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Artificial intelligence in innovation research: A systematic review, conceptual framework, and future research directions

Marcello M. Mariani [a,e,*], Isa Machado [a], Vittoria Magrelli [b], Yogesh K. Dwivedi [c,d]

[a] Henley Business School, University of Reading, Greenlands, Henley on Thames Oxfordshire, RG9 3AU, United Kingdom
[b] Faculty of Economics and Management, Free University of Bozen-Bolzano, Italy
[c] Emerging Markets Research Centre (EMaRC), School of Management, Swansea University, Bay Campus, Fabian Bay, Swansea, SA1 8EN, Wales, UK
[d] Department of Management, Symbiosis Institute of Business Management, Pune & Symbiosis International (Deemed University), Pune, Maharashtra, India
[e] University of Bologna, Bologna, Italy

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ABSTRACT

Artificial Intelligence (AI) is increasingly adopted by organizations to innovate, and this is ever more reflected in scholarly work. To illustrate, assess and map research at the intersection of AI and innovation, we performed a Systematic Literature Review (SLR) of published work indexed in the Clarivate Web of Science (WOS) and Elsevier Scopus databases (the final sample includes 1448 articles). A bibliometric analysis was deployed to map the focal field in terms of dominant topics and their evolution over time. By deploying keyword co-occurrences, and bibliographic coupling techniques, we generate insights on the literature at the intersection of AI and innovation research. We leverage the SLR findings to provide an updated synopsis of extant scientific work on the focal research area and to develop an interpretive framework which sheds light on the drivers and outcomes of AI adoption for innovation. We identify economic, technological, and social factors of AI adoption in firms willing to innovate. We also uncover firms' economic, competitive and organizational, and innovation factors as key outcomes of AI deployment. We conclude this paper by developing an agenda for future research.

1. Introduction

Technological innovation developments in organizations have been the object of increasing scholarly attention over the last few decades as firms have rapidly discovered how to use technology to enhance their innovativeness and performance (Beilin et al., 2019; Bai and Li, 2020; Hoffman et al., 1988; Musiolik et al., 2020). More specifically, organizations have soon learned that they can blend innovative technologies with their capabilities to enhance their competitive advantage (Porter, 1985). Among digital technologies that are allowing firms to constantly innovate in the digital age, there is artificial intelligence (AI) which is increasingly affecting how firms innovate (Kakatkar et al., 2020; Mariani and Fosso Wamba, 2020; Wamba and Mishra, 2017) and how consumers respond to AI-informed innovations (Mustak et al., 2021).

Economists have recently tried to make sense of the impact of AI on innovation (Cockburn et al., 2019), and they have called for more research at both the industry and organizational level. So far, management scholars dealing with technology-driven innovation have focused mainly on themes such as the barriers in the implementation of AI systems in organizations (Desouza et al., 2020; Haefner et al., 2021), and ways through which AI can support organizational processes (Frank et al., 2019), decision making (Kakatkar et al., 2020; Verganti et al., 2020), operations (Belhadi et al., 2021), business models (Di Vaio et al., 2020) and the achievement of organizational objectives (Hutchinson, 2021). While this body of research is very recent, it apparently displays several features: (1) it seems rather fragmented; (2) its nature is mostly exploratory; (3) innovation scholars do not have a clear, holistic, and comprehensive picture of what has been researched and where are the most relevant new research gaps that might provide fruitful avenues for further enquiry in the focal domain.

More specifically, despite AI being increasingly critical in innovation studies, so far, no systematic effort has been made to synthesize and assess comprehensively and quantitatively through a systematic literature review (SLR) the knowledge produced on the role of AI in innovation management. Furthermore, innovation management scholars miss a structured framework clearly mapping out extant literature in relation

* Corresponding author. Henley Business School, University of Reading, Greenlands, Henley on Thames Oxfordshire, RG9 3AU, United Kingdom.
E-mail addresses: m.mariani@henley.ac.uk (M.M. Mariani), i.c.machado@pgr.reading.ac.uk (I. Machado), vittoria.magrelli@unibz.it (V. Magrelli), y.k.dwivedi@swansea.ac.uk (Y.K. Dwivedi).

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to the drivers and outcomes of AI adoption in the innovation field. To bridge these research gaps, and in line with tenets of literature review research (Donthu et al., 2021) we carry out a SLR to answer the following research question: "***What is the emerging intellectual structure of the innovation literature dealing with AI?***"

To answer this research question, we conduct a SLR to identify the evolution of research in the field of AI in innovation, investigate the scientific knowledge produced so far and portray advancement of innovation research pertaining to AI. After having identified the relevant sample of the review (N = 1448 articles), we use a SLR approach also to identify the drivers and outcomes of AI adoption for innovation purposes. Adopting a SLR allows to embrace a systematic, transparent and reproducible approach which is capable of diminishing researchers' bias (Snyder, 2019).

This paper makes several contributions to the area at the intersection of innovation and AI by adopting a multidisciplinary perspective. First, we provide an updated overview of the volume and trend of research outputs at the intersection of AI and innovation, thus contributing to the technology innovation management field. Second, we single out economic, technological, and social factors as drivers of AI adoption in firms willing to innovate. Third, we identify firms' economic, innovation, competitive and organizational factors as key outcomes of AI adoption in firms aiming to innovate. Fourth, we leverage a bibliometric analysis to uncover seminal work in the field of AI in innovation research and to map the research field over time. Fifth, we contribute to the innovation literature by developing an interpretive framework which sheds light on the drivers and outcomes of AI adoption for innovation, thus offering a theoretical contribution to the technology innovation management field. Sixth, we identify the most frequently used theories to provide clear directions for further inquiry. Seventh, we develop a rich research agenda that contributes to expand the perimeter of the field, while revealing new research gaps that can lead to fruitful avenues for further enquiry in the focal field.

The article is structured as follows. In section 2, we review the recent debate on AI in the innovation domain. Section 3 describes the methodology adopted in this study. Section 4 portrays the findings in relation to the descriptive statistics of extant publications, major themes and topics that emerged from the bibliographic coupling analysis, theoretical lenses deployed in the literature, and a comprehensive framework to identify drivers and outcomes of AI adoption. Section 5 elucidates the major contributions. Section 6 illustrates the limitations, while developing a rich research agenda. Section 7 draws synthetically the conclusions.

2. Recent debate on AI in innovation studies

As the aim of this study is to map the intellectual structure of innovation literature dealing with AI, we first introduce several key concepts and definitions to better inform this systematic literature review.

There seems to be general scholarly consensus that the first description of AI appeared in science fiction almost eight decades ago. In 1942 American science fiction writer Isaac Asimov published his book *Runaround* where a robot was developed by the engineers Gregory Powell and Mike Donavan paying attention to the so called "Three rules" of robotics. In a relatively short time, Asimov's book became a source of inspiration for many scientists, especially in the fields of computer science and robotics. At roughly the same time, the English mathematician Alan Turing worked for the British government on a supercomputer (The Bombe) to break the *Enigma* code used by the German army during WWII (Haenlein and Kaplan, 2019). This experience was conducive in the fifties to the production of an article describing how to create intelligent machines and test their intelligence. Apparently, the circumlocution Artificial Intelligence was officially coined in 1956 when American cognitive scientist Marvin Minsky and computer scientist John McCarthy hosted the Dartmouth Summer Research Project on Artificial Intelligence (DSRAI) at Dartmouth College, USA. Since then, AI and its relevance have recorded many ups and downs and currently AI technologies are reaching a peak of inflated expectations (Gartner, 2019).

A number of scholars in business and management has recognized that AI has multiple ramifications. These ramifications have been theorized recently by Davenport and Ronanki (2018) and Huang and Rust (2018). For instance, Davenport and Ronanki (2018) distinguish three types of AI: process automation, cognitive insight and cognitive engagement. More recently, AI has been defined as "the use of computational machinery to emulate capabilities inherent in humans, such as doing physical or mechanical tasks, thinking, and feeling" (Huang and Rust, 2021, p.31). In innovation contexts, AI has been defined as systems developed with the "objective of creating human-like behaviour in machines for perception, reasoning, and action" (Prem, 2019, p.2). AI has gained power due to rapid advances in computational capabilities and a huge variety of new technologies (e.g., computer vision, machine learning, and natural language processing) (Mariani et al., 2022), as well as a blast of available data to train algorithms (Bornet et al., 2021).

The increasing relevance of AI in innovation is witnessed by the production of several studies on topics such as AI supporting innovation analytics (Kakatkar et al., 2020), AI enabling digital experimentation and digital innovation (Mariani and Nambisan, 2021), AI and sustainable business models (Di Vaio et al., 2020), AI in supply chain management (Toorajipour et al., 2021), strategic uses of AI (Borges et al., 2021), AI and big data integration within business processes (Wamba and Mishra, 2017), and AI capabilities in industrial markets (Akter et al., 2021). However, to the best of our knowledge, there is only one literature review focusing on AI within innovation: Haefner et al. (2021) review the literature on AI and innovation management using the behavioural theory of the firm to identify the application of AI systems in the innovation process, and illustrate the challenges that firms may face during the innovation process.

Our study is unique and distinctively different compared to the only existing literature review on AI and innovation management (Haefner et al., 2021) for a number of reasons. First, our study embraces a bibliometric and quantitative approach to examine the relevant literature, whereas Haefner et al. (2021) adopted a narrative approach. Second, the work of Haefner et al. (2021) is confined to "innovation management", while our study captures holistically the way AI has been researched in innovation studies. Third, bibliometric techniques allowed us to dig in depth about several key topics, and to portray the scholarly debate on the drivers and outcomes of AI adoption by firms trying to pursue product, process, and business model innovation.

As such, this work makes the following contributions. First, to the best of our knowledge, our study is the first (or among the first) to conduct a SLR on AI in the wider innovation research context (without a mere focus on innovation management) and to provide an integrated and holistic view of this emerging research area. Second, we leverage on several bibliometric techniques (e.g., citation analysis, co-citation analysis, bibliographic coupling, co-word analysis) as well as network analysis to scrutinize the intellectual structure emerging from the literature, and, subsequently, provide a comprehensive framework which sheds light on the drivers and outcomes of AI adoption for innovation. Third, we single out and examine the wide range of theoretical lenses adopted in this research area to enable a better theoretical and conceptual interpretation of AI in innovation research.

3. Methodology

To develop an updated synopsis of existing research at the intersection of AI and innovation and evaluate quantitatively the literature, we conducted a systematic literature review (SLR). SLRs are considered the appropriate tool to systematically assess and evaluate a given body of literature (Tranfield et al., 2003). We deployed a SLR method over other literature review methods for a number of reasons: first, SLRs are more objective than narrative literature reviews (Tranfield et al., 2003); second, SLRs allow to produce holistic conclusions stemming from a detailed, transparent and planned process that enable reproducibility (Cubric, 2020; Snyder, 2019; Williams et al., 2020); third, SLRs entail the adoption of a quantitative approach that allows to identify where there is research, but also where there are research gaps (Snyder, 2019; Tranfield et al., 2003), thus helping generate robust research agendas to advance the field (Williams Jr. et al., 2020). Thus far, the SLR method has been largely adopted in the social sciences (Tranfield et al., 2003) and more specifically in the management literature (Cubric, 2020; Williams et al., 2020; Zupic and Čater, 2015), with the aim of presenting findings in a relevant and accessible manner to scholars and decision-makers (Tranfield et al., 2003; Williams Jr. et al., 2020).

By following the SLR methodology proposed by Tranfield et al. (2003), and Williams Jr. et al. (2020), data was gathered by collecting documents from two key databases: Scopus and Web of Science (WOS) (Christofi et al., 2021). These databases were chosen as they assemble a collection of the most important sources of academic research and scholarly articles in the social sciences field (Vieira and Gomes, 2009).

The Elsevier owned and managed Scopus database is deemed one of the most complete scientific databases indexing research production across a myriad of academic disciplines. It covers more than 22,000 scientific publications from over 5000 international publishers (Mariani et al., 2022). The Clarivate owned Web of Science (WOS) Core Collection offers access to seven databases - Science Citation Index expand (SCIE), Social Sciences Citation Index (SSCI), Arts & Humanities Citation Index (AHCI), Emerging Sources Citation Index (ESCI), Conference Proceedings Citation Index (CPCI), Book Citation Index (BKCI), and Current Chemical Reactions and Index Chemicus, starting from 1900. WOS references cross-disciplinary research covering over 28,000 journals from 3300 publishers with high criteria standards and rigorous protocols (Gaur and Kumar, 2018; Mustak et al., 2021; Vanhala et al., 2020). Both databases allow organizing and integrating data retrieved from different sources (i.e., articles, books chapters, conference papers) in any bibliographic format for each cited reference. Additionally, this embedding feature guarantees the scientific rigour, making this attribute valuable for bibliometric analysis (Mustak et al., 2021) establishing reliability, validity and relevance of the documents retrieved in both databases (Mariani et al., 2018). To support our choice to produce a robust, accurate and effective research we used the same set of terms/keywords to perform an initial advanced search in both Scopus and WOS databases, as presented in Fig. 1.

