Types of innovation and artificial intelligence: a systematic quantitative literature review and research agenda

Journal of Business Research 155 (2023) 113364

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

Types of innovation and artificial intelligence: A systematic quantitative literature review and research agenda

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ARTICLE INFO

Keywords:
Types of innovation
Systematic quantitative literature review
Artificial intelligence
Bibliometric techniques

ABSTRACT

This study provides a systematic overview of innovation research strands revolving around AI. By adopting a Systematic Quantitative Literature Review (SQLR) approach, we retrieved articles published in academic journals, and analysed them using bibliometric techniques such as keyword co-occurrences and bibliographic coupling. The findings allow us to offer an up-to-date outline of existing literature that are embedded into an interpretative framework allowing to disentangle the key antecedents and consequences of AI in the context of innovation. Among the antecedents, we identify technological, social, and economic reasons leading firms to embrace AI to innovate. In addition to detecting the disciplinary foci, we also identify firms' product innovation, process innovation, business model innovation and social innovation, as key consequences of AI deployment. Drawing on the key findings from this study, we offer research directions for further investigation in relation to different types of innovation.

1. Introduction

Technological innovation developments in organisations have received increased scholarly attention recently, because businesses have increasingly leveraged multiple technologies to improve their capability to innovate and innovation consequences (Wamba-Taguimdje et al. 2020; El-Kassar and Singh, 2019; Akter et al., 2021). Organizations have recognised that by incorporating modern digital technologies into their capabilities and operations, they can improve their competitive advantage and innovation performance and processes (Spanjol et al., 2018). Artificial intelligence (AI) is one of the digital technologies that allows businesses to advance and grow in the digital age, influencing how businesses innovate (Verganti et al., 2020; Wamba et al., 2020) and respond to customers' changing needs (Mustak et al., 2021).

Nonetheless, research on AI in innovation has been examined less frequently, with the exception of scholarly work focusing on the barriers to implementing AI systems in businesses for product innovation (e.g., Paschen et al., 2020; Tariq et al., 2017), and a few studies emphasizing the benefits that AI systems can bring to internal organisational processes. Furthermore, the literature on innovation appears to have overlooked how AI systems could assist businesses in achieving their innovation goals. Overall, in this area, there are still more questions than answers, and likely more research gaps. Furthermore, no systematic quantitative literature review (SQLR) has been conducted to date to quantitatively evaluate research on AI and innovation. Compared to the recent literature reviews on the topic (e.g., Haefner et al., 2021), this work is novel, different and unique on several levels. Firstly, unlike the work of Haefner et al. (2021), this work adopts a SQLR approach that allows to leverage bibliometric techniques to identify themes and gaps in extant research (Tranfield et al., 2003). Secondly, this work focuses on a number of different types of innovation, namely product, process, business model, incremental, radical, digital, social, sustainable, open, service, disruptive, market and organizational innovation. Thirdly, this work adopts a SQLR approach that allows to leverage bibliometric techniques to identify themes and gaps in extant research (Tranfield et al., 2003; Zupic and Cater, 2015). More broadly, by embracing a SQLR approach, we leverage on a method that allows to reproduce the findings and reduce researchers' biases (Tranfield et al., 2003).

This study contributes to the field of innovation and artificial intelligence in several ways. First, we quantify and track the volume of research in the area of AI applications in innovation and use bibliometric analysis to trace the field longitudinally. Second, we advance research in

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https://doi.org/10.1016/j.jbusres.2022.113364
Received 3 July 2022; Received in revised form 31 August 2022; Accepted 5 October 2022
Available online 17 November 2022
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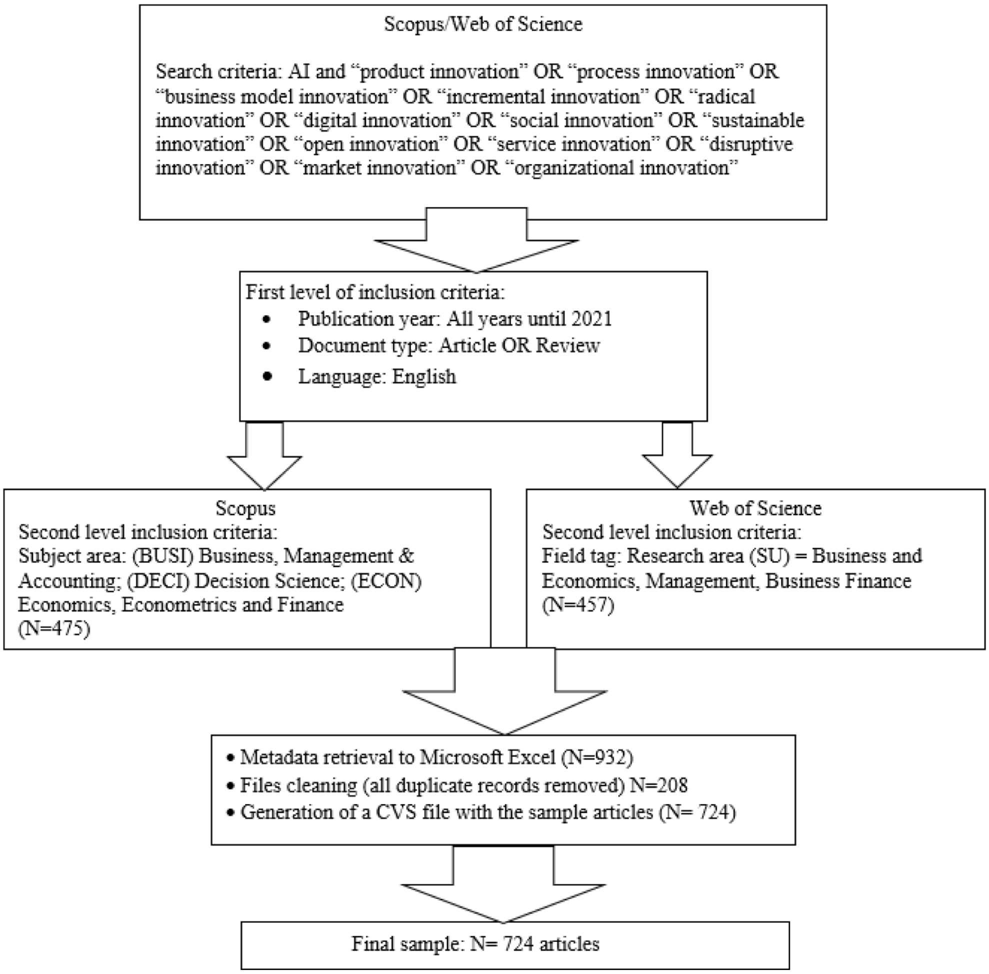

Fig. 1. Protocol details of the study on AI in Innovation. Notes: 1) Data was retrieved in January 2022; 2) AI was searched using multiple keywords including "artificial intelligence", "Artificial Intelligence", and, consistently with Mustak et al. (2021), the related keywords of "machine learning", "neural network*", "deep learning", "data mining", "text mining", "big data", "soft computing", "fuzzy logic", "biometrics", "geotagging", "IoT", "internet of things", "robot*", "automation", "natural language processing".

this area by developing a framework that synthesizes antecedents and consequences of the adoption of AI to achieve different types of innovation, thereby laying out a comprehensive agenda for future research. We start by describing the methodology adopted in this study.

