the results presented above, this effect does not hold true when analysed in detail. The influence of AI on radical knowledge generation seems to be highly dependent on the specific type of AI that is considered, as AI techniques have a negative influence on radical knowledge generation while AI applications have a positive one. Furthermore, the firm-specific characteristics also play a major role in the effect of AI, e.g., by increasing the effect of AI techniques in smaller firms. On the other hand, the larger a firm, the more positive the effect of AI applications becomes. Lastly, the relatedness of a firms' knowledge base also plays an important role in the generation of radical knowledge. Being more related to AI technique knowledge helps in facilitating radical knowledge. This holds particularly true for smaller firms.

The plurality of these results shows that AI knowledge in itself is not the perfect answer for all firms in order to increase the likelihood of creating radical knowledge. Nevertheless, focusing on AI techniques, especially for SMEs, seems to be beneficial in creating radical knowledge, thus opening up the possibility for a catch-up process for smaller firms. This implies that managers of SMEs should focus on building (related) knowledge and competences in AI techniques rather than AI applications, which tend to require a large diversified knowledge base that larger firms in particular have (e.g. Pomfret & Shapiro, 1980). Summing up, this article contributes to the discussion of radical innovation within the framework of the development of AI and enhances the mostly theoretical paper of Cockburn et al. (2019) in supporting their conclusion that AI has two different functions. On the one hand, AI acts as a GPT, connecting different technologies by being a bridging platform. On the other hand, AI can be described as an IMI, which acts as a catalyst and method to generate new inventions that build upon previous knowledge. Therefore, this paper showed that it is not advisable to generalize AI development, as which type of AI is involved must be considered, as they are working in different ways and have different effects within different application cases. Consequently, more targeted policy approaches that consider the different features of AI and their varying contribution to the emergence of radical innovations across firms are needed in this context. Such approaches would ultimately maximize the full potentials of all firms.

When considering our results, some limitations must be discussed. First, in line with previous research (e.g. Alderucci et al., 2020; Cockburn et al., 2019; Damioli et al., 2021), we operationalize AI through patent data, even though patent data may not reflect the true usage of AI in firms, as not all innovations are patented (e.g. Griliches, 1990).[26] Furthermore, patenting AI in the EU can be quiet challenging regarding the laws of patenting code (Chikhaoui & Mehar, 2020; European Patent Office, 2017). Despite this, we assume that the patent count acts as a sufficient proxy for the scope of this paper, but future research should focus on new data on the usage of AI (see Raj & Seamans, 2019). Second, our time horizon of 10 years is rather small given the development of radical knowledge as well as AI knowledge may take some time to develop. This is due to data constraints on the firm level, which also prevent the inclusion of further control variables (e.g. R&D expenditures) and should be a focus of future research as well. A difference between long-term and short-term effects of AI on radical knowledge creation could be plausible in this context. Another problem that arises with these data constraints is attributed to PATSTAT, as the most recent years of patent data are not yet up to date and therefore less populated.[27] Third, our measurement of radical knowledge is based on CPCs and new combinations between them. Other measures of radicalness should be tested and applied, for instance, text-based measures (e.g. Arts et al., 2021; Feng, 2020), as well as non-patent-based indicators (e.g. Hervás-Oliver et al., 2018; Kinne & Lenz, 2019).

Despite these limitations, this paper contributes to closing an important gap in the field of AI research and opens up many different paths of research on the impact of AI on radical innovations and its long-term effects through generating radical knowledge.[28] Further research could analyse the catch-up process or the generation of new markets through the use of AI. Additionally, the diverging processes of AI techniques and AI applications in radical knowledge generation could not be limited to the size of the firm but also the age. Thus, further research could analyse the different influence of AI within young and incumbent firms on radical knowledge generation.