Firstly, we identified multiple keywords based on recent (systematic) literature reviews and bibliometric studies focusing on artificial intelligence in the management and marketing field (see for instance Mustak et al., 2021). The keywords include "AI", "artificial intelligence", as well as keywords related to AI subfields and related enabling and supporting technologies and techniques such as "machine learning", "neural network*", "deep learning", "data mining". The Scopus database was searched by looking for combinations of the aforementioned AI-related keywords and "innovat*" in the title, abstract, or keywords (Williams et al., 2020; Christofi et al., 2021). This yielded 10,258 documents. In line with systematic literature reviews conducted elsewhere (Battisti et al., 2021; Christofi et al., 2021; Gaur and Kumar, 2018; Williams et al., 2020), we narrowed down our search considering only articles and review papers (Gaur and Kumar, 2018) in English language in the subject area (Christofi et al., 2021) of Business, Management and Accounting; Decision Science; Economics, Econometrics and Finance. This narrowed down the sample to 1272 articles. Secondly, we searched the WOS database core collection by employing the same combination of keywords previously used on Scopus to search publications. We also added the operator AND to confine the results to the area of Business, Management, Business Finance, Economics. This yielded 825 documents. We excluded all duplicates from our dataset (i.e., articles that were present in both databases were included only once in our final database), that led us to obtain a total of 1448 documents as our final sample. Finally, we retrieved the metadata for these 1448 articles which included author names, titles, country of corresponding author/s, total number of publications, citation counts (i.e., total citations, average article citations, and number of citing articles with and without self-citations), journal sources, keywords, and countries as well as institutional affiliations.

4. Data analysis and findings

This analysis and findings section is organized in several subsections. First, we present the descriptive analyses, followed by the bibliographic coupling and co-citation clusters analyses. Next, we elucidate the analysis of key co-occurrence and the temporal mapping of the central keywords. The final subsection reveals the findings related to the

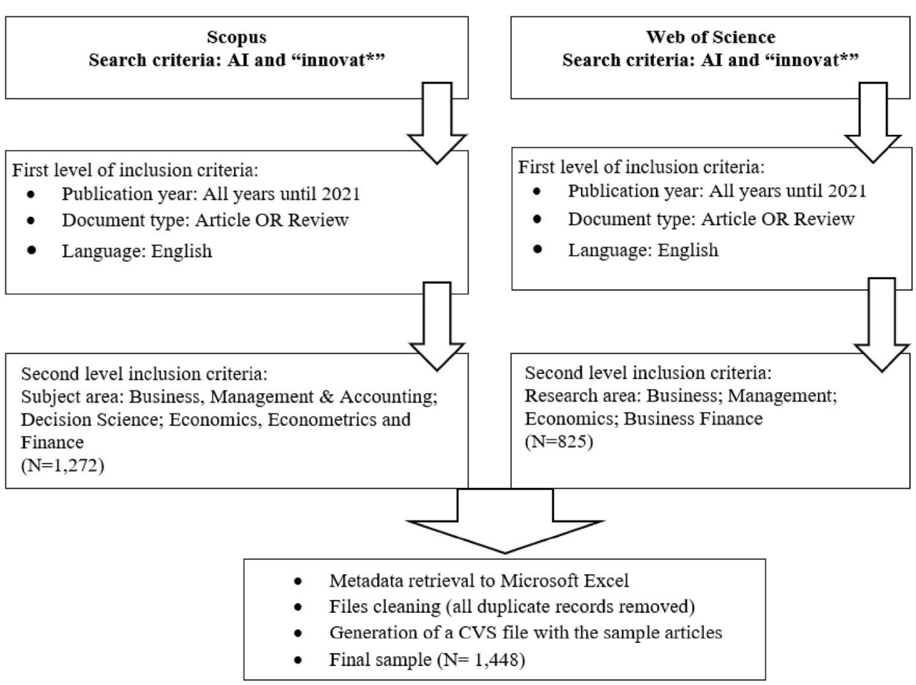

Fig. 1. Protocol details of this study.

theoretical lenses deployed to inform the literature field and the most used methodologies in the literature.

4.1. Descriptive analyses

In this section, we develop a descriptive analysis of the focal sample attained by means of our SLR queries. To achieve the aim of the analysis, we deployed the number of publications as a proxy of research productivity and the number of citations as a proxy of research impact.

4.2. Theoretical lenses of the works at the intersection of AI in innovation

In order to identify the different theoretical perspectives that innovation scholars have used to inform their studies, the abstracts were analyzed searching for the keywords "theory" and "model" to identify the theories and models that the articles contributed to Mariani et al. (2022). In total, 730 articles mentioned a theory or a model in the abstract. From those articles, 164 different theories and models were identified, and Table 1 provides a summary of the 5 most frequently used theories organized by frequency of mention.

4.2.1. Technological innovation system (TIS) theory

The technological innovation systems (TIS) framework is a popular tool for researching the emergence and growth of new technological systems. Technological innovation systems structurally consist of actors and institutions, as well as how they interact with each other (Markard, 2020). The goal of technological innovation systems theory is to improve systems-design understanding of innovation processes and is widely used in processes of system building (Musiolik et al., 2012; Musiolik,2020).

4.2.2. Fuzzy theories

Fuzzy theories are useful in explaining multiple reasoning processes. Fuzzy set theory is the most common approach to deal with difficult, subjective, and imprecise assessments, and it is useful for measuring the textual attributes of available data. Using fuzzy set approach, Gubán et al. (2019) developed an empirically based model to measure innovation performance and sustainability innovation potential technology. A fuzzy set approach was also applied by Beilin et al. (2019) to forecast financial indicators to determine the degree of competitiveness and attractiveness of businesses. Serrano García et al. (2017) used a fuzzy inference diagnostic system for organisational capacities for innovation in order to design organisational strategies to improve organisational capabilities for innovation in a university. Alidrisi (2021) used a fuzzy analytical network (ANP) to prioritize the 5Vs in Big Data as a decision-making platform in order to apply green supply chain management practices and improve supply chain finance.

4.2.3. Technology acceptance model (TAM)

The technology acceptance model (TAM) is one of the most popular models used to explain the antecedents of technology acceptance (Gao and Bai, 2014). According to TAM, perceived ease of use and perceived usefulness are important factors in predicting user acceptance of a technology (Davis, 1989). Lancelot Miltgen et al. (2013) combined elements of technology acceptance model (TAM), diffusion of innovations (DOI) and unified theory of acceptance and use of technology (UTAUT) to investigate individual acceptance of biometric identification. Recently Chatterjee et al. (2021b) combined a TAM model with a technology-organization-environment (TOE) framework to identify factors influencing the adoption of Industry 4.0 and especially AI in manufacturing and production firms.

4.2.4. Dynamic capabilities theory

Dynamic Capabilities theory is one of the most used theoretical lenses in management research to determine firms' strategies to adapt in a volatile environment. Dynamic capabilities allow firms to sense opportunities and threats, seize opportunities, and maintain competitiveness through reconfiguring the business assets and resources (Teece et al., 1997a, 1997b).

Dynamic capabilities theory is based on firms' ability to develop, integrate and restructure internal and external capabilities to enhance their competitive advantage (Teece, 2020). Warner and Wäger (2019) investigate how incumbent firms in traditional industries build dynamic capabilities for digital transformation. Based on senior executives' experiences with leading digitalization projects (including AI projects) at incumbent firm, they develop a model to uncover the factors that cause, facilitate, and obstruct the creation of dynamic capabilities for digital transformation. Recently, Gallego-Gomez and De-Pablos-Heredero (2020) combined dynamic capabilities theory and resource-based view approach to investigate the implementation of AI systems in the banking sector. The used approach was useful to determine how firms can build managerial skills focused on saving costs, increasing efficiency, customer satisfaction and competitive advantage.

4.2.5. Diffusion of innovation theory

The diffusion of innovation theory explains how new ideas, technology, or products developments ramp up and spread over time within a target community (Rogers, 2003). Diffusion innovation theory is widely used in information technology (IT) topics. Wang and Swanson (2007) investigate the launch of an information technology - professional service automation - to develop a framework of institutional entrepreneurship for launching IT innovations. To investigate factors determining firms' intention to adopt Big Data Analytics (BDA) in logistics and supply chain, Lai et al. (2018) combined diffusion theory with th technology-organization-environment (TOE) framework to assess 210 organizations intentions to adopt BDA. An exemplary empirical study from Butt et al. (2021) combined innovation diffusion theory, technology acceptance model, and flow theory in order to explore the roles of perceived easiness, usefulness, advantage, compatibility, enjoyment, customization, and interactivity of the gamers' intention to play with AI-powered avatars.

4.3. Methodology of the studies

To provide an overview of the different methodologies adopted in the studies in our systematic literature review, the abstracts were analyzed searching for the relevant keywords in relation to the type of

Table 1
Most frequently used theories.

Theories	Sample articles
Technological innovation systems (TIS)	• Musiolik et al. (2012) • Musiolik et al. (2020)
Fuzzy theories (i.e., fuzzy set theory, fuzzy logic)	• Serrano García and Robledo Velásquez (2013) • Beilin et al. (2019)
Technology acceptance model (TAM)	• Lancelot Miltgen et al. (2013) • Chatterjee et al. (2021b)
Dynamic Capabilities	• Randhawa et al. (2016) • Ciampi et al. (2021)
Diffusion of Innovation theory	• Wang and Swanson (2007) • Butt et al. (2021)

Table 2
Articles' most frequent methodological approaches.

Methodology	Sample Articles
Quantitative	Boon and Park (2005); Ali et al. (2020)
Qualitative	Warner and Wäger (2019); Mariani and Fosso Wamba (2020)
Conceptual	Coenen and Díaz López (2010); Antons et al. (2020);
Literature review	Gunther et al. (2017); Haefner et al. (2021)
Mixed methods	Tu (2018); Harwood and Garry (2017)

methodology in the articles. As clear from Table 2, most of the studies (39%) in our database adopted an empirical quantitative approach; 35% are conceptual studies; 24% of the studies deployed an empirical qualitative approach; and 2% entail literature reviews. We also found 2 studies using a mixed methods research design and both focus on IoT topic. Table 2 provides an overview of the most used methodological approaches.

4.4. Publications by year

We mapped the evolution of publications on the topic of AI in innovation field over time until November 2021. Fig. 2 shows the frequency distribution of studies in AI in innovation studies over time. The growing number of published studies related to artificial intelligence in innovation, especially in recent years, is reflective of the increasing academic interest in the AI field. However, in line with other literature reviews conducted recently, it seems that we are still at the early stages of research (Di Vaio et al., 2020; Mariani et al., 2022 Mustak et al., 2021).

Relevant literature was produced in the field of AI in innovation in the '80s and specifically with a publication in *Futures* in 1981. Two years later a new article was published in *Long Range Planning.* In the '90s around 3 to 4 papers were published, recording a rise in the number of publications by the end of 1999. This trend continued in the first years of 2000s. Additionally, the number of publications tripled around the year 2007 with an exponential growth in the number of publications in the following years. While we did not manage to cover entirely 2021 (at the moment of writing), more than 280 articles were published in 2021.

4.5. Publications by country

In terms of geographical distribution, our queries retrieved publications from multiple countries. The top 5 countries in terms of number of publications are illustrated in Table 3. The US dominates the ranking with 227 documents (and 5968 citations), followed by China (151 publications), Italy (125 publications), Germany (123 documents), and the United Kingdom (119 publications). This geographical distribution appears to reflect the countries' technological achievements, which may be driven by large-scale government funding and national industrial policies that encouraged investments in Industry 4.0 technologies in general and AI in particular (Mariani et al., 2022).

4.6. Publishing activity by journal

The growing number of publications is spread across a broad variety of research outlets. The journals publishing most of the research on AI and innovation are represented in Fig. 3. *Technological Forecasting and Social Change* is the outlet hosting the highest share of articles (159), with the first publication in 1994.

One of the first articles at the intersection of AI and innovation was published in 1981 on the topic of Innovation, automation and the long-

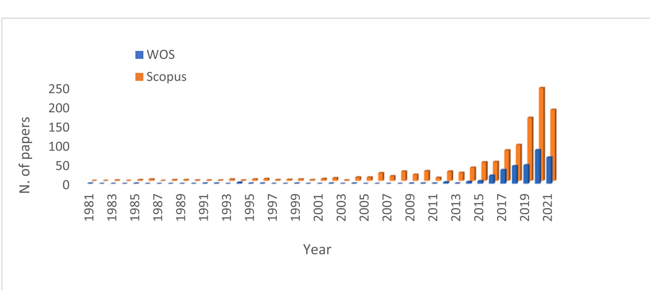

Fig. 2. Frequency distribution of articles on Artificial Intelligence in innovation literature.

Table 3
Top countries in terms of research publications on AI in Innovation.