2. Method and data

We conducted a thorough search of the topic area and employed systematic quantitative literature review (SQLR) technique to methodically review and assess the relevant literature, consistently with previous key scientific works (Fisch & Block, 2018; Zupic & Čater, 2015). The data for this study was collected by gathering documents from two major databases: Scopus and Web of Science (WOS). The aforementioned sources of data were adopted because they compile a set of the most relevant scientific outputs in the field of business and management. Both databases enable the organisation and integration of data gathered from various sources (e.g., articles, book chapters, etc.) in ready to use bibliometric formats. Fig. 1 delineates the protocol that we followed for this study.

To begin, we searched the Scopus database for titles, abstracts, and keywords containing the terms "AI," "artificial intelligence," other keywords that cover AI subfields such as machine learning,[1] and different types of innovation including: "product innovation", "process innovation", "business model innovation", "incremental innovation", "radical innovation", "digital innovation", "social innovation", "sustainable innovation", "open innovation", "service innovation", "disruptive innovation", "market innovation" and "organizational innovation". This resulted in 932 documents. In accordance with other SQLRs, we limited our search to articles and review papers in a number of subject areas including "Decision Sciences"; "Business, Management and Accounting"; "Economics, Econometrics and Finance". We used a further exclusion criterion, namely the scientific outputs had to be written in English language. The application of these exclusion criteria reduced the number of scientific outputs in the sample to 475. Second, we used the same combination of keywords to run a query on the Web of Science database. We applied exclusion criteria and confined the results to the area of Business and Economics; Business Finance; Management. This produced 457 documents. To avoid double counting, duplicated documents across databases were removed, thus generating a merged sample of 724 documents. Lastly, we extracted metadata for the documents included in the final sample, including titles, authors' full names, corresponding author/s' country, overall number of publications, number of citations, academic outlets, keywords, as well as institutional affiliations and countries. Consistently with protocols for SQLRs (Tranfield et al., 2003), we looked at references cited by the papers that were found through the searches and checked for papers that we already knew about and would expect to be in the final dataset.

[1] The additional keywords, consistently with Mustak et al. (2021) who carried out a bibliometric study on AI in marketing, include: "machine learning", "neural network*", "deep learning", "data mining", "text mining", "big data", "soft computing", "fuzzy logic", "biometrics", "geotagging", "IoT", "internet of things", "robot*", "automation", "natural language processing".

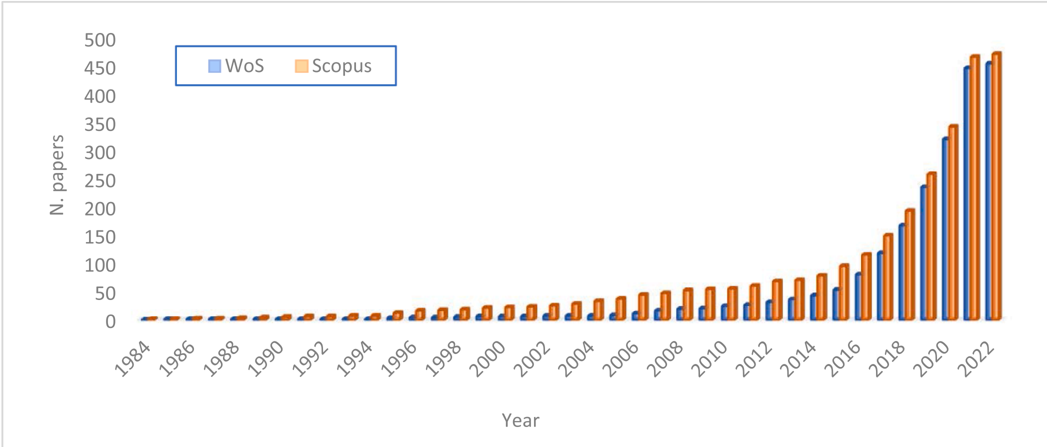

Fig. 2. Cumulative time distribution of trend studies on Innovation research and Artificial Intelligence.

Table 1
Leading countries regarding research output produced on innovation types and AI.

Country	N. Publications	N. Citations
USA	89	111
Italy	73	338
Germany	71	162
United Kingdom	55	157
Australia	40	140
France	33	125

3. Findings

3.1. Descriptive analysis

3.1.1. Publications by year

We tracked the evolution of publications on the topics of innovation research and artificial intelligence up to January 2022. The cumulative time distribution of studies in innovation research and artificial intelligence is shown in Fig. 2. The increasing number of published research on AI and different innovation types, particularly over the most recent period, reflects the expanding scholarly awareness of and interest in this topic. Yet, consistently with recent literature review studies, it appears that the field is in a nascent stage (Mariani et al., 2022; Mustak et al., 2021). Some preliminary studies in the focal field were published in the first half of the 1980s, specifically a work by Rosenthal (1984) published in the *Journal of Operations Management*. *Human Systems Management* published another article two years later. In the 1990s, three to four papers were published each year.

This pattern continued in the early 2000s. The number of publications grew threefold around 2006, with the growth following an exponential trend in subsequent years. The rapid growth in the number of articles might be something to be considered somehow normal and physiological given that we are focusing on a nascent research stream.

3.1.2. Geography of scientific production

As far as the geographical makeup of the focal scientific production is concerned, the leading countries in terms of the number of documents are the United States with 89 documents (and 111 citations), Italy (73 documents), Germany (71), the United Kingdom (55), Australia (40), and France (33) (see Table 1). This might mirror the countries' public and private investments in digital technologies in general and AI in particular over the last decades (Mariani et al., 2022).

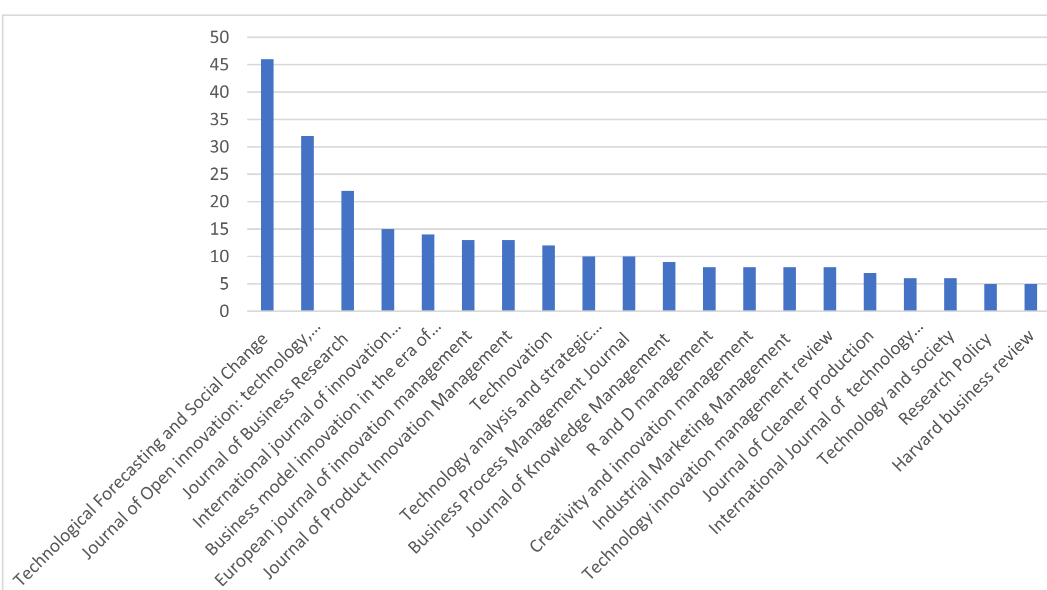

Fig. 3. Top 20 publications outlets on Innovation Research and AI.