[26] Since patents are less frequently used in the service sector (e.g. Morikawa, 2019), our results may be biased towards the manufacturing sector, which might not fully reflect the potential differences in the role of firm size in the innovation processes between manufacturing and knowledge-intensive service companies (e.g. Audretsch et al., 2020).

[27] However, we argue that our results are not biased because this problem occurs equally on both sides of our regression. Furthermore, a potential bias through this problem is additionally addressed by applying a propensity score matching allowing to match AI patenting firms with non-AI patenting firms (see Sect. 3.3).

[28] Although we speak about an influence/impact of AI, we do not claim this to be causal.

Appendix

Table 4 Regression results with larger timelag

	Dependent variable: number of radical patents t + 3					
	(1)	(2)	(3)	(4)	(5)	(6)
AI patents	0.127 (0.183)	9.73e-6 (0.216)				
Techniques			0.175 (0.246)	0.063 (0.290)	0.262 (0.214)	0.210 (0.249)
Applications			−0.374 (0.703)	−0.548 (0.673)	−0.093 (0.484)	−0.152 (0.487)
SME		−1.55*** (0.101)		−1.55*** (0.101)	−1.49*** (0.108)	−1.52*** (0.102)
AI X SME		0.674*** (0.133)				
RelDens techniques					−0.050*** (0.012)	−0.051*** (0.013)
RelDens applications					0.013* (0.005)	−0.005* (0.003)
Techniques X SME				0.655*** (0.170)		
Applications X SME				0.535 (0.539)		
RelDens techniques X firm size						0.098*** (0.007)
RelDens applications X firm size						0.029** (0.011)
Patents	0.003*** (0.0002)	0.003*** (0.0002)	0.003*** (0.0002)	0.003*** (0.0002)	0.003*** (0.0004)	0.003*** (0.0002)
Fixed-effects						
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
BvD independence FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
S.E. clustered	Year and country	Year and country	Year and country	Year and country	Year and country	Year and country
Observations	38,479	27,756	38,479	27,756	27,756	27,756
Squared corr	0.25	0.37	0. 26	0.37	0.38	0.40
Pseudo R2	0.27	0.35	0.27	0.35	0.35	0.36
BIC	38,348.5	26,802.3	38,335.1	26,794.3	26,754.0	26,657.5

Clustered standard errors in parentheses; $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5 Regression results with ORBIS SME Classification

	Dependent variable: number of radical patents t+1					
	(1)	(2)	(3)	(4)	(5)	(6)
AI patents	−0.045 (0.030)	−0.042 (0.029)				
Techniques			−0.078* (0.038)	−0.071* (0.036)	−0.062 (0.056)	−0.064 (0.053)
Applications			0.187. (0.100)	0.167. (0.096)	0.064 (0.122)	0.083 (0.120)
SME		−1.72*** (0.244)		−1.72*** (0.241)	−1.62*** (0.264)	−1.85*** (0.240)
AI X SME		0.868*** (0.050)				
RelDens techniques					0.025 (0.030)	0.017 (0.030)
RelDens applications					0.011* (0.005)	0.011** (0.004)
Techniques X SME				0.874*** (0.062)		
Applications X SME				1.22** (0.384)		
RelDens techniques X firm size						0.082*** (0.015)
RelDens applications X firm size						0.024** (0.009)
Patents	0.003*** (0.0002)	0.002*** (0.0002)	0.003*** (0.0001)	0.003*** (0.0001)	0.002*** (0.0004)	0.002*** (0.0004)
Fixed-effects						
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
BvD independence FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
S.E. clustered	Year and country	Year and country	Year and country	Year and country	Year and country	Year and country
Observations	54,970	54,970	54,970	54,970	54,970	54,970
Squared corr	0.38	0.40	0. 39	0.42	0.39	0.40
Pseudo R2	0.33	0.35	0.32	0.36	0.36	0.36
BIC	38,348.5	26,802.3	38,335.1	26,794.3	26,754.0	26,657.5

Clustered standard errors in parentheses; $p<0.1$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

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