Country	N. Publications	N. Citations
USA	227	5968
China	151	1904
Italy	125	2490
Germany	123	2348
United Kingdom	119	3280

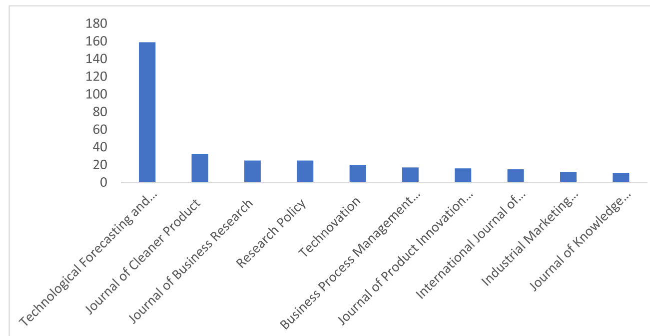

Fig. 3. Top 10 publications outlets on AI in innovation research.

wave theory, by Rod Coomb, in *Futures.* The number of publications increased in the ensuing years. After 2004, we can detect a rise in the number of published articles, with ten articles published in diverse research outlets. After 2012, the number of published articles almost quadruples in number (33) reaching the top with 117 publications in 2017. In 2021, more than 280 articles have been published to date by the time of writing this paper.

4.7. Bibliometric analysis

In recent years, a growing number of literature review articles have employed bibliometric analysis to measure and map (multidisciplinary) research, and identify knowledge gaps in the social sciences and the management field (Zupic and Čater, 2015). Bibliometric analysis is widely used as a set of analytical techniques and methods to identify leading authors and seminal work (Donthu et al., 2021), and identify and map novel research trends (Mariani and Borghi, 2019). In Table 4, we list the methods used to perform our bibliometric analysis.

To map the knowledge revolving around AI in innovation studies we used the VOSviewer (Version 1.6.17) software as it is an open free software that enables researchers to conduct bibliometric data analysis easily. The use of free software contributes to the transparency, reliability and replicability of the research (Antons et al., 2020).

To explore the connections of leading researchers in the field, to identify the status of the present knowledge, to identify the most influential publications leading the field we deployed bibliographic coupling by co-citations network and journal co-citation analysis. By analysing connecting documents often cited together in another publication through bibliographic coupling we can assume thematic similarity, allowing to illustrate the intellectual structure of a research field (Donthu et al., 2021). This methodology provides a robust and objective scientific analysis for science mapping (Donthu et al., 2021; Mariani et al., 2022) reducing the risk of biases.

To identify the relationships among cited publications to understand the evolution of fundamental themes we developed co-citation clusters. Bibliometric maps and graphical representations (Van Eck and Waltman, 2010) were developed. To identify existing relationships between topics and concepts by connecting words across the literature pool we employed Keyword co-occurrence analysis. To map how topics and concepts evolve in the literature over time, we mapped central keywords

Table 4
List of bibliometric analyses performed in this study.

Bibliometric Method	Algorithmic computational Tool	Aim
Bibliographic coupling by co-citations network andjournal co-citation analysis	VOSviewer	To explore the connections of leading researchers in the field, to identify the status of the present knowledge, to identify the most influential publications leading the field.
Co-citation clusters and landmark publications	VOSviewer	To identify the relationships among cited publications to understand the evolution of fundamental themes. To identify core knowledge and its contribution to the field over time.
Keyword co-occurrence analysis	VOSviewer	To identify existing relationships between topics and concepts by connecting words across the literature pool.
Mapping central keywords over time	VOSviewer	To map how topics and concepts evolve in the literature over time.
Density visualization	VOSviewer	To identify the conceptual/theoretical base of the research focuses on the literature.

over time. To identify the conceptual/theoretical base of the research focuses on the literature we deployed density visualization.

4.7.1. Bibliographic coupling and journal co-citation analysis

The advancement of scientific research is deeply connected with the recognition of the work of other scientists that can take the form of citations. Accordingly, techniques such as bibliographic coupling are particularly relevant to capture this form of recognition. In particular, bibliographic coupling is based on the assumption that two or more publications that share common references are related as far as their content is concerned (Donthu et al., 2021). Bibliographic coupling represents a robust technique to illustrate how a new research stream is evolving over time (Mariani and Borghi, 2019; Mariani et al., 2022; Zupic and Čater, 2015). Table 5 depicts the most prominent researchers that have examined AI in innovation studies.

The journal bibliographic coupling and co-citation analyses allow identifying the journals hosting the highest share of publications in the focal area (Zupic and Čater, 2015). Fig. 4 illustrates the bibliographic coupling network between leading academic journals with articles in AI in innovation and displays the dominance of several international journals such as *Technological Forecasting and Social Change, Journal of Cleaner Production, Journal of Business Research*, *Research Policy*, and *Technovation.*

4.7.2. Co-citation clusters

For the co-citation cluster analysis, we identified semantic similarities based on citation connection across the reference lists to measure publications' influence. Publications cited together are similar in their content, and deal with core themes and concepts. These prominent publications contribute to the development of the research on AI in innovation over time (Donthu et al., 2021). A co-citation analysis represents a reliable technique to make sense of the connections among documents in the reference lists across publications in a literature base (Zupic and Čater, 2015). When a co-citation network is constructed at the level of cited reference, its can allow to identify the connection of the semantic similarities network useful to uncover seminal work (Donthu et al., 2021). Fig. 5 depicts the authors network in the literature of AI in innovation. In line with other bibliometric work in the social sciences, we consider by default articles with a minimum of 50 citations of a cited reference in the literature pool. This produced seven clusters from our sample of 1448 documents.

The identified clusters reveal the knowledge foundations of the most influential publications and thematic similarities (Donthu et al., 2021) in the field on AI in innovation research.

Cluster 1 (in green) includes studies on servitization and industry 4.0, smart tourism, IoT and dynamic capabilities. Cluster 2 (in dark blue colour) includes studies about smart cities and open innovation. Cluster 3 (in light blue) consists of studies pertaining to innovation systems and networks in technological innovation. Studies in cluster 4 (red colour) revolve around technology forecasting and technological opportunities. Cluster 5, in purple colour, entails mostly studies on knowledge management, open innovation and technological change. Cluster 6, in orange colour, includes studies linked to customer acceptance of digital technologies. Last. Cluster 7 (yellow) includes studies on green innovation and supply chain.

4.7.2.1. Digital transformation cluster. In cluster 1, the studies mostly revolve around the digital transformation and the related phenomena of the industry 4.0 and servitization. Some authors have argued that the Digital transformation is allowing firms to improve their business models, restructure their operations, and create new business models (Warner and Wäger, 2019). In the manufacturing industries, the Industrial Internet of Things (IIoT) brings about a modification of business models that rely less on lower skilled workers and boost efficiency (Arnold et al., 2016).

Digital technologies allow firms to provide digital solutions to the customers whilst collecting customer data to empower capabilities affecting the manufacturing processes (Frank et al., 2019). Also, service industries are being radically transformed by digital technologies including AI as well as big data and IoT (Borghi and Mariani, 2021;

Table 5
Leading researchers in the field of AI in Innovation.

Authors	Title	Journal	Citation counts
Ostrom et al. (2015)	Service Research Priorities in a Rapidly Changing Context	Journal of Service Research	713
Erevelles et al. (2016)	Big Data consumer analytics and the transformation of marketing	Journal of Business Research	326
Huang and Rust (2018)	Artificial Intelligence in Service	Journal of Service Research	287
Randhawa et al. (2016)	A Bibliometric Review of Open Innovation: Setting a Research Agenda	Journal of Product Innovation Management	277
Makridakis (2017)	The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms	Futures	265
Harrison et al. (1996)	Innovative firm behavior and local milieu: Exploring the intersection of agglomeration, firm effects, and technological change	Economic Geography	257
Loebbecke and Picot (2015)	Reflections on societal and business model transformation arising from digitization and big data analytics: A research agenda	Journal of Strategic Information Systems	235
Kostoff et al. (2004)	Disruptive technology roadmaps	Technological Forecasting and Social Change	223
Karmarkar (2004)	Will you survive the services revolution?	Harvard Business Review	214

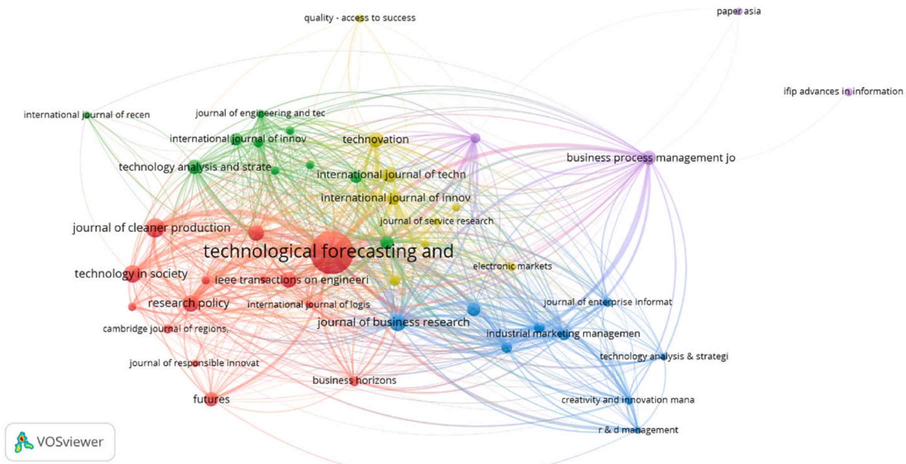

Fig. 4. Co-citation network of outlets in the literature on AI in innovation research.

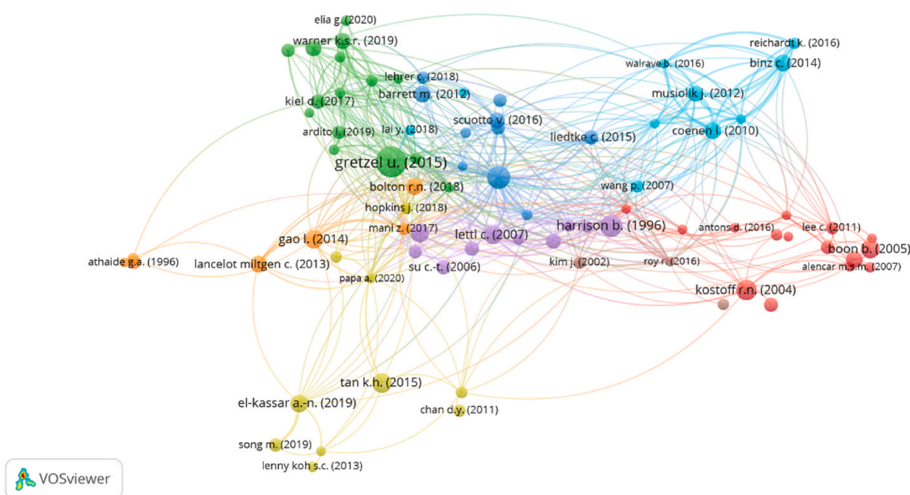

Fig. 5. Clusters identified through bibliographic coupling.

Mariani and Borghi, 2019; Mariani and Borghi, 2021). Additionally, digital technologies are supporting smart destinations whereby data are deployed in real time to enhance product development and improve value co-creation (Gretzel et al., 2015).

4.7.2.2. Smart cities and open innovation cluster. Cluster 2 embeds studies pertaining to open innovation and smart cities. In recent years, organizations have adopted a more open approach to innovation by cooperating with external actors exchanging knowledge, technology, and resources beyond organisational boundaries in a collaborative manner (Randhawa et al., 2016). In the digital era, large amount of data is produced from open innovation (Scuotto et al., 2016) and this data can potentially feed AI for product innovation.

Smart cities are public-private networks that provide services to citizens and their organizations with technological support, whilst taking into account the social and economic impact on society (Abella et al., 2017), generating vast amount of data through open innovation. Organizations collaborative efforts and cooperation in the network (Czakon et al., 2020) combined with web-based applications collective knowledge, contribute to transform smart cities into innovation ecosystems (Scuotto et al., 2016). By generating and compiling large quantities of data, smart cities can improve their internal processes and put into action collaborative options to create innovative products and services (Abella et al., 2017).

4.7.2.3. Technological innovation systems cluster. In cluster 3 we found studies focused on innovation systems and networks in technological innovation. An innovation system is defined as an ensemble of actors, organizations and institutions that collectively develop, diffuse, and utilize a new technology or innovation (Coenen and Díaz López, 2010). An important component of innovation systems are system resources - collective structures such as standard processes, development programmes, common goals, or experimental facilities - that all members of the network can use collaboratively (Musiolik et al., 2020).

4.7.2.4. Technology forecasting and technological opportunities cluster. Studies in cluster 4 are mainly related to technological forecasting and technological opportunities. Technology forecasting has been applied by firms to enhance management capabilities to examine rapidly available information to detect emergent technologies through visual representations (Zhu et al., 2002). In a different study (Boon and Park, 2005), data mining techniques have been deployed to mine R&D document databases for patent analysis. The information extracted is used to create patent maps and patent networks for technology opportunities that can be used to support new product development. The graphical representation of the relationships between patents in the networks helps firms identify possible disruptive technologies at the early stages of the innovation process, thus supporting technology forecasting (Kostoff et al., 2001) and the creation of innovative products (Kostoff et al., 2004).