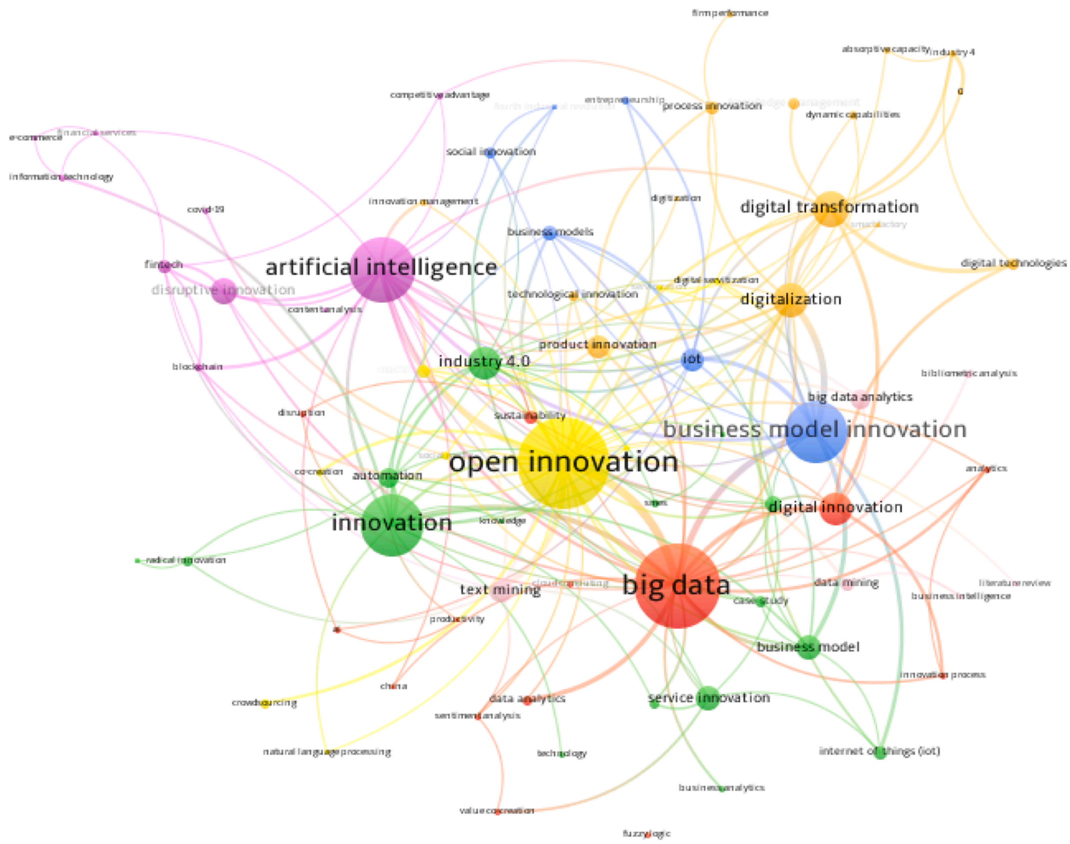

Fig. 4. Keyword co-occurrence.

3.1.3. *Scientific outputs by journal*

A vast number of publications is scattered across a wide range of journals over time. Fig. 3 depicts the journals that publish the majority of AI and innovation research. As can be noted, with its first publication in 1991, *Technological Forecasting and Social Change* published the highest number of articles (46), followed by the *Journal of Open Innovation*, and the *Journal of Business Research*.

3.2. *Bibliometric analysis*

Recently, bibliometric analysis is being deployed in a rising number of literature review papers in the social sciences and management domain to quantify and map research and recognise research gaps. More specifically, bibliometric analysis as a set of analytical methodologies and procedures for identifying key authors and seminal work, as well as identifying and mapping new research trends (Donthu et al. (2021). To provide an overview and map AI in innovation research, VOSviewer was deployed as it is open and is becoming a standard. We used co-citations network evaluation, journal co-citation analysis as well as bibliographic coupling to investigate the relationships of major researchers in the field, to proxy the state of the art in the focal domain. Additionally, one can assume topic similarity by analysing articles frequently mentioned jointly in another publication through bibliographic coupling, allowing us to depict the intellectual structure of a research field. This method of analysis reduces the risk of bias. Bibliographic coupling was used, consistently with the recommendations of Zupic & Čater (2015) for SQLR relying on bibliometric methods, as it allows to leverage bibliographic data extracted from research databases to develop a structured map of the examined scientific field. We deployed co-citation clusters to identify connections between the cited publications: this allowed to proxy the evolution of research areas. Bibliometric maps and graphical representations were produced. We employed keyword co-occurrence analysis to detect extant connections among topics and concepts. Central keywords were mapped cover time to track the evolution of topics.

3.2.1. *Journal co-citation analysis and bibliographic coupling*

Citations represent a form of recognition and endorsement in the academic field, and they were used through bibliographic coupling to provide a snapshot of the most prominent scholars that dealt with AI n their innovation studies (see Table A1 in the Appendix). The bibliographic coupling and co-citation analyses applied to journals allowed us to discover those journals with the greatest number of publications within the focal field.

3.3. *Disciplinary focus*

Based on our literature review, we identified five major disciplinary foci. Table A2 (see Appendix) depicts the five major research streams in the literature of AI in innovation research, based on our sample of 724 documents. To inform this SQLR, this section defines the conceptual underpinnings of AI in each of these fields.

3.3.1. *Marketing*

The implementation of AI in the Marketing domain has been investigated in relation to consumer behaviour (Acar & Toker, 2019; Masih & Joshi, 2021; Yang & Hu, 2021) consumer analytics (Erevelles et al., 2016; Johnson et al., 2019; Lee et al., 2019), service analytics (Akter et al., 2021; De Luca et al., 2021; Varsha et al., 2021; Wamba-Taguimdje et al., 2020) and marketing management capabilities, activities and strategies.