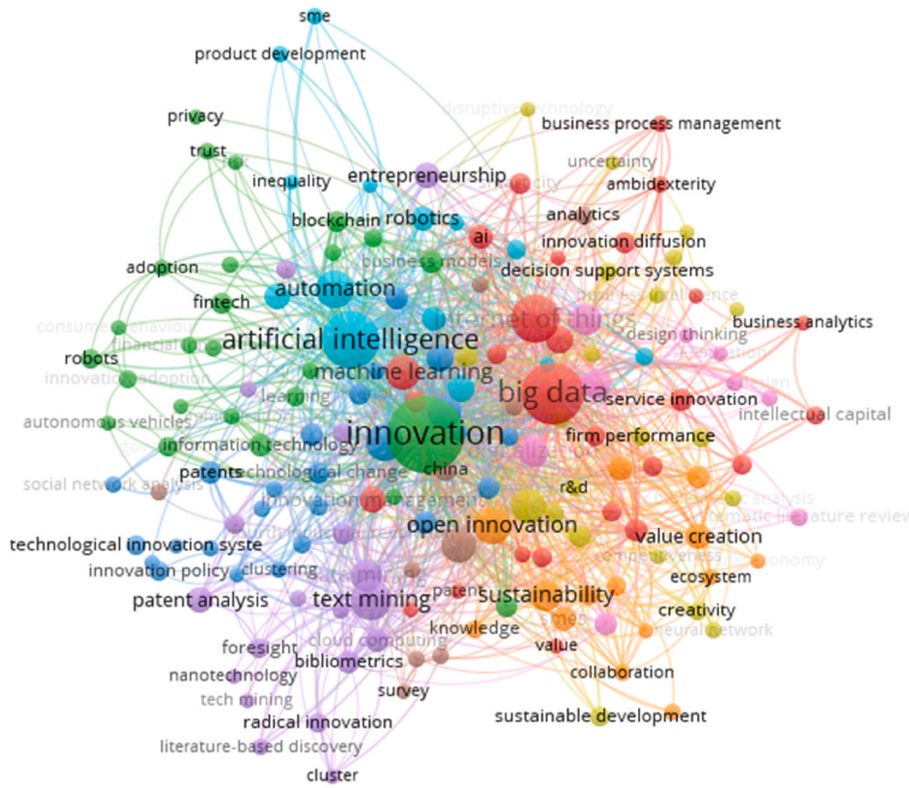

Fig. 6. Keyword co-occurrence in the literature on AI in Innovation literature.

4.7.2.5. Knowledge management and radical innovation cluster. Cluster 5 includes studies revolving around knowledge management, open innovation and technological change. Knowledge management is a critical component in technological innovation. The implementation of knowledge management practices has been found to enhance product and process innovation (Lee et al., 2013). Other studies have found that the development of a firm's internal knowledge management capability for radical innovation based on open ecosystems leveraging internal and external data, strengthens firms innovation capability (Santoro et al., 2018). In disruptive technologies implementation such as IoT, firms' involvement with consumers plays a key role as it allows to better manage firm's knowledge of the consumer base in relation to their proneness to adapt new technologies (Lettl, 2007). Additionally, customer knowledge for innovative product development plays an important role for knowledge management as customer attitudes can help firms reduce project risk whilst promoting business competitiveness (Su et al., 2006).

4.7.2.6. Digital technology consumer acceptance cluster. Cluster 6 entails mostly studies on consumer acceptance of digital technologies. Lancelot Miltgen et al. (2013) investigate the challenges of end-user biometrics (i.e., fingerprints, face recognition, iris recognition, hand geometry, and voice recognition) to assess consumers' AI acceptance. They found that compatibility, perceived usefulness and facilitating conditions are the most important variables in biometrics systems acceptance. Consumer acceptance of digital technologies and AI in service innovation has been investigated by Bolton et al. (2018): they emphasize that there are customer experience barriers involving automated technology such as virtual assistants and service robots, when the aim is to deliver customer service excellence in services.

4.7.2.7. Green innovation and supply chain cluster. Cluster 7 embeds studies that mostly revolve around green innovation and the application of big data on the development of green initiatives in the supply chain. Studies on the logistic industry show the importance of relying on big data analytics and IoT for operational cost reduction, improve workers' safety and lower the environmental impacts (Hopkins and Hawking, 2018). Other studies focus on how big data and related AI can be implemented to improve green product and green process innovation on the supply chain for sustainable performance and competitive advantage (El-Kassar and Singh, 2019). Last, it has been found that big data can support firms to enhance their supply chain innovation capabilities to increase competitiveness (Tan et al., 2015), and promote eco-efficiency, eco-innovation, and sustainability (Kiani Mavi et al., 2019).

4.7.3. Landmark publications

Based on the co-citation clusters network, we can identify the publications that have contributed to shaping and developing research on AI in innovation studies. Table 6 identifies works at the intersection of AI in innovation. For this analysis, we applied a normalization association strength method (Van Eck and Waltman, 2010) to measure the link strength between the publications based on co-citation patterns. The association strength method captures how frequently two articles are cited together by others, and how frequently two articles co-occur in the reference list of another publication (Zupic and Čater, 2015). The assumption is that shared articles typically disclose thematic similarities that reveal knowledge foundations and their contribution to the field over time. As clear from the table, most of the works are related to specific subfields of AI involving machine learning and data mining.

Table 6
Landmark publications on AI in Innovation literature.

Authors	Title	Journal
Lavalle et al. (2011)	Big data, analytics and the path from insights to value.	MIT Sloan Management Review
Chen et al. (2012)	Business Intelligence and analytics: From big data to Big Impact.	MIS Quarterly
Wamba and Mishra (2017)	How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study.	International Journal of Production Economics
Wamba and Mishra (2017)	Big data analytics and firm performance: effects of dynamic capabilities.	Journal of Business Research
Davenport et al. (2012)	How big data is different.	MIT Sloan Management Review
Manyika et al. (2011)	Big data: the next frontier for innovation, competition, and productivity	McKinsey Global Institute
Mcafee and Brynjolfsson (2012)	Big data: the management revolution.	Harvard Business Review
Akter and Wamba (2016)	Big data analytics in E-commerce: a systematic review and agenda for future research.	Electronic Markets
Erevelles et al. (2016)	Big Data consumer analytics and the transformation of marketing.	Journal of Business Research
Gandomi et Haider (2015)	Beyond the hype: Big data concepts, methods, and analytics.	International Journal of Information Management

4.7.4. Keywords co-occurrence analysis

We applied a keyword co-occurrence analysis to proxy the relationships between topics and concepts in the field. Keyword co-occurrence analysis is based on the assumption that the words appearing together are linked to each other by a thematic relationship. Furthermore, we mapped the evolution of the keywords and concepts to understand how they evolved and developed over time. Fig. 6 illustrates the keyword co-occurrence networks in the literature pertaining to AI in innovation studies. To map out the keywords (and to subsequently explore the development of central keywords in the literature), we ran a co-word analysis for network visualization. As is clear from the figure, "innovation" displays the highest co-occurrence frequency values (this is the reason why it is the biggest node of the network), and it is well connected with other words such as "artificial intelligence", "big data", "Internet of Things", and "automation".

To name the keyword co-occurrence networks in our analysis, we used the keywords with the highest occurrence in each keyword co-occurrence network: innovation, artificial intelligence, big data, and Internet of Things.

In parallel, and in line with the thematic analysis approach adopted in earlier studies (Braun and Clarke, 2006; Jedynak et al., 2021) the researchers read carefully the data, identifying codes and later themes relevant for the focal phenomenon. The themes emerging from the qualitative thematic analysis converged with the themes identified by means of the keyword co-occurrence analysis. Accordingly, the overall approach followed for the thematic analysis was eventually a mixed method approach entailing both quantitative and qualitative approaches.

4.7.4.1. Innovation. The concept of technology-led innovation has received a lot of attention from academics. For example, technological developments in the manufacturing (Rosenthal, 1984) and construction (Tatum and Funke, 1988) industries, as well as related innovation, have been extensively investigated. New technologies were integrated into corporate operations in various sectors as a strategy to boost productivity, efficiency, competitiveness, and performance (Akter et al., 2020) respond quickly to changing markets (Mariani and Nambisan, 2021), and stay competitive (Hutchinson, 2021).

4.7.4.2. Artificial intelligence. AI has been defined as systems designed with the " objective of creating human-like behaviour in machines for perception, reasoning, and action" (Prem, 2019, p.2). AI has risen in power as a result of significant advances in computational capacity and a wide range of new technologies (e.g., computer vision, machine learning, and natural language processing) (Mariani et al., 2022), as well as the blast of data to train algorithms (Bornet et al., 2021). The growing number of publications over time attests to AI's growing relevance in innovation, particularly in terms of how AI supports innovation decisions (Kakatkar et al., 2020). AI enabling digital experimentation and digital innovation (Mariani and Nambisan, 2021), AI and sustainable business models (Di Vaio et al., 2020), AI in supply chain management (El-Kassar and Singh, 2019), strategic uses of AI (Yams et al., 2020).

4.7.4.3. Big data. In a wide range of industries and contexts, big data helps companies manage internal and external data to uncover new market possibilities and maintain their competitive advantage (Zhang et al., 2019). For example, using big data tools to retrieve, process, analyse, and report customer online opinions and behaviours allows companies to create more tailored products (Ciampi et al., 2021) and services (Mariani and Borghi, 2020; Mariani and Borghi, 2021) that provide them a competitive edge. Furthermore, big data predictive analytics allows businesses to improve product, service, and business model innovation (Blackburn et al., 2017; Mariani and Nambisan, 2021).

4.7.4.4. Internet of things (IoT). Kevin Ashton coined the term "Internet of Things" in the field of supply chain management in 1999. The adoption of IoT technology and devices using IoT technology (biometrics, sensors, radio frequency identification (RFID)) allows devices and services to interact autonomously (Jedynak et al., 2021). For example, IoT technology has been implemented in health care sector (Papa et al., 2020); in the agricultural sector (Gurbuz and Ozkan, 2020); or in the context of smart cities (Scuotto et al., 2016b).

4.7.5. Mapping central keywords over time

To explore the development of central keywords over time, we run a dynamic co-word analysis. Fig. 7 illustrates the evolution of concepts in the focal research area.

The development of central keywords over time suggests that studies in nanotechnology patenting, neural networks, and decision support systems have become more frequent around 2011. Table 7 illustrates the frequency of the keywords in the literature. Starting from 2013, the publications on data mining and innovation adoption emerge. Around 2015, technological innovation and process innovation studies become more frequent and, in 2016, the keywords start highlighting text mining and product innovation. In 2017, concepts such as business model, product development, governance, crowdsourcing and innovation diffusion become increasingly frequent in the focal literature.

Around 2018, studies including the words "big data", "IoT", "artificial intelligence", "disruptive innovation", "robotics" and "cloud computing" become more numerous. Studies published produced in 2019 start displaying more frequently words such as Industry 4.0, digital transformation, digitalization, business model innovation, digital innovation, blockchain and sustainably, whereas studies published in 2020 tend to focus on digital technologies and circular economy. The increasing relevance of concepts related to sustainability – such as the circular economy – displays that environmental and social dimensions tend to become more relevant, given the increasing number of firms committed to sustainable innovation. Interestingly, it seems that increasing use of AI related keywords reflects technological

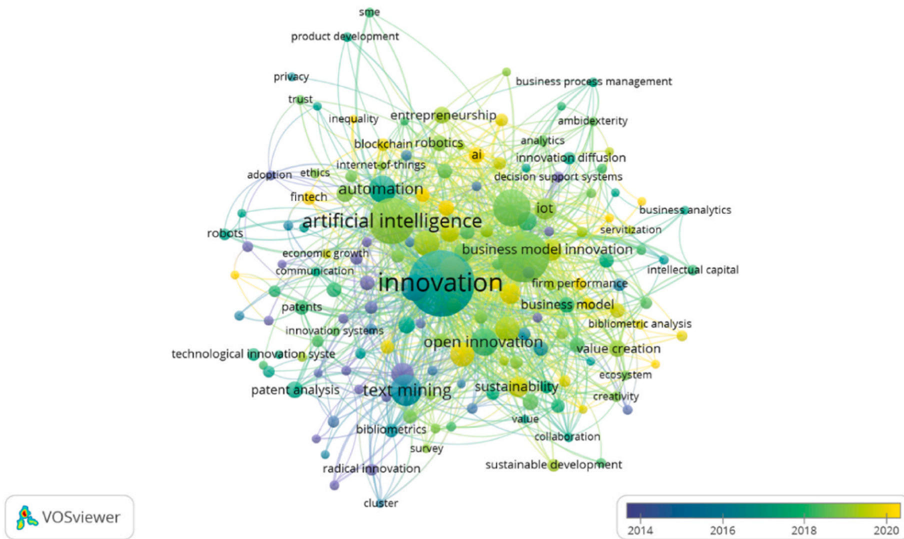

Fig. 7. Temporal mapping of central keywords on AI in the Innovation literature.

Table 7
Frequency of keywords.

Keyword	Occurrences	Total link strength
Innovation	686	2825
Artificial Intelligence	227	1005
Big Data	209	921
Automation	109	473
Data mining	102	496
IoT	102	460

advancements of AI, as a consequence of the increasing large-scale government financing of AI initiatives across different sectors of the economy (Mariani et al., 2022).