3.3.2. *Strategy*

Designing and implementing AI-based processes allows businesses to improve their strategies to create value to customer by enhancing products or services (Chaudhuri et al., 2021; Singh et al., 2021; Urbinati

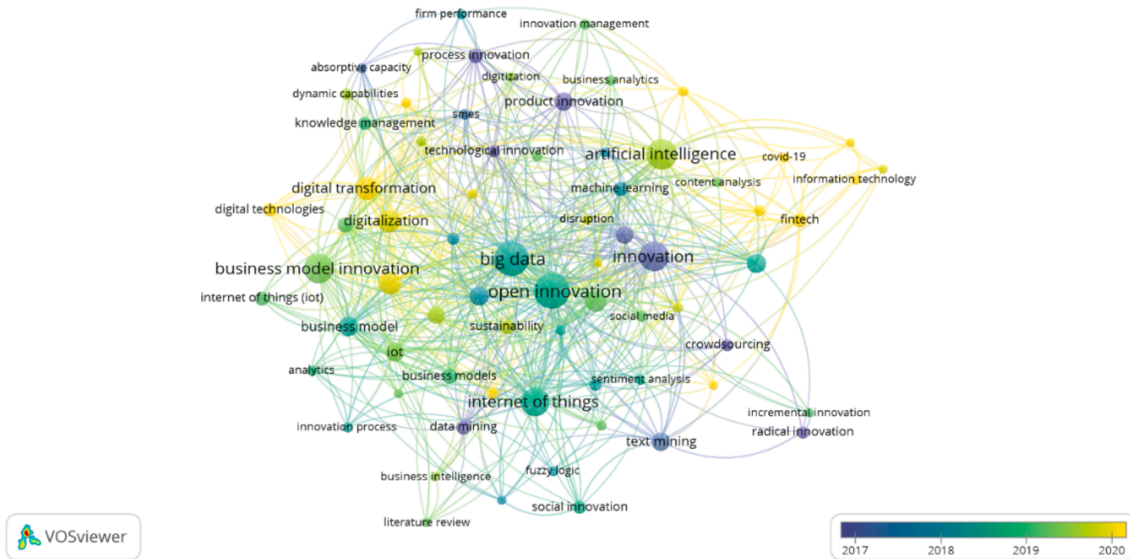

Fig. 5. Dynamic co-word map for central keywords detection.

et al., 2019). With AI, firms can enhance their innovation process for sustainable development of processes and innovation performance (Makowski & Kajikawa, 2021; Trabucchi et al., 2019; Scuotto et al., 2017). Additionally, AI plays an important role in the configuration of firm's business model innovation, supporting firms to reconfigure strategies and businesses model innovation to succeed (Burström et al., 2021; Fukawa et al., 2021; Foltean and Glovatchi, 2021; Tyagi, 2019; Spil et al., 2016).

3.3.3. Human resources management

Human capital is crucial for firms' success and the investment on human resources skills and education is a major factor for the deployment of AI systems. The implementation of AI systems has been investigated in relation to productivity and performance (Cheah and Wang, 2017; Del Giudice et al., 2021), job design, development and planning (Jazdauskaite et al., 2021; Prem, 2019; Visvizi et al., 2021; Sexton et al., 2005) and compliance (Arias-Pérez & Vélez-Jaramillo, 2022; Dabbous et al., 2021; Rampersad, 2020). AI contributes to create new professions, predict turnover and manage workforce (Jazdauskaite et al., 2021; Prem, 2019; Sexton et al., 2005; Kuo et al., 2017; Visvizi et al., 2021).

3.3.4. Entrepreneurship

AI has been examined in relation to digital entrepreneurship (Battisti et al., 2022; Bhardwaj, 2021; Brown, 2017; Ferràs et al., 2020; Geissinger et al., 2019; Mariani & Nambisan, 2021; Yu et al., 2016) and entrepreneurial ecosystems (Cetindamar et al., 2020; Chae & Goh, 2020; Mohammadi & Karimi, 2021; Kolloch & Dellermann, 2018; Palmié et al. 2020; Sun & Zhang, 2021).

AI deployment plays a key role in the development of digital entrepreneurship; customizing products/services as a competitive and entrepreneurial strategy; identifying and acquiring knowledge; managing product/service innovation issues for new products/services through innovation analytics (Kakatkar et al, 2020; Mariani & Wamba, 2020; Mariani & Nambisan, 2021). AI also plays a key role in entrepreneurial ecosystems for sharing information, creating and diffusing new products and fostering innovation evolution.

3.3.5. Finance

The implementation of AI in finance has been investigated in relation to financial products and services development (Alidrisi, 2021; Anshari et al., 2020; Manser Payne et al., 2021; Cong et al., 2021; Franco-Riquelme and Rubalcaba, 2021; Nair et al., 2021; Rasiwala & Kohli, 2021) and performance and forecasting (Manuylenko et al., 2021; Shinde et al., 2021; Hendershott et al., 2021; Méndez-Suárez et al., 2019; Arias-Pérez et al., 2021).

3.4. Significant publications

The co-citation clusters network was deployed to detect the articles that played an important role in forming the focal research field. A relevant number of studies in our sample pertain to specific subfields of AI (e.g., Chesbrough, 2003; McAfee & Brynjolfsson, 2012; Nambisan et al., 2017; Wamba et al., 2017).

3.5. Keywords co-occurrence analysis

The technique of keyword co-occurrence analysis was deployed to unveil the connections among conceptual items and topics. The technique assumes that terms that appear simultaneously are connected to each other through a thematic relationship. Additionally, we represented the progression of the conceptual items and keywords. As clear from Fig. 4, the word "big data" exhibits the greatest co-occurrence frequency, as it is tightly linked to other words such as "innovation", "open innovation", "artificial intelligence", "product innovation", and "business model innovation". The keywords with the highest occurrence in each keyword co-occurrence network were deployed to label the keyword co-occurrence networks. They are the follow ones: big data, innovation, open innovation, artificial intelligence, business model innovation.

3.6. Tracking central keywords

A dynamic co-word analysis was performed to track central keywords in the years. Fig. 5 illustrates the results of such analysis. More specifically, papers revolving around radical innovation have become more frequent around 2013. Starting from 2015, data mining becomes dominant across scientific outputs. Around 2016, process, product, and technological innovation articles show an increasing frequency. In 2017 the dominant keywords become text mining, innovation, automation, service innovation, crowdsourcing, and absorptive capacity. In 2018, concepts such as big data, open innovation, Internet of Things, innovation process, social innovation, disruptive innovation, and business model gain growing relevance in the focal literature.

Studies published in 2019 use terms such as artificial intelligence, business model innovation, industry 4.0, value creation, digitalization, big data analytics, digital innovation, innovation management and

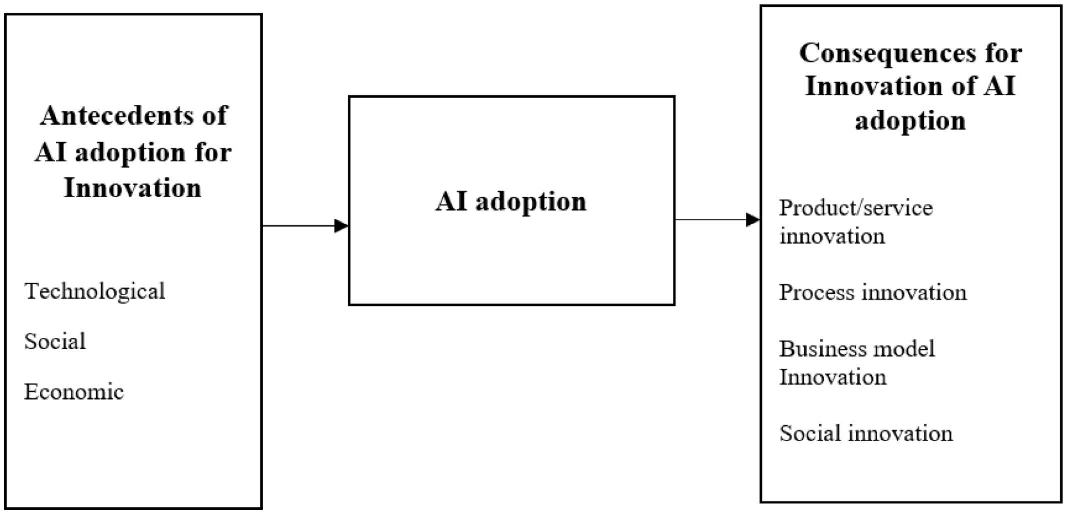

Fig. 6. Framework of antecedents-consequences of AI acceptance/adoption and innovation.