4.7.6. *Density visualization*

By leveraging density visualization techniques, we identified clusters of concepts connected with keywords appearing together in the literature. Density visualization provides a snapshot of the distribution of variables (in our case keywords), using a kernel density (Van Eck and Waltman, 2010). Kernel density is based on the probability density function of variables by co-term occurrences. From an operational viewpoint, for the density visualization, we created a map based on text data, after having extracted information from the title and the abstract fields of the articles and by subsequently applying a full counting method. By default, a minimum of 20 occurrence threshold of a term in the literature pool generated 5 major clusters by relevance. Fig. 8 illustrates a density visualization of the prominent terms' clusters. The cluster displaying the highest density is highlighted in green colour and entails studies related to the application of big data analytics, dynamic capabilities, business processes, sustainable development, organisational firm performance. A second cluster, red coloured, consists of studies on technology development and technological forecasting, text and data mining, patenting and innovation performance. The dark blue colour cluster entails studies on product innovation, digital technologies, digital platforms and digital innovation. The yellow-coloured

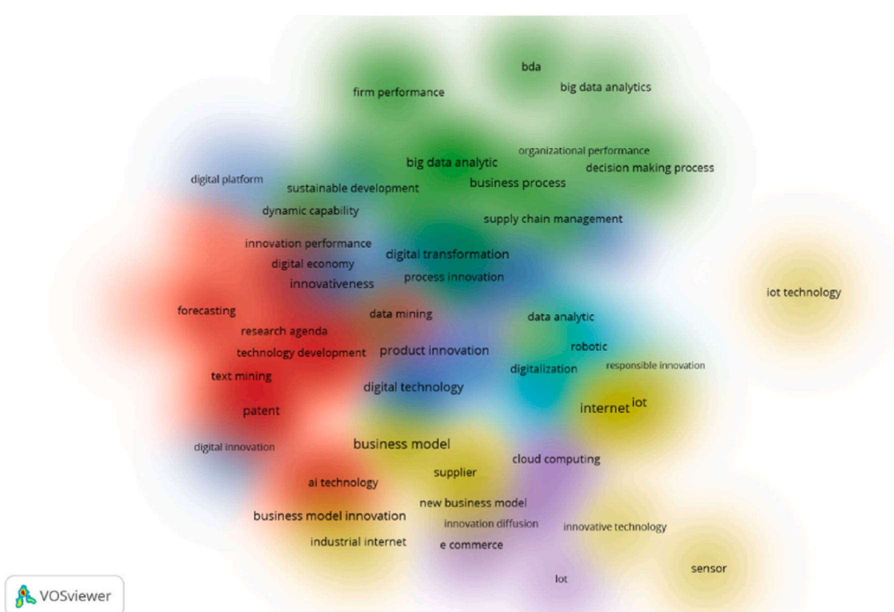

Fig. 8. Density visualization of the prominent terms in the literature on AI in innovation studies.

cluster includes studies on business models, industrial internet, innovative technology, IoT technology and sensor technology. Finally, the cluster in purple embeds research on IoT adoption, bringing together concepts of e-commerce, cloud computing and innovation diffusion.

4.8. Analysis of the most cited articles

We focused on the 30 most cited documents in our database as those articles offer valuable contributions to the research field representing reference points for scholars doing research in the field (Snyder, 2019). In line with other SLRs guidelines (e.g., Donthu et al., 2021) we identified in 120 the minimum number of citations for the articles to be part of this part of the analysis. After and in depth reading, we created a matrix reporting: the research topic; the nature of the study (conceptual or empirical); the research design (methodology); the time frame (cross-section or longitudinal); the theory adopted; the level of analysis (institutional, organizational, individual); in the case of empirical and quantitative studies: dependent variable, independent variables, moderating and mediating variables. The matrix can be useful to portray the different feature of the most cited studies. Table 8 portraits the most cited articles in our literature sample and is organized from the most cited to the least cited article.

Subsequently we analysed the most recurring words in the titles and abstracts of the articles included in our database (N=1,448) by means of a word cloud visualization. A word cloud graphically represents the most frequent terms appearing in the titles and abstracts of the articles; a word that appears more frequently displays a greater font size. Figure 9 (see Fig. 9) illustrates such word cloud. At a short glance, it seems that the most recurring words are "innovation" (this is by construction, given the choice of terms for the search query) and "technology".

4.9. A framework encompassing drivers and outcomes of AI adoption

To map out extant research into our study framework depicted in Fig. 10 we group the articles into two groups: drivers of AI adoption for innovation (Table 9) and outcomes of AI adoption (Table 10). We discuss the drivers and the outcomes of our framework in the ensuing subsections.

4.9.1. Drivers of AI adoption for innovation

We analyzed the literature to identify the drivers of AI adoption for innovation. Table 9 categorizes and illustrates studies revolving around the drivers of AI adoption for innovation. We categorized the studies into three different categories: economic drivers (cost, productivity, time, decision-making), technological drivers (big data, IoT, digital platforms), and social drivers (sustainability, waste management).

4.9.1.1. Economic drivers. When firms decide to adopt AI technology, they can do it for economic reasons such as cost reduction (Rose et al., 2020; Verganti et al., 2020), compression of time for new product development (Chou and Kimbrough, 2016; Hutchinson, 2021), enhancement of firm productivity (Hwang and Katayama, 2009; Kayser et al., 2018; Li et al., 2019; Makowski and Kajikawa, 2021) and support decision-making processes leading to better economic outcomes (Havins, 2020; Paredes-Frigolett and Gomes, 2016; Yilmaz Eroglu and Kilic, 2017).

4.9.1.1.1. Costs. To reduce costs, firms adopt AI systems to help them to reduce manufacturing costs which typically translate into offering products and services at competitive prices (Verganti et al., 2020). Additionally, the adoption of AI empowered systems promotes a reduction of R&D costs, enabling firms to compress the costs incurred to create and design new products (Rose et al., 2020).

4.9.1.1.2. Productivity. AI implementation allows firms to improve their operations, particularly in the manufacturing industry. Typically this involves enhancing assembly lines processes, and ultimately increasing productivity (Hwang and Katayama, 2009). Additionally, the adoption of automated technology such as self-innovating AI (Makowski and Kajikawa, 2021) could independently identify new opportunities for new product development, while controlling productivity and improving manufacturing capacity (Li et al., 2019). As AI systems generate large amount of valuable data, big data analytics firms could make this data useful to make transformation process more efficient and effective (Kayser et al., 2018).

4.9.1.1.3. Time. Time is of the essence and a key element in the analysis of technology-enabled innovation. Firms can spend time improving existing products (incremental innovation) versus developing new products (radical innovation). AI adoption allows firms to save time for both incremental and radical product innovation (Chou and Kimbrough, 2016), and to dedicate more time to research and development (Hutchinson, 2021).

4.9.1.1.4. Decision-making. The adoption of AI models can support firms' decision-making to improve financial performance (Havins, 2020). For instance, some studies have illustrated the Hybrid Genetic Local Search Algorithm to identify factors that can better support decision making in firms aiming to enhance innovation performance (Yilmaz Eroglu and Kilic, 2017). The Multi-criteria decision analysis for automated data retrieval from structured and unstructured data sources and platforms (e.g., Internet) has been found relevant to support not only innovation, but also decision-making processes (Paredes-Frigolett and Gomes, 2016) to improve financial performance.

4.9.1.2. Technological drivers. Firms' adoption of innovative AI technology allows them to manage a huge amount of structured and unstructured data available from different sources. Big data (Blackburn et al., 2017; Caputo et al., 2020; Ciampi et al., 2021; Zhang et al., 2019), IoT (Butschan et al., 2019; Gurbuz and Ozkan, 2020; Papa et al., 2020) and digital platforms (Antons et al., 2020; Klein et al., 2020; Thorleuchter and Van Den Poel, 2016) are the most common technological drivers for firms adopting AI to innovate.

4.9.1.2.1. Big data. The adoption of big data helps firms to manage internal and external data to identify new market opportunities and to maintain their competitive advantage in a wide range of industries and contexts (Zhang et al., 2019). For example, the use of big data tools to retrieve, process, analyse and report customer online opinions and behaviours allows to develop more customized products (Ciampi et al., 2021) and services (Mariani and Borghi, 2020; Mariani and Borghi, 2021) that allow firms to gain a competitive advantage. Additionally, the implementation of AI based analytical tools to manage large datasets allows firms to make better R&D decisions. Moreover, predictive analytics stemming from big data allow firms to enhance product, service and business model innovation (Blackburn et al., 2017; Mariani and Nambisan, 2021). Big data plays a critical role in accelerating firms' sensing capabilities to respond to rapid market changes and thus improve firms' economic performance (Caputo et al., 2020).

4.9.1.2.2. Internet of things (IoT). The industrial internet of things (IIoT) represents the expansion and application of the internet of things (IoT) throughout the manufacturing industry. The implementation of IIoT improves firms' productivity, and provides real time analytics to increase the efficiency of operations. In the context of IoT, the adoption of smart wearable healthcare (SWH) devices using IoT technology (biometrics, sensors) that collects, monitor and control individuals' health allow the firm to collect data that can support decision-making process (Papa et al., 2020) and develop more tailored healthcare services. In the agricultural sector, smart IoT applications are being implemented into the supply chain, with three objectives: allowing farmers to better plan the seeding and harvesting activities; deploying analytics to tailor services; reducing the ecological footprint (Gurbuz and Ozkan, 2020).

4.9.1.2.3. Digital platforms. Digital platforms can be defined as a combination of digital technology applications which facilitate the

Table 8
Top 30 Works at the intersection of AI in Innovation.

Article (author and title)	Type of article	Research Topic	Dependent Variable/s	Independent Variable/s	Moderating	Mediating	Theory adopted	Methods adopted	Empirical setting	Longitudinal or cross sectional	Level of analysis	Citation counts
Ostrom et al. (2015) Service Research Priorities in a Rapidly Changing Context	Empirical /Mixed methods	Investigate technological innovation in service research	N/A	N/A	N/A	N/A	Service theory	Mixed methods	Qual: 23 roundtables with 19 academics Quant: 334 surveys	2013/2014	37 countries	713
Gretzel et al. (2015) Smart tourism: foundations and developments	Conceptual	Explore the evolution of smart tourism ecosystems to propose further research	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Organizational	509
Erevelles et al. (2016) Big Data consumer analytics and the transformation of marketing	Empirical/ Qual	theoretical framework that explores when and how Big Data leads to a firm's sustainable competitive advantage	Consumer insights	-consumer activities record as Big Data, - extracting insights from Big Data - utilizing insights to enhance dynamic/adaptive capability	physical, human, and organizational capital resources	N/A	Resource-based theory (RBT)	Inductive/ Deductive reasoning	N/A	N/A	N/A	326
Huang and Rust (2018) Artificial Intelligence in Service	Empirical/ Quant	Theory of job replacement	AI job replacement	- mechanical analytical intuitive and empathetic intelligences	N/A	N/A	N/A	Mathematical model base to observe the development of AI with respect to the 4 intelligences	N/A	N/A	N/A	287
Randhawa et al. (2016) A Bibliometric Review of Open Innovation: Setting a Research Agenda	Conceptual/ Literature review	Study to investigate the development of Open Innovation concept over time	N/A	N/A	N/A	N/A	N/A	Co-citation, and text mining by deploying Leximancer and 321 Scopus articles	N/A	N/A	N/A	277
Makridakis (2017) The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms	Conceptual	Study that describes the 4 AI scenarios and their potential to create a utopian or dystopian world.	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	265
Harrison et al. (1996) Innovative firm behavior and local milieu: Exploring the intersection of agglomeration, firm effects, and technological change	Empirical/ Quant	Study to explore the implementation of metalworking establishments from 1987 to 1996	Innovative behavior	Adoption of a process technology	location	N/A	Innovative firm behavior	N/A	21 industries	Cross section	USA	257

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Table 8 (*continued*)

Article (author and title)	Type of article	Research Topic	Dependent Variable/s	Independent Variable/s	Moderating	Mediating	Theory adopted	Methods adopted	Empirical setting	Longitudinal or cross sectional	Level of analysis	Citation counts
Loebbecke and Picot (2015) Reflections on societal and business model transformation arising from digitization and big data analytics: A research agenda	Conceptual	To investigate how digitization and big data analytics drive the transformation of business and society	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	235
Kostoff et al. (2004) Disruptive technology roadmaps	Conceptual/ Literature review	To investigate identification of potential disruptive technologies	N/A	N/A	N/A	N/A	N/A	Text mining -TexTosterone system	N/A	N/A	N/A	223
Karmarkar (2004) Will you survive the services revolution?	Conceptual	Study to identify the challenges for companies to manage their information chain for value creation.	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	214
Tan et al. (2015) Harvesting big data to enhance supply chain innovation capabilities: An analytic infrastructure based on deduction graph	Empirical/ Quant	Study to develop and test an analytical model	Competence set	products	revenue	department	N/A	Deduction graph model	Case study	N/A	China	210
Lettl (2007) User involvement competence for radical innovation	Conceptual	Study to explore critical components of a user involvement competence for radical innovations in medical technology	N/A	N/A	N/A	N/A	Resource dependency theory	– Content analysis -deductive-inductive approach	Case study	N/A	N/A	192
Boon and Park (2005) A systematic approach for identifying technology opportunities: Keyword-based morphology analysis	Conceptual/ Literature review	Study to analyze patents for technological forecasting	N/A	N/A	N/A	N/A	N/A	Text mining + co-occurrence to 137 patents deploying keyword-based Morphology analysis (MA)	N/A	N/A	N/A	191