Table 2
Antecedents of AI acceptance/adoption conducive to innovation.

Type	Category	Authors
Technological antecedents	Big Data	Ciampi et al (2021)
		Erevelles et al (2016)
		Ma & Zhang (2022)
		Akter et al (2021)
	IoT	Yang et al (2020)
		Hsiao et al (2021)
		Lee (2019)
		Xing et al (2021)
	Digital platforms	Mariani & Nambisan (2021)
		Şimşek et al. (2022)
		Fukawa et al (2021)
		Füller et al (2021)
Social antecedents	Sustainability	del Vecchio et al (2021b)
		Fernandes and Castela (2019)
		Weiss et al (2019)
		Nair et al (2021)
		De Bernardi & Azucar (2020)
	Waste management	Chasin et al (2020)
		Schuh et al (2011)
		Tariq et al (2017)
Economic antecedents	Cost	Alshawaaf & Lee (2021)
		Belanche et al (2021)
		Mariani & Nambisan (2021)
		Dudnik et al (2021)
		Ferràs et al (2020)
	Productivity	Karacay & Alpkan (2019)
		del Vecchio et al (2021a)
		Llinas & Abad (2020)
		Saleem et al (2020)
	Time	Fiore & Bourgeois (2017)
		Helm et al (2021)
		Božič & Dimovski (2019)
	Decision-making	Li et al (2020)
		Trocin et al (2021)
		Verganti et al (2020)
		Wamba-Taguimdje et al (2020)

sustainability, while work published in 2020 revolves mostly around digital transformation, information technology, entrepreneurship, and competitive advantage.

3.7. An in-depth analysis of the level of analysis

After an in depth reading of the documents in our database, we carried out and in depth analysis of the level of analysis (macro, organizational, individual) and empirical setting/geographical scope. We found that 53 % of the articles in our literature sample focused their analysis at organizational level in one national empirical setting; 27 % do not disclose neither their level of analysis nor their geographical scope; 20 % of the studies focus their analysis at the organizational level in international settings.

4. A framework of innovation and AI

We develop a framework[2] - depicted in Fig. 6 – that classifies scientific outputs into two clusters: (a) antecedents of AI acceptance/adoption for innovation, and (b) innovation consequences of AI acceptance/adoption.

In subsection 4.1 we discuss the antecedents of AI adoption conducive to innovation, and in subsection 4.2 the innovation consequences of AI adoption.

4.1. Antecedents

We examined the focal body of research to recognise and classify antecedents of AI acceptance leading to types of innovation. Table 2 classifies research outputs pertaining to the aforementioned antecedents into three different clusters: technological, social, and economic antecedents. They are discussed respectively in subsections 4.1.1, 4.1.2, and 4.1.3.

4.1.1. Technological antecedents

In the analyzed literature, big data tools (Akter et al., 2021; Ciampi et al., 2021; Ereveles et al., 2016; Ma & Zhang, 2022;), IoT (Hsiao et al., 2021; Lee, 2019; Xing et al., 2021; Yang et al., 2020) and digital platforms (Füller et al., 2021; Fukawa et al., 2021; Nambisan et al., 2019; Şimşek et al., 2022) constitute the most cited technology-related antecedents for firms implementing AI for innovation.

Big data adoption enables businesses to manage data in order to sense and scope business opportunities, to exploit those opportunities with the aim of enhancing their competitiveness. Big data tools, for example, can be used to collect, process, analyse, and report on customer online opinions and behaviours, allowing for the development of more bespoke services and products, and ultimately support businesses competitive advantage. Furthermore, using AI-enabled tools to analyse

[2] We need to observe and clarify that in the framework proposed, the technological environment - and more specifically AI technologies - is influenced by firm's activities that in turn depend on firms' resources and investment decisions.

Table 3
Articles methodological approaches.

Methodology	Sample Articles
Quantitative	Dymitrowski and Mielcarek (2021); Rampersad (2020); Vorley et al (2020)
Qualitative	Burström et al (2021); Trocin et al (2021); Xing et al (2021)
Conceptual/ Literature review	Blöcher and Alt (2020); Chae (2014); Singh et al (2021); Fosso Wamba et al (2021); Yun et al (2021); Del Giudice et al (2021)
Mixed methods	Harwood et al (2019); Akter et al (2021); Markfort et al (2022)

Table 4
Research directions on AI-enabled innovation.

Research directions	Research questions
Antecedents of AI adoption for innovation	**RQ1.** How do organizations balance the demand for more data-based insights with the uncertainties associated with evolving AI technologies in deciding the extent and timing of AI adoption?
	RQ2. How does the stage of an industry lifecycle influence firms' AI adoption for innovation projects? Do firms in more mature industries adopt later than others?
	RQ3. How do the stages of a firm's innovation process shape firm's AI adoption for innovation?
	RQ4. To what extent do managers' ecological concerns and corporate social responsibility influence investment in AI (compared to other digital technologies) to assist innovation decisions?
	RQ5. In what ways do organizational contextual characteristics (size, geographic location, diversity of business divisions) shape AI adoption decisions in innovation?
Impact of AI adoption on innovation consequences	**RQ6.** How does the extent of firm's engagement with AI technologies influence the development of new products and services? What is the role of dynamic capabilities in helping companies derive more from their AI investments in innovation?
	RQ7. What are the interaction effects between AI capabilities and other innovation capabilities on innovation consequences?
	RQ8. What is the influence of AI adoption on shaping novel business opportunities in normal times vs periods of crisis?
	RQ9. How do organizations that have embraced AI respond/create needs for green and sustainable products/services also in relation to the Sustainable Development Goals (SDGs)?

massive amounts of data enables companies to improve R&D decision-making. Additionally, predictive big data analytics allow firms to undertake and enhance different forms of innovation. (Ma & Zhang, 2022; Mariani & Nambisan, 2021).

The internet of things (IoT) empowered by AI systems exemplifies the expansion of digital innovation (Nambisan et al., 2019). The implementation of IoT enhances firms' operational efficiency. IoT technology combined with AI systems has been implemented in the smart cities context, and in the hospitality sector to create service innovation. In the healthcare context, embracing IoT-empowered smart wearable devices enables organizations to gather data relevant to create more customised healthcare products and services. Within the fish

Table A1
Prominent researchers.

Authors	Title	Journal	Citation counts
Kitchin (2014)	Big Data, new epistemologies and paradigm shifts	Big Data and Society	918
Ostrom et al. (2015)	Service Research Priorities in a Rapidly Changing Context	Journal of Service Research	782
Gretzel et al. (2015)	Smart tourism: foundations and developments	Electronic Markets	593
(Dodgson et al., 2006)	The role of technology in the shift towards open innovation: The case of Procter & Gamble	R and D Management	515
Erevelles et al. (2016)	Big Data consumer analytics and the transformation of marketing	Journal of Business Research	385
Randhawa et al. (2016)	A Bibliometric Review of Open Innovation: Setting a Research Agenda	Journal of Product Innovation Management	326
Santoro et al. (2020)	The Internet of Things: Building a knowledge management system for open innovation and knowledge management capacity	Technological Forecasting and Social Change	229
Karmarkar (2004)	Will you survive the services revolution?	Harvard Business Review	222
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	Technological Forecasting and Social Change	220
Frank et al. (2019)	Servitization and Industry 4.0 convergence in the digital transformation of product firms: A business model innovation perspective	Technological Forecasting and Social Change	201

farming sector, the supply chain is being endowed with IoT empowered by AI to enhance farming planning activities, customize services, sustainable development of the fish farming ecosystem.

Firms can benefit from digital platforms as an open-source strategy, to increase the dimension of user networks, promoting customer engagement in a customised and dynamic environment to develop and deliver customer value. More specifically, data retrieved from digital platforms could be valuable in generating new ideas, identifying new customer demand, or resolving a specific customer issue (Füller et al., 2021). Furthermore, digital platforms can be used to improve consumer engagement and experience and to minimize the risk of innovation through digital testing and experimentation (Mariani & Nambisan, 2021). Digital platforms benefits firms in the sense that they foster digital innovation and business model transformation (Mariani & Nambisan, 2021; Şimşek et al., 2022) and strengthen the capabilities of digital entrepreneurs to adapt rapidly to the changing markets (Nambisan et al., 2021).

4.1.2. Social antecedents

As a result of national legislation aimed at mitigating the consequences of climate change, businesses are innovating by developing new greener products and services. AI implementation supporting green products/service allow businesses become more sustainable in their production activities, thus lowering the ecological footprint of production (Chasin et al., 2020; De Bernardi and Azucar, 2020; Del Vecchio et al., 2021b; Fernandes and Castela, 2019; Weiss et al., 2019).

One strategy available to firms to enhance their capability to pursue sustainable consequences in the R&D stage, is to extract and analyse user

Table A2
Research disciplines.

Discipline or functional area	Areas	Authors	Title
Marketing	**Consumer behaviour**	Acar and Toker (2019)	Predicting consumer personality traits in the sharing economy: The case of airbnb
		Masih and Joshi (2021)	Understanding Health-Foods Consumer Perception Using Big Data Analytics
		Yang and Hu (2020)	When do consumers prefer AI-enabled customer service? The interaction effect of brand personality and service provision type on brand attitudes and purchase intentions
	Consumer analytics	Erevelles et al. (2016)	Big Data consumer analytics and the transformation of marketing.
		Johnson et al. (2019)	The marketing organization's journey to become data-driven
		Lee et al. (2019)	Multisensory experience for enhancing hotel guest experience
	Service analytics	Wamba-Taguimdje et al. (2020)	Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects
		Varsha et al. (2021)	The Impact of Artificial Intelligence on Branding
		Akter et al. (2021)	How to Build an AI Climate-Driven Service Analytics Capability for Innovation and Performance in Industrial Markets?
		De Luca et al. (2021)	How and when do big data investments pay off? The role of marketing affordances and service innovation.
Discipline or functional area	**Concepts**	**Authors**	**Title**
Strategy	**Product/Service Innovation**	Chaudhuri et al. (2021)	Adoption of robust business analytics for product innovation and organizational performance: the mediating role of organizational data-driven culture.
		Singh et al. (2021)	One-Voice Strategy for Customer Engagement.
		Urbinati et al. (2019)	Creating and capturing value from Big Data: A multiple-case study analysis of provider companies.
	Process Innovation	Makowski and Kajikawa (2021)	Automation-driven innovation management? Toward Innovation-Automation-Strategy cycle.
		Trabucchi and Buganza (2019)	Data-driven innovation: switching the perspective on Big Data
		Scuotto et al. (2017)	Shifting intra- and inter-organizational innovation processes towards digital business: An empirical analysis of SMEs
	Business Model Innovation	Burström et al. (2021)	AI-enabled business-model innovation and transformation in industrial ecosystems: A framework, model and outline for further research.
		Fukawa et al. (2021)	Dynamic Capability and Open-Source Strategy in the Age of Digital Transformation.
		Foltean and Glovațchi (2021)	Business Model Innovation for IoT Solutions: An Exploratory Study of Strategic Factors and Expected Outcomes
		Tyagi (2019)	Merger control in the telecom industry: a landscape transformed
		Spil et al. (2016)	Digital Strategy Innovation; Toward Product and Business Model Innovation to Attain e-Leadership
Discipline or functional area	**Concept**	**Authors**	**Title**
Human Resources Management	**Productivity and performance**	Cheah and Wang (2017)	Big data-driven business model innovation by traditional industries in the Chinese economy
		Del Giudice et al. (2021)	Humanoid robot adoption and labour productivity: a perspective on ambidextrous product innovation routines
		Fonseca et al. (2019)	Human capital and innovation: the importance of the optimal organizational task structure
	Job design, development, and planning	Jazdauskaite et al. (2021)	Evaluation of the impact of science and technology on the labour market
		Prem (2019)	Artificial Intelligence for Innovation in Austria
		Visvizi et al. (2021)	Think human, act digital: activating data-driven orientation in innovative start-ups.
		Kimseng et al. (2020)	Applications of Fuzzy Logic to Reconfigure Human Resource Management Practices for Promoting Product Innovation in Formal and Non-Formal R&D Firms
		Sexton et al. (2005)	Employee turnover: a neural network solution
	Compliance	Arias-Pérez and Vélez-Jaramillo (2022)	Ignoring the three-way interaction of digital orientation, Not-invented-here syndrome and employee's artificial intelligence awareness in digital innovation performance: A recipe for failure
		Dabbous et al. (2021)	Enabling organizational use of artificial intelligence: an employee perspective
		Rampersad (2020)	Robot will take your job: Innovation for an era of artificial intelligence
Discipline or functional area	**Concept**	**Authors**	**Title**
Entrepreneurship	**Digital entrepreneurship**	Battisti et al. (2022)	Creating new tech entrepreneurs with digital platforms: meta-organizations for shared value in data-driven retail ecosystems
		Bhardwaj (2021)	Adoption, diffusion and consumer behavior in technopreneurship.
		Brown (2017)	Sensor-based entrepreneurship: A framework for developing new products and services.
		Ferràs et al. (2020)	Smart Tourism Empowered by Artificial Intelligence.
		Geissinger et al. (2019)	Digital entrepreneurship and field conditions for institutional change– Investigating the enabling role of cities.
		Mariani and Nambisan (2021)	Innovation Analytics and Digital Innovation Experimentation: The Rise of Research-driven Online Review Platforms
		Yu et al. (2016)	Internet of things capability and alliance
	Entrepreneurial ecosystems	Cetindamar et al. (2020)	Exploring the knowledge spillovers of a technology in an entrepreneurial ecosystem—The case of artificial intelligence in Sydney.
		Chae and Goh (2020)	Digital Entrepreneurs in Artificial Intelligence and Data Analytics: Who Are They?
		Mohammadi and Karimi (2021)	Entrepreneurial ecosystem big picture: a bibliometric analysis and co-citation clustering.
		Kolloch and Dellermann (2018)	Digital innovation in the energy industry: The impact of controversies on the evolution of innovation ecosystem
		Palmié et al. (2020)	The evolution of the financial technology ecosystem: An introduction and agenda for future research on disruptive innovations in ecosystems
		Sun and Zhang (2021)	Building digital incentives for digital customer orientation in platform ecosystems