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Table 8 (*continued*)

Article (author and title)	Type of article	Research Topic	Dependent Variable/s	Independent Variable/s	Moderating	Mediating	Theory adopted	Methods adopted	Empirical setting	Longitudinal or cross sectional	Level of analysis	Citation counts
Santoro et al. (2018) The Internet of Things: Building a knowledge management system for open innovation and knowledge management capacity	Empirical/ Quant	Study to investigate firms' internal knowledge management capacity	IoT	-Knowledge management systems, -knowledge management capacity, -open innovation, -innovation capacity	N/A	N/A	N/A	path analysis and structural equation modeling (SEM) techniques to 298 questionnaires	N/A	N/A	Organizational Italy	187
Gao and Bai (2014) A unified perspective on the factors influencing consumer acceptance of internet of things technology	Empirical/ Quant	Study to identify factors for consumer intention to use IoT technology	Behavioural Intention to Use	-technology factors (perceived usefulness, perceived ease of use, and trust); - social factor (social influence); -individual user characteristics (perceived enjoyment and perceived behavioral control)	N/A	N/A	N/A	structural equation modelling (SEM) to 368 questionnaires	N/A	N/A	Individual	180
El-Kassar and Singh (2019) Green innovation and organizational performance: The influence of big data and the moderating role of management commitment and HR practices	Empirical/ Quant	Study to explore the relationships among green innovation and influence on performance and on competitive advantage	green innovation practices (products and processes)	-competitive advantage -Environmental -organizational performance.	N/A	N/A	N/A	partial least squares structural equation modeling (PLS-SEM) using the Smart PLS 3 software to 215 questionnaires	N/A	N/A	Organizational Lebanon, Egypt, Saudi Arabia and UAE	171
Gunther et al. (2017) Debating big data: A literature review on realizing value from big data	Conceptual/ Literature review	Review of Information Systems (IS) literature on Big Data value realization	N/A	N/A	N/A	N/A	N/A	67 WoS and AIS electronic library articles	N/A	N/A	N/A	169
Barrett et al. (2012) Reconfiguring boundary relations: Robotic innovations in pharmacy work	Conceptual	To investigate the use of robots in hospital pharmacies	N/A	N/A	N/A	N/A	Tunning approach	Thematic analysis to interviews	N/A	N/A	N/A	157
Ng and Wakenshaw (2017) The Internet-of-Things: Review and research directions	Conceptual/ Literature review	To understand the impact of IoT on Marketing research	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	152

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Table 8 (*continued*)

Article (author and title)	Type of article	Research Topic	Dependent Variable/s	Independent Variable/s	Moderating	Mediating	Theory adopted	Methods adopted	Empirical setting	Longitudinal or cross sectional	Level of analysis	Citation counts
Dwivedi et al. (2021) Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy	Conceptual	Multidisciplinary board of experts to discuss AI challenges and opportunities in a universal context	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	151
Lancelot Miltgen et al. (2013) Determinants of end-user acceptance of biometrics: Integrating the "big 3" of technology acceptance with privacy context	Empirical/ Quant	To investigate the actual and future attitudes and behaviors of the youngsters as regards biometrics iris scanning.	Behavioural intention to recommend using the technology (Biometrics)	-Perceived usefulness -Perceived ease of use -compatibility -Facilitation conditions -Perceived risks -Trust in technology -Privacy concerns -innovativeness -Intention of acceptance -Recommendation	N/A	N/A	N/A	partial least squares (PLS) PLS factor loadings, average variance extracted (AVE), composite reliability (CR), and Cronbach's alpha to 117 questionnaires	N/A	N/A	Individual	150
Zhu et al. (2002) Automated extraction and visualization of information for technological intelligence and forecasting	Conceptual/ Literature review	Nanotechnology mapping and visualization	N/A	N/A	N/A	N/A	N/A	Text mining deploying VantagePoint software to 3552 records from INSPEC database	N/A	N/A	N/A	150
Prasad (1993) Symbolic processes in the implementation of technological change: a symbolic interactionist study of work computerization.	Empirical/ Qual	To investigate how personal and cultural constructions of computerization mediate organization members eventual relationships with information technology	N/A	N/A	N/A	N/A	Grounded theory	Theoretical coding	Observation-34 interviews	longitudinal	USA	148
Bolton et al. (2018) Customer experience challenges: bringing together digital, physical and social realms	Conceptual	explore innovations in customer experience at the intersection of the digital, physical and social realms.	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	148

(*continued on next page*)

Table 8 (*continued*)

Article (author and title)	Type of article	Research Topic	Dependent Variable/s	Independent Variable/s	Moderating	Mediating	Theory adopted	Methods adopted	Empirical setting	Longitudinal or cross sectional	Level of analysis	Citation counts
Coenen and Díaz López (2010) Comparing systems approaches to innovation and technological change for sustainable and competitive economies: An explorative study into conceptual commonalities, differences and complementarities	Conceptual	Study to compare 3 frameworks: sectoral systems of innovation (SSI), technological innovation systems (TIS) and socio-technical systems (ST-Systems)	N/A	N/A	N/A	N/A	Technological innovation systems (TIS)	N/A	N/A	N/A	N/A	145
Binz et al. (2014) Why space matters in technological innovation systems - Mapping global knowledge dynamics of membrane bioreactor technology	Conceptual/ Literature review	Knowledge creation in membrane bioreactor (MBR) technology field	N/A	N/A	N/A	N/A	N/A	575 patents analysis deploying Web of Knowledge and NetMiner3 software	N/A	N/A	N/A	144
Warner and Wäger (2019) Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal	Conceptual	Study to explore how incumbent firms in traditional industries build dynamic capabilities for digital transformation	N/A	N/A	N/A	N/A	N/A	summative content analysis of 18 interviews, industry reports and Nvivo pattern analysis	Case study	N/A	Organisational -Germany	140
Frank et al. (2019) Servitization and Industry 4.0 convergence in the digital transformation of product firms: A business model innovation perspective	Conceptual	To develop a framework connecting Servitization and Industry 4.0 from a business model innovation (BMI) perspective	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	137
Scuotto et al. (2016a) Internet of Things: Applications and challenges in smart cities: a case study of IBM smart city projects	Conceptual	To investigate the combination between the use of IoT and the implementation of the Open Innovation (OI) model in smart cities	N/A	N/A	N/A	N/A	N/A	N/A	Case study IBM	N/A	N/A	135

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Table 8 (*continued*)

Article (author and title)	Type of article	Research Topic	Dependent Variable/s	Independent Variable/s	Moderating	Mediating	Theory adopted	Methods adopted	Empirical setting	Longitudinal or cross sectional	Level of analysis	Citation counts
Musiolik et al. (2012) Networks and network resources in technological innovation systems: Towards a conceptual framework for system building	Conceptual	Study to investigate the co-operative networks in the Fuel cell technology and Hydrogen (NIP) sector	N/A	N/A	N/A	N/A	Technological innovation systems (TIS) Resourced based view (RBV)	N/A	7 case studies	N/A	N/A	133

Fig. 9. Word cloud with the most prominent words in the literature on AI in innovation studies.

exchange of information between user groups (Klein et al., 2020) and stakeholders. Digital platforms can provide a customised and dynamic environment that promotes client engagement and massive data flow (Bolton et al., 2018). Digital platforms can be used to enhance the customer journey and experience (Mariani et al., 2022) but also to help digital entrepreneurs (Nambisan, 2017) improve and customize their products. More specifically, the information extracted through digital platforms could be useful to identify new ideas to identify a new customer need or to solve a particular customer problem (Kakatkar et al., 2020) and for new product development (Thorleuchter and Van Den Poel, 2016).

4.9.1.3. Social drivers. In light of national policies trying to reduce the effects of climate change, firms willing to innovate are deploying more greener and innovative solutions into their business operations. AI deployment as an innovative green solution promotes firms' sustainability, help them to improve their production processes, to reduce waste in product development, and to lower the production costs (Brdulak, 2020; Ozcan et al., 2021; Schuh et al., 2011; Tariq et al., 2017).

4.9.1.3.1. Sustainability. One way firms could improve their sustainability at the R&D stage, is by retrieving data from social media platforms (i.e., Twitter, Facebook and Instagram) to identify new ideas for new product development (Ozcan et al., 2021) as digital platforms provide important information regarding consumers opinions about sustainable products. Additionally, the data retrieved automatically from their reviews supports businesses to detect and monitor environmental concerns and improve the ecological value of new and existing products and services (Mariani and Borghi, 2020). The implementation of AI systems supports firms to promote sustainable transformation in production and innovation processes (Tariq et al., 2017).

4.9.1.3.2. Waste management. Research and Development of a new product is time consuming and expensive. Firms are implementing innovative strategies into their businesses to ensure project success. By identifying customers' expectations and needs at the beginning of the project through AI, firms reduce waste product development (Schuh et al., 2011) making better use of their resources and materials

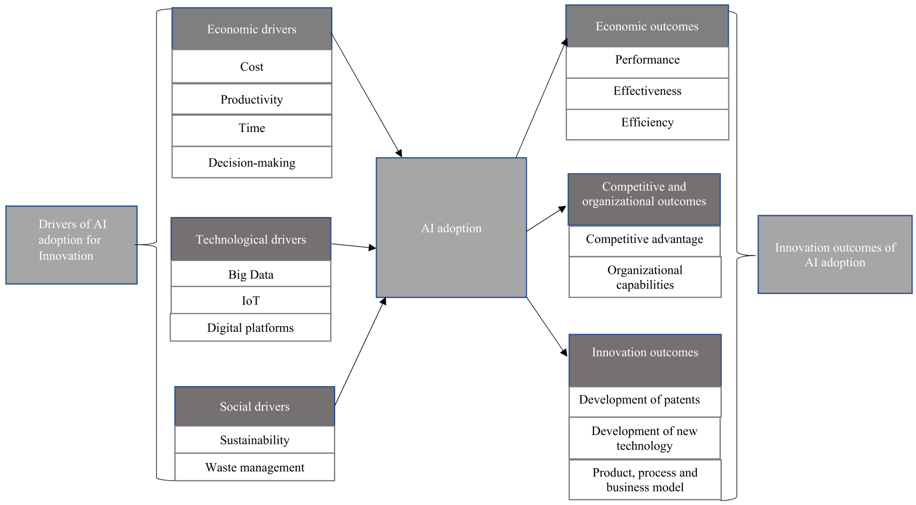

Fig. 10. Framework encompassing the drivers and outcomes of AI adoption for innovation.

promoting sustainability at product development stage. Additionally, with the implementation of AI systems in combination with IoT, firms and cities can monitor their pollution, waste or even remotely control equipment or electric illumination systems (Brdulak, 2020).

4.9.2. Outcomes of AI adoption for innovation

We analyzed the literature to identify outcomes of AI adoption for innovation. Table 10 categorizes and illustrates studies revolving around the outcomes of AI adoption Our findings suggest that there are three major categories of outcomes: economic outcomes (performance, effectiveness, efficiency); competitive and organizational outcomes (competitive advantage, organisational capabilities) and innovation outcomes (development of patents; development of new technology; product, process and business model innovation).

4.9.2.1. Economic outcomes. The economic outcomes of firms' AI adoption are linked to firm performance (Bai and Li, 2020; Beilin et al., 2019; Musiolik et al., 2020), effectiveness (Desouza et al., 2020; Yu and Huang, 2014) and firm efficiency (Calvetti et al., 2020; Haefner et al., 2021; Prem, 2019).

4.9.2.1.1. Performance. AI systems are valuable for firms to adopt measurements models to evaluate their own and their partners' performance, and evaluate the risks related to partnerships, to enhance the value stemming from partners (Beilin et al., 2019). AI can aid organizations to develop standard processes, programmes, goals, or experimental facilities that all stakeholders can use (Musiolik et al., 2020) in a network sharing knowledge to achieve better performance. AI systems aid firms to develop collaborative strategies and actions for performance enhancement and market innovation (Bai and Li, 2020).

Table 9
Drivers of AI adoption for Innovation.

Type	Category	Authors
Economic drivers	Cost	Verganti et al. (2020) Rose et al. (2020)
	Productivity	Hwang and Katayama (2009) Makowski and Kajikawa (2021) Kayser et al. (2018) Li et al. (2019)
	Time	Chou and Kimbrough (2016) Hutchinson (2021)
	Decision-making	Havins (2020) Yilmaz Eroglu and Kilic (2017) Paredes-Frigolett and Gomes (2016)
Technological drivers	Big Data	Blackburn et al. (2017) Ciampi et al. (2021) Caputo et al. (2020) Zhang et al. (2019)
	IoT	Butschan et al. (2019) Papa et al. (2020) Gurbuz and Ozkan (2020)
	Digital platforms	Klein et al. (2020) Antons et al. (2020) Thorleuchter and Van Den Poel (2016)
Social drivers	Sustainability	Tariq et al. (2017) Ozcan et al. (2021)
	Waste management	Brdulak (2020) Schuh et al. (2011)

Table 10
Outcomes of AI adoption for Innovation.