Discipline or functional area	Concept	Authors	Title
Finance	**Products and services**	Alidrisi (2021)	Measuring the Environmental Maturity of the Supply Chain Finance: A Big Data-Based Multi-Criteria Perspective
		Anshari et al. (2020)	Financial Technology and Disruptive Innovation in Business
		Manser Payne et al. (2021)	Digital servitization value co-creation framework for AI services: a research agenda for digital transformation in financial service ecosystems
		Cong et al. (2021)	Internet of Things: Business Economics and Applications
		Franco-Riquelme and Rubalcaba (2021)	Innovation and SDGs through Social Media Analysis: Messages from FinTech Firms.
		Nair et al. (2021)	AI-Enabled Chatbot to Drive Marketing Automation for Financial Services
		Daluwathumullagamage and Sims (2021)	Fantastic Beasts: Blockchain Based Banking
		Rasiwala and Kohli (2021)	Artificial Intelligence in FinTech
	Performance and forecasting	Manuylenko et al. (2021)	Development and Validation of a Model for Assessing Potential Strategic Innovation Risk in Banks Based on Data Mining-Monte-Carlo in the “Open Innovation”
		Shinde et al. (2021)	Blockchain for Securing AI Applications and Open Innovations
		Hendershott et al. (2021)	FinTech as a Game Changer: Overview of Research Frontiers
		Méndez-Suárez et al. (2019)	Artificial Intelligence Modelling Framework for Financial Automated Advising in the Copper Market
		Arias-Pérez et al. (2021)	Big data analytics capability as a mediator in the impact of open innovation on firm performance.

generated content stemming from digital platforms. Digital platforms provide valuable information about consumer attitudes and behaviours toward sustainable products, thereby enabling firms to identify new ideas for more sustainable products. Furthermore, the information extracted automatically from customers’ online reviews allows firms to track the onne ecological discourse about their products/services (Maran and Borghi, 2021). Additionally, AI systems embedded into supply chains empower businesses by improving their financial sustainability, reducing their environmental footprint, fostering the creation of greener businesses models, supporting innovation sustainability.

Given that new product research and development is expensive and time consuming, companies are incorporating creative strategies into their operations. By implementing AI systems at the start of the project, firms can identify consumers’ wishes and expectations to enhance the efficiency in the use of row materials and resources by reducing waste. Furthermore, by means of AI applications, (smart) cities can recycle waste, while minimize electrical consumption, and reducing their production costs (El-Kassar and Singh, 2019).

4.1.3. Economic antecedents

Firms may deploy AI technologies for a variety of reasons, including cost savings (Alshawaaf and Lee, 2021; Belanche et al., 2021; Dudnik et al., 2021; Ferràs et al., 2020; Mariani & Nambisan, 2021; Wirtz, 2019), reducing product development time (Fiore and Bourgeois, 2017; Helm et al., 2021; Božič and Dimovski, 2019), improving firm productivity (Karacay and Alpkan, 2019; Del Vecchio et al., 2021a; Llinas and Abad, 2020; Saleem et al., 2020), and supporting decision-making processes (Li et al., 2020; Trocin et al., 2021; Verganti et al., 2020).

To cut expenses, businesses use AI systems to assist them in lowering production costs, which often translates into selling products and services at lower prices and improving process efficiency (Wirtz et al., 2018). Furthermore, AI allows low-cost digital experimentation using research -driven online platforms to test new products and services. AI systems support businesses in promoting the development of new affordable automated services, providing social value to a broader audience at low-cost, reducing costs and improving services.

The implementation of AI systems promotes businesses productivity by reducing human intervention, enhancing product quality, and accelerating the production process. Additionally, the adoption of automated technology assists businesses to customize services and products. The deployment of AI systems allows manufacturing small- and medium-sized enterprises (SMEs) to create new business opportunities, improving manufacturing capacity and profits.

Timing is crucial and a critical component in determining a firm’s ambidexterity. It is important to find a balance between time spent refining existing products (exploitation) and time spent inventing new items (exploration). Additionally, AI in the guise of cognitive analytics promotes the automation of processes with AI, helping businesses save time when they extract information from unstructured data, so that they can reduce time in new product development.

The acceptance/adoption of AI algorithms could assist managers’ decision-making to improve firms’ performance, by developing creative solutions. For example, the use of fuzzy sets in conjunction with AI can support firms in the reconfiguration of human resource management activities, market forecasting, or product innovation acceptance, providing support to decision-makers.

4.2. Innovation consequences of AI adoption

Regarding the innovation consequences, our findings suggest that there are four major categories of innovation consequences: product and service innovation; process innovation; business model innovation; and social innovation. They are discussed respectively in subsections 4.2.1, 4.2.2, 4.2.3, and 4.2.4.

4.2.1. Product/service innovation

In R&D, AI deployment enables businesses to support their strategic marketing activities, including make sense of market potential for new products/services (Akter et al., 2021; Antons and Breidbach, 2017; Bolton et al., 2018; Del Giudice et al., 2021; Fan et al., 2022; Kuo et al., 2017; Mariani & Nambisan, 2021; Singh et al., 2021; Zhan et al., 2017). In particular, AI enables innovation analytics (Mariani & Nambisan, 2021) that support firms to exploit and explore product innovation (Mariani & Fosso Wamba, 2020; Del Giudice et al., 2021), and allow for the rapid release of products to the market. In general, AI and analytics enable businesses to lessen innovation-related risk while improving innovation goals.

4.2.2. Process innovation

AI implementation enhances firms capabilities to restructure and reengineer their processes for process innovation (Agostini et al., 2019; Blöcher and Alt, 2020; Chatterjee et al., 2021; Cooke, 2021; El-Kassar and Singh, 2019; Frank et al., 2019; Huang et al., 2019; Mikalef and Krogstie, 2020; Sjödin et al., 2020; Wamba and Mishra, 2017).The adoption of AI combined with other digital technologies, supports businesses to adapt or to replace products/services, change the way they create, deliver and capture value, improve their technological capabilities. Such combination offers firms a wide range of possibilities to enhance innovation potential, increasing firms’ ability to improve existent products/services (incremental innovation) or to design and develop new products (radical innovation) by enhancing their process innovation capabilities; disrupting traditional operation strategies. Additionally, AI encourages the implementation of greener solutions in business processes (El-Kassar and Singh, 2019), and supports firms to restructure their operation processes creating business impact in the industry. The implementation of AI technology improves firm performance whilst businesses respond rapidly to market demand, translating into increased competitive advantage (Chatterjee et al., 2021).