Type	Category	Authors
Economic outcomes	Performance	Beilin et al. (2019) Bai and Li (2020) Musiolik et al. (2020)
	Effectiveness	Desouza et al. (2020) Yu and Huang (2014)
	Efficiency	Calvetti et al. (2020) Prem (2019) Haefner et al. (2021)
Competitive and organizational outcomes	Competitive advantage	Milovidov (2018) Muhlroth and Grottke (2020)
	Organizational capabilities	Warner and Wäger (2019) Yams et al. (2020)
Innovation outcomes	Development of patents	Candelin-Palmqvist et al. (2012) Boon and Park (2005) Alencar et al. (2007)
	Development of new technology	An and Ahn (2016) Gavilanes-Trapote et al. (2015)
	Product, process and business model innovation	Zhan et al. (2017) Chatterjee et al. (2021a) Loebbecke and Picot (2015)

4.9.2.1.2. Effectiveness. The deployment of AI allows firms to manage effectively their data and their partnership network. Firms assess their data, technological capacity, organisation human capabilities and their surrounding environment (Desouza et al., 2020) to identify potential threats to firms' effectiveness. Additionally, AI systems support firms to reduce process costs, save time and resources to be more effective (Desouza et al., 2020).

The implementation of digital technology in airports is an example how organizations could leverage their AI adoption. The implementation of automated customer boarder clearance systems facilitates customers to travel using a digital Passport and face recognition. The use of AI technology systems for immigration purposes sets an effective system for boarder security management (Yu and Huang, 2014). Additionally, sets an effective tool for workforce management, is more accurate preventing human error, making as well better use of the their local settings (Yu and Huang, 2014) for their operations to be more effective. With a more accurate use of AI systems tools, customer saves time transforming and improving their experience.

4.9.2.1.3. Efficiency. AI contributes for firms' efficiency. In the construction industry, AI systems and techniques for workforce management allows to monitor workers performance: those deployments bring benefits to firms for their operation efficiency (Calvetti et al., 2020). Individual performance monitoring could bring together firms' efficiency and workers professional development (Calvetti et al., 2020) possibly decreasing workforce turnover. AI also provides support to managers who are collaborating: firms enhance their internal capabilities and generate efficiency gains when collaborative activity between managers is powered by AI (Haefner et al., 2021). Additionally, human capital is an important key element in firm value creation: training is an important factor for workers to improve their precision ultimately translating into firm efficiency (Prem, 2019).

4.9.2.2. Competitive and organizational outcomes. The implementation of AI systems allows firms to increase their competitive advantage (Milovidov, 2018; Muhlroth and Grottke, 2020) in unstable market environments, reshape firms' (dynamic) capabilities (Warner and Wäger, 2019), thus offering opportunities for a shift from incremental to radical innovation capabilities (Yams et al., 2020).

4.9.2.2.1. Competitive advantage. The implementation of AI systems allows firms to improve their competitive advantage in unstable market environments. Managing data with AI techniques could minimize human subjectivity in the R&D stage, improving the opportunity to identify and develop new ideas, and identify new emergent technology (Milovidov, 2018). More generally, the deployment of AI can reduce managers' biases and improve managerial decisions making (Milovidov, 2018) that can bring about increased innovation performance and competitive advantage. AI can also be used also to improve market segmentation and therefore improve market positioning ultimately translating into competitive advantage (Muhlroth and Grottke, 2020).

4.9.2.2.2. Organizational capabilities. Dynamic capabilities allow firms to sense opportunities and threats, seize opportunities, and maintain competitiveness through reconfiguring the business assets and resources (Teece et al., 1997a, 1997b). Digital technologies such as AI transforming firms' dynamic capabilities as now they can readjust (increase or decrease) their operations processes in a quicker, easier, and cheaper manner (Warner and Wäger, 2019), maximizing their profits and revenue. Additionally, the implementation of AI allows firms to shift from incremental innovation to radical innovation strengthening organizational innovation capabilities (Yams et al., 2020) as firm strategic renewal.

4.9.2.3. Innovation outcomes. The use and implementation of AI support firms' products, process and business model innovation (Chatterjee et al., 2021a; Loebbecke and Picot, 2015; Zhan et al., 2017). Additionally, AI can help firms identify new opportunities for product development, by generating more opportunities to create, secure and exploit intelectual proprety rights (Alencar et al., 2007; An and Ahn, 2016; Boon and Park, 2005; Candelin-Palmqvist et al., 2012; Gavilanes-Trapote et al., 2015).

4.9.2.3.1. Development of patents. Firms intelectual property, especially patents, are an indicator of business's innovation activity and performance, and are tightly related to technological innovation development (Alencar et al., 2007). AI can support firms by extracting from documents a large amount of data on research and development, that can assist to detect trends for innovative product development.

4.9.2.3.2. Development of new technology. The implementation of AI systems helps firms to detect emergent tecnhologies leading to innovation development. AI supports firms to perform for patent analysis for tecnhological forecasting contributing to enterpreneurial development (An and Ahn, 2016). By extracting information of patents through AI, firms can identify new opportunities for technological development aimed at product or process innovation (Gavilanes-Trapote et al., 2015). Tecnhological forecasting provides firms with valuable geospatial information about the develeopment of technologies in a certain region over time. Tecnhological forecasting used to develop new tecnhologies for product or process innovation (An and Ahn, 2016) allows businesses to create strategies suitable for different geographical settings (Gavilanes-Trapote et al., 2015).

4.9.2.3.3. Product, process and business model innovation. The use and implementation of AI allows firms to identify and prioritize consumer demand and determine the market potential in the research stage (Mariani and Nambisan, 2021). More specifically, AI can support the generation of innovation analytics (Kakatkar et al., 2020) either based on customers' user generated content about products and services or through digital experimentation (Mariani and Nambisan, 2021; Thomke, 2020). Innovation analytics in their turn support product, process or business model innovation (Mariani and Nambisan, 2021) and suggest if the launch of a new product is warranted or not (Kakatkar et al., 2020; Mariani and Fosso Wamba, 2020) and allow to release products rapidly into the market (Zhan et al., 2017). Generally, AI and data analytics allow firms to reduce their innovation risk and improve the innovation performance (Chatterjee et al., 2021a).

5. Discussion and contributions

This study has made several research and theoretical contributions to advance the research area at the intersection of AI and innovation and more generally the technology innovation management literature. First, we quantitatively evaluated the rapidly evolving research at the intersection of AI and innovation by producing an up-to-date and in-depth overview of extant literature and the ongoing debate in the field. This addresses recent calls for more research on the role of AI in innovation contexts (e.g., Cockburn et al., 2019) and systematizes the emergent yet expanding body of research revolving around the role of AI in innovation (e.g., Haefner et al., 2021; Kakatkar et al., 2020; Mariani and Nambisan, 2021). Moreover, given the rapid development of digital technologies (AI in particular) and related innovation management practice, this SLR aims to assist innovation scholars and practitioners to keep track of novel research findings that are beyond their main area of specialization and that represent indeed a frontier in innovation research. Second, our findings suggest that there are seven established topical areas that are informing developments in the research field at the intersection of AI and innovation: digital transformation (e.g., Frank et al., 2019; Warner and Wäger, 2019); smart cities and open innovation management and radical innovation (e.g., Abella et al., 2017; Randhawa et al., 2016); technological innovation systems (e.g., Coenen and Díaz López, 2010; Musiolik et al., 2020); technological forecasting and technological opportunities (e.g., Boon and Park, 2005; Kostoff et al., 2004); knowledge management and radical innovation (e.g., Lettl, 2007; Santoro et al., 2018); digital technology consumer acceptance (e.g., Bolton et al., 2018; Miltgen et al., 2013); green innovation and supply chain (e.g., El-Kassar and Singh, 2019; Kiani Mavi et al., 2019). Interestingly, several studies cover more than one theme and/or different disciplinary areas (Dwivedi et al., 2021; Loebbecke and Picot, 2015; Mariani et al., 2022; Scuotto et al., 2016). On one hand, this reflects the fact that innovation literature covers a broad set of disciplinary domains including entrepreneurship, marketing, strategic management, finance, and organizational behaviour, and indeed our literature review is multi-disciplinary in nature. On the other hand, this seems to suggest that scholars are already doing research across topical areas which might imply that they are trying to gain a more comprehensive view of the phenomenon they are analysing. Third, this study makes a contribution to the innovation literature by leveraging the SLR findings to develop an interpretive framework which sheds light on the drivers of AI adoption for innovation (economic, technological and social) and outcomes of AI adoption for innovation (economic, competitive and organizational, and innovation) providing a theoretical contribution to innovation research studies beyond extant knowledge (e.g., Haefner et al., 2021). Accordingly, through our interpretative framework we synthesize the observed piecemeal and fragmented results, and offer a more holistic understanding of the focal field to innovation researchers and practitioners. Fourth, we have singled out the most deployed theoretical lenses adopted in the focal research stream and identified the most frequently used: Technological innovation systems (TIS) theory; Fuzzy theories (i.e., fuzzy set theory, fuzzy logic); Technology acceptance model (TAM); Dynamic Capabilities; Diffusion of Innovation theory. By identifying the most widely used theories and methods, we also contributed novel ideas and directions for innovation scholars to conduct and undertake novel research in the field of technology innovation management, rather than repeat and recycle extant research. Last, we have contributed to develop directions and guidelines for future scholarship (reported in the Research Agenda section below) by identifying novel research gaps and providing a rich research agenda for further enquiry. This will inform the future evolution of (technology) innovation management research in the next decade and contribute to advance the frontier of innovation research, enabling the next generation of innovation scholars to tackle novel scientific challenges.

6. Limitations and research agenda

6.1. Limitations

This study displays a few limitations. First, we decided to collect data from Elsevier Scopus and Clarivate WOS over Google Scholar. Future research may collect data from Google Scholar, thus gathering further research outputs. Second, we decided for a ready on the shelf tool for our SLR (the software VOSviewer); future research could use additional tools such as CiteSpace for bibliometric maps visualization. Third, further research might look also at the level of analysis adopted across all the articles of the sample by carrying out a more granular analysis of the articles. Last, as most of the studies reviewed have an empirical nature, further research might dissect more analytically the role played by moderating and mediating variables, beyond direct influences.

6.2. Research agenda

Based on this SLR, we identify several knowledge gaps and research opportunities in the field of AI in innovation research. Table 11 summarizes a research agenda based on the identification of several key unanswered research questions in the area at the intersection of AI and innovation.

First, our review emphasizes some important knowledge gaps in relation to the economic drivers (categories 1–3), technological drivers (categories 4–6) and social drivers (category 7) encouraging firms to adopt AI for innovation goals and activities. Second, our SLR identifies research gaps in relation to the economic outcomes (categories 8–10), organizational outcomes (categories 11–12) and innovation outcomes (categories 13–15) of AI adoption for innovation.

There are clearly some challenges that scholars interested in addressing the aforementioned sets of questions should face. First, as most of the empirical studies are quantitative, qualitative methods should be embraced more widely to better capture processes of AI adoption and use over time, as well as their outcomes, in a longitudinal fashion. Therefore we encourage extensive use of longitudinal data to uncover the underlying mechanisms of the time-varying effects (e.g., De Massis and Kotlar, 2014) inherent in developing AI-enabled innovation. Experiments might also help understand the cognitive underpinning of innovation managers' behaviours and decision processes. Second, it seems that mixed methods such as sequential exploratory methods (Creswell and Clark, 2017) could be suitably employed by scholars to address more comprehensively the research questions put forward in the research agenda. Third, innovation literature has emphasized that firm size matters as it influences organizational resources and capabilities to engage in innovation (Chen and Hambrick, 1995). Certainly, future research might shed light on the (moderating) impact of firm size on organizational adoption of AI and ultimately on AI-enabled innovations. Fourth, some literature has pointed out that, regardless of firm size, firms pursuing innovation can either develop digital technologies in house or outsource them (e.g., Mariani and Fosso Wamba, 2020). Future research might investigate if and to what extent different ways of embracing AI (internally vs. contracting it to external vendors) influence the way organizations actually innovate. Fifth, as some research has found that innovation is more dependent on external knowledge than internal research and development activities (e.g., (Calabrò et al., 2019; Kang and Kang, 2009), it might be fruitful to examine if firms are more likely to achieve favorable innovation outcomes by embedding AI into their R&D activities or rather set up partnership to promote AI-enabled innovations. Sixth, extant studies have neglected that AI adoption for innovation purposes might differ across different types of firms (private, public, non-profit, family-led). For instance, recent research has shown that family-managed firms face difficulties in transitioning toward digital transformation (Ceipek et al., 2020) and that family-influenced firms differ from other types of firms in terms of how they engage in digital business opportunities and business model innovation (Soluk et al., 2021). Future research, especially qualitative case-based research, might explore the processes of AI development in firms with high level of family involvement to shed light on family firm idiosyncrasies regarding AI enabled innovation. Seventh, integrating data science and data analytics literature with mainstream innovation research might offer new research avenues by advancing the innovation analytics research stream (Mariani and Fosso Wamba, 2020; Mariani and Nambisan, 2021), and by enabling the emergence of innovation management research in the area of generative AI (Mariani, 2020). Eight, the COVID-19 pandemic is affecting firms of all sizes and types, but research still lacks profound insights into the managerial implications of this phenomenon. While

Table 11
Selected opportunities for future research on AI in Innovation based on the SLR.