4.2.3. Business model innovation

Many successful organisations have implemented AI into their operations and developed unique AI-based business models (Anton et al., 2021; Burström et al., 2021; Kulkov, 2021; Lee et al., 2019; Mishra and Tripathi, 2021; Nocker and Sena, 2021; Sjödin et al., 2021; Sorescu, 2017; Wamba-Taguimdje et al., 2020; Weiss et al., 2019). A business model innovation is defined as "a change in the value creation, value appropriation, or value delivery function of a firm that results in a significant change to the firm's value proposition" (Sorescu, 2017, p. 692). Companies that successfully integrate AI into their business models and operations can unleash disruptive innovation, thus modifying their entire value chains (Wamba-Taguimdje et al., 2020). Aditonally, to improve their value proposition, firms simply need to embrace change in one dimension (value creation, value appropriation, or value delivery), resulting in business model innovation. Several successful organisations have incorporated AI in their operations and developed innovative AI-based business models (Lee et al., 2019), creating new value for stakeholders (Kulkov, 2021). However, business model innovation is dynamic, and to achieve a long term success firms should build a network of external stakeholders around their business model innovation, developing complementary products/services to create new value (Nocker and Sena, 2021; Lee et al., 2019), influencing the global competitive environment.

4.2.4. Social innovation

Social innovation initiatives - typically launched to develop products and services meeting social needs (Morrar and Arman, 2017) - have recently emerged as an alternative approach of collaboratively producing innovative and sustainable solutions to new and complex social and economic problems. AI-powered platforms are a reliable alternative for addressing critical social issues in order to boost economic growth and improve people's lives (Battisti et al., 2022), impacting positively individuals, businesses and society (Morrar and Arman, 2017). Additionally, social innovation initiatives allow business to produce social value creation (Faludi, 2020) by developing environmental, social and economic initiatives to create social innovation.

4.3. Methodological approaches in the research reviewed

To offer a synopsis of the methods deployed in the research covered in this SQLR, we examined the methodologies deployed. Table 3 illustrates the methods adopted and shows that the majority (55 %) consists of conceptual studies; (45 %) adopted an empirical approach (31 % of the empirical studies consist of quantitative studies; 14 % are qualitative studies). A few studies (4) studies adopted mixed methods.

5. Discussion, conclusion, and future research

Building on this SQLR, we identified a number of research directions. Table 4 provides an illustration of research directions and develops unanswered research questions in the domain of AI and the forms of innovation analysed. The table includes an indicative list of major research gaps and questions without the ambition to be exhaustive. That said, the high number of research gaps and unanswered research questions identified is not surprising, given that the research field is not yet mature.

Regarding **antecedents of AI** deployment conducive to innovation, we have found that AI adoption has been investigated in relation to technological, social and economic antecedents. First, a number of studies have focused on (big) data as a technological precondition and antecedent for effective AI adoption in view of innovation decisions (e.g., Mariani & Nambisan, 2021; Wamba & Mishra, 2017) and more generally data rich environments as conducive to innovation (Bharadwaj & Noble, 2017). It has been recognized that predictive (innovation) analytics from big data can help identify and select new customer problems as well as identify new product solutions (Kakatkar et al., 2020). Indeed, big data and analytics are essential for: 1) firms' sensing capabilities when they derive insights on consumer needs and market potential of a new product (Mariani & Nambisan, 2021) and when they discover new market opportunities; 2) firms' seizing capabilities, when firms rely on big data to develop customized services and products. Extant research seems to suggest that there is an increasing demand for more data-based insights. However, AI technologies evolve very rapidly, and this might affect the extent and timing of AI adoption. Therefore, an important question for future research is:

(RQ1) *How do organizations balance the demand for more data-based insights with the uncertainties associated with evolving AI technologies in deciding the extent and timing of AI adoption?*

Second, firms adopting AI for innovation purposes operate in different industries such as energy and commodities (Weiss et al., 2016; Dudnik et al., 2021; Shinde et al., 2021), manufacturing (Rosenthal, 1984; Caputo et al., 2016; Frank et al., 2019; Llinas and Abad, 2020; Ma and Zhang, 2022), and services (Gretzel et al., 2015; Buhalis et al., 2019; Lee et al., 2019; Ferràs et al., 2020; Mariani & Borghi, 2019). Different industries can be in different stages of their lifecycle: introduction, growth, maturity, decline and/or rejuvenation (Klepper, 1997; Lumpkin and Dess, 2001). For example, the adoption of AI at the early stages of an industry life cycle might be related to firms' capability to anticipate and sense markets opportunities that might enable to create new products and services at a later stage (growth). In the maturity stage, the innovation activity progressively moves from a focus on product innovation to an increasing attention to the innovation processes (Hutcheson et al., 1995; Klepper 1997) and therefore in this stage AI might be particularly relevant to support process innovation. In the decline stage of the industry lifecycle typically firms tend to be less prone to engage with product innovation. However, firms in a declining industry might deploy AI to enable business model innovation, thus rejuvenating the industry by means of AI-enabled radical innovations.

Therefore, an important question for future research is:

(RQ2) *How does the stage of an industry lifecycle influence firms' AI adoption for innovation projects? Do firms in more mature industries adopt later than others?*

Third, research shows the importance of AI adoption in the different stages of the innovation process:1) idea generation; 2) problem-solving; 3) implementation (Tushman, 1977). For instance, building on the double diamond framework (Dorst & Cross, 2001) that breaks down the innovation process into four phases (problem exploration, problem selection, solution exploration, solution selection), Kakatkar et al. (2020) have shown that AI can support problem exploration and selection as well as solution exploration and selection. Based on problem solving/finding paradigm, Garbuio and Lin (2021) have recently suggested that AI can potentially support problem finding as they address cognitive impediments in innovative idea generation. While most of the empirical studies conducted so far have focused on AI adoption in the solution selection stage, once the customer problem has been identified (Mariani & Nambisan, 2021), certainly more empirical studies are needed to dig in depth about how AI is supporting the very early stages of the idea generation, thus facilitating problem exploration. Moreover, we argue that these studies should be longitudinal in nature as they would need to reveal how AI adoption might differ across the stages of the innovation process from idea generation to implementation. Therefore, an important unanswered question to address is:

(RQ3) *How do the stages of a firm's innovation process shape firm's AI* *adoption for innovation?*

Fourthly, the increasing corporate attention to the Sustainable Development Goals (SDG) and to corporate social responsibility (CSR) is encouraging firms to embrace sustainability as a core organizational value. Multiple firms are adopting circular economy processes and also implementing greener solutions as a result of national legislation aimed at minimising the effects of climate change. Research conducted so far has shown that AI is supporting firms to shape novel initiatives for more sustainable product development (Cripps et al., 2020) and to enhance the eco-friendliness of existing services/products. Moreover, it has been argued that AI adoption can lead firms to optimise their operations, containing waste in new product development, and lowering their environmental imprint and footprint (Tariq et al., 2017; De Bernardi and Azucar, 2020). While this emerging body of research has been partially made sense of (Di Vaio et al., 2020), it remains doubtful