Research gap categories	Questions for future research
Category 1: Cost and time (economic drivers)	1) Do firms invest in AI (over other technologies) to detect shifting consumer preferences to reduce cost associated with the launch of new products and services? Are there differences between SMEs and large enterprises? Are there differences between different types of organizations (e.g., family vs. non-family firms, public vs. private sector firms; domestic vs. multinationals)? 2) How does AI help to reduce cost associated with the launch of new products and services? 3) Do firms invest in AI (over other technologies) to detect shifting consumer preferences to compress the time-to-market associated with new products and services? Are there differences between SMEs and large enterprises? Are there differences between different types of organizations (e.g., family vs. non-family firms, public vs. private sector firms; domestic vs. multinationals)? 4) How does AI help to compress the time-to-market associated with new products and services? 5) Do firms develop AI initiatives to help innovation managers determine when it is appropriate to launch a new product/service to minimize firms' testing, experimentation, and production costs? Are there differences between SMEs and large enterprises? Are there differences between different types of organizations (e.g., family vs. non-family firms, public vs. private sector firms; domestic vs. multinationals)?
Category 2: Productivity (economic drivers)	1) Do firms invest in AI to innovate their processes in the pursuit of productivity? Are there differences between SMEs and large enterprises? Are there differences between different types of organizations (e.g., family vs. non-family firms, public vs. private sector firms; domestic vs. multinationals)? 2) Do firms invest in AI to innovate their business models in the pursuit of productivity? Are there differences between SMEs and large enterprises? Are there differences between different types of organizations (e.g., family vs. non-family firms, public vs. private sector firms; domestic vs. multinationals)? 3) Do firms invest in AI to enhance the productivity and efficiency of their operations? Are there differences between SMEs and large enterprises? Are there differences between different types of organizations (e.g., family vs. non-family firms, public vs. private sector firms; domestic vs. multinationals)?
Category 3: Decision-making (economic drivers)	1) Do firms invest in AI (over other technologies) to support innovation managers' decisions? Are there differences between SMEs and large enterprises? Are there differences between different types of organizations (e.g., family vs. non-family firms, public vs. private sector firms; domestic vs. multinationals)? 2) Are firms investing in AI (over other technologies) to support innovation managers' decisions striking an appropriate balance between machine-driven vs. human-driven decisions? Are there differences between SMEs and large enterprises? Are there differences between different types of organizations (e.g., family vs. non-family firms, public vs. private sector firms; domestic vs. multinationals)? 3) How do innovation managers receive AI-based insights before making innovation decisions? Are there differences between SMEs and large enterprises? Are there differences between different types of organizations (e.g., family vs. non-family firms, public vs. private sector firms; domestic vs. multinationals)?
Category 4: Big Data (technological drivers)	1) What type of Big Data are more suitable to support AI-empowered product innovation decisions? 2) What type of Big Data are more suitable to support AI-empowered process innovation decisions? 3) What type of Big Data analytics (descriptive, exploratory, predictive, prescriptive, cognitive) are more suitable to support AI-empowered process innovation decisions? 4) What are the features of big data (volume, variety, velocity, veracity, etc.) that are most likely to support incremental vs. radical innovation? 5) What are the features of big data (volume, variety, velocity, veracity, etc.) that are most likely to support product vs. process innovation? 6) What are the features of big data (volume, variety, velocity, veracity, etc.) that are most likely to support business model innovation? 7) What role do big data play in business model design vs. business model reconfiguration? 8) What do firms do to face the risks associated with data leaks in innovation projects? 9) To what extent different processes of embracing Big Data to empower AI (in-house vs. outsourcing) support incremental vs. radical innovation? 10) To what extent different processes of embracing Big Data to empower AI (in-house vs. outsourcing) support product vs. process innovation? 11) To what extent different processes of embracing Big Data to empower AI (in-house vs. outsourcing) support business model innovation?
Category 5: IoT (technological drivers)	1) To what extent does the combination of AI and IoT support product innovation decisions? Are there differences between SMEs and large enterprises? Are there differences between different types of organizations (e.g., family vs. non-family firms, public vs. private sector firms; domestic vs. multinationals)? 2) To what extent does the combination of AI and IoT support process innovation decisions? Are there differences between SMEs and large enterprises? Are there differences between different types of organizations (e.g., family vs. non-family firms, public vs. private sector firms; domestic vs. multinationals)? 3) To what extent does the combination of AI and IoT support business model innovation decisions? Are there differences between SMEs and large enterprises? Are there differences between different types of organizations (e.g., family vs. non-family firms, public vs. private sector firms; domestic vs. multinationals)? 4) To what extent does the combination of AI and IoT support incremental/radical innovation decisions? Are there differences between SMEs and large enterprises? Are there differences between different types of organizations (e.g., family vs. non-family firms, public vs. private sector firms; domestic vs. multinationals)? 5) To what extent different processes of embracing IoT to empower/complement AI (in-house vs. outsourcing) support incremental vs. radical innovation? 6) To what extent different processes of embracing IoT to empower/complement AI (in-house vs. outsourcing) support product vs. process innovation? 7) To what extent different processes of embracing IoT to empower/complement AI (in-house vs. outsourcing) support business model innovation?
Category 6: Digital platforms (technological drivers)	1) What are the features of digital platforms (on both the consumer and developer/manager side) that are most likely to support incremental vs. radical innovation? 2) What are the features of digital platforms (on both the consumer and developer/manager side) that are most likely to support product vs. process innovation?

(*continued on next page*)

Table 11 (*continued*)

Research gap categories	Questions for future research
	3) What are the features of digital platforms (on both the consumer and developer/manager side) that are most likely to support business model innovation? 4) How should different platform stakeholders be orchestrated to effectively pursue innovation through the use of AI? 5) How do innovation managers create and appropriate innovation value from digital platforms? 6) How can digital entrepreneurs exploit consumer information disseminated across digital platforms to support innovation decisions?
Category 7: Sustainability and waste management (social drivers)	1) To what extent does corporate CSR drive investments in AI (over other technologies) to support product/process and business model innovation? 2) To what extent do corporate environmental concerns drive investments in AI (over other technologies) to support product/process and business model innovation? 3) To what extent do innovation managers' environmental concerns drive investments in AI (over other technologies) to support product/process and business model innovation? 4) To what extent do innovation managers' environmental concerns drive investments in AI (over other technologies) allowing innovation strategies to be sustainable and sustained over time? 5) How does market demand for green and sustainable products drive AI-enabled product/process/business model innovation?
Category 8: Performance (economic outcomes)	1) Is there a linear function between the level of firms' engagement with AI and firms' innovation performance? 2) Do firms that invest significantly in AI display better innovation performance than firms that invest modestly in AI? 3) How does open innovation powered by AI influence firm innovation performance? 4) To what extent different processes of embracing AI (in-house vs. outsourcing) influence firm innovation performance? 5) Do firms that invest significantly in AI display a better attitude towards business model innovation than firms that invest modestly in AI?
Category 9: Effectiveness (economic outcomes)	1) Is there a linear function between the level of firms' engagement with AI and firms' capability to achieve their goals and strategic objectives? 2) Are firms that invest significantly in AI better in achieving their goals and strategic objectives than firms that invest modestly in AI? 3) Are firms that invest significantly in-house in AI better in achieving their goals and strategic objectives than firms that invest in AI by purchasing it from technology vendors? 4) Does the level of AI use influence the capability of firms to set goals and strategic objectives?
Category 10: Efficiency (economic outcomes)	1) How can AI be used to improve the efficiency of product and service innovation? 2) To what extent different processes of embracing AI (in-house vs. outsourcing) influence the efficiency of product and service innovation? 3) How can AI be used to improve the efficiency of process innovation? 4) To what extent different processes of embracing AI (in-house vs. outsourcing) influence the efficiency of process innovation? 5) How can AI be used to improve the efficiency of business model innovation? 6) To what extent different processes of embracing AI (in-house vs. outsourcing) influence the efficiency of business model innovation? 7) Is there a linear function between the level of firms' engagement with AI and firms' efficiency? 6) Are firms that invest significantly in AI more efficient than firms that invest modestly in AI? 7) Do efficiency gains achieved through AI compensate the value added by human creativity in product and service innovation? 8) Do efficiency gains achieved through AI compensate the value added by human creativity in process innovation? 9) Do efficiency gains achieved through AI compensate the value added by human creativity in business model innovation?
Category 11: Competitive advantage (organizational outcomes)	1) Is there a linear function between the level of firms' engagement with AI in innovation activities and firms' competitive advantage? 2) Do firms that invest significantly in AI for their innovation activities achieve a superior competitive advantage than firms that invest modestly in AI? 3) To what extent different processes of embracing AI (in-house vs. outsourcing) influence firms' capability to achieve a superior competitive advantage? 4) How does open innovation powered by AI influence firms' competitive advantage? 5) Are firms using AI to support their innovation decisions maintaining a competitive advantage for a longer time compared with firms using AI more parsimoniously?
Category 12: Organizational capabilities (organizational outcomes)	1) Is increased use of AI enhancing organizational capabilities? 2) What strategic/tactical integration of AI in firms' processes improves organisational capabilities? 3) To what extent and how does the use of AI improve firms' dynamic capabilities (more specifically, sensing, seizing and reconfiguring capabilities)? 4) How does AI affect basic organizational capabilities and dynamic capabilities supporting innovation? 6) Is there an AI management maturity level that needs to be reached for dynamic capabilities to support innovation decisions?
Category 13: Development of patents (innovation outcomes)	1) How can AI be used by firms to improve their R&D activities leading to intellectual property rights? 2) What strategic integration of AI in firms can be used to increase the number of patents developed? 3) How can the development of patents through AI compensate human creativity in product and service innovation? 4) How can the development of patents through AI compensate human creativity in process innovation?
Category 14: Development of new technology (innovation outcomes)	1) How can AI be used to improve the development of new technology for product and service innovation? 2) How can AI be deployed to improve the development of new technology for process innovation? 3) How can AI be employed to improve the development of new technology for business model innovation? 4) Do firms that engage more with AI development of new technology for process innovation more easily than firms that engage less with AI? Are there differences between SMEs and large enterprises? Are there differences between different types of organizations (e.g., family vs. non-family firms, public vs. private sector firms; domestic vs. multinationals)? 5) Do firms that engage more with AI development of new technology for business mode innovation more easily than firms that engage less with AI? Are there differences between SMEs and large enterprises? Are there differences between different types of organizations (e.g., family vs. non-family firms, public vs. private sector firms; domestic vs. multinationals)?

(*continued on next page*)

Table 11 (*continued*)

Research gap categories	Questions for future research
Category 15: Product, process, and business model innovation (innovation outcomes)	1) How does firms' engagement with AI influence firms' product innovation? 2) How does firms' engagement with AI influence firms' process innovation? 3) How does firms' engagement with AI influence firms' business model innovation? 4) Do firms that engage more with AI outperform firms that engage less with AI in terms of product innovation? Are there differences based on firm size? Are there differences between different types of organizations (e.g., family vs. non-family firms, public vs. private sector firms; domestic vs. multinationals)? 5) Do firms that engage more with AI outperform firms that engage less with AI in terms of process innovation? Are there differences based on firm size? Are there differences between different types of organizations (e.g., family vs. non-family firms, public vs. private sector firms; domestic vs. multinationals)? 6) Do firms that engage more with AI outperform firms that engage less with AI in terms of business model innovation? Are there differences based on firm size? Are there differences between different types of organizations (e.g., family vs. non-family firms, public vs. private sector firms; domestic vs. multinationals)? 7) What type of AI (mechanical, thinking, feeling) is more likely to influence incremental vs. radical innovation? 8) What type of AI (mechanical, thinking, feeling) is more likely to influence product, process or business model innovation? Are there differences between manufacturing vs. service industries whereby the need for human interaction is typically different?

some firms are coping with this crisis by introducing digital innovations (Borghi and Mariani, 2022), other firms are rejecting digital innovation projects due to resource constraints (Soluk et al., 2021). Future research might unveil how in times of crisis firms engage differently in AI-enabled innovation and develop new digital business opportunities. Last but not least, we call for a multi-disciplinary approach that might blend the fields of management, innovation, information systems, and computer science to generate more holistic responses to the research questions identified.

7. Conclusion

Combining a wide set of bibliometric techniques – spanning co-citation analysis, bibliographic coupling, co-word analysis – this work has contributed to reveal, present and map out the emerging intellectual structure (Donthu et al., 2021) of the innovation literature pertaining to AI. In so doing, it has helped to portray and illustrate the ongoing scientific debate on AI in the innovation field. Moreover, the study has made multiple research and theoretical contributions at the intersection of AI in innovation research (see section 5). Finally, by developing a rich research agenda, we hope and believe that this study has identified novel research gaps and research questions conducive to further fruitful enquiry. This will inform the future evolution of (technology) innovation management research in the next decade and contribute to advance the frontier of innovation research, enabling the next generation of innovation scholars to tackle novel scientific challenges. More specifically, the proposed research agenda will help innovation scholars interested in digital technologies (Artificial Intelligence in particular) to identify and address key research questions that will move the ongoing scientific debate on digital technologies in the innovation field to the next level. The proposed research agenda might also become a useful springboard for collaborative multi- and inter-disciplinary research on the focal field.

Declaration of interests

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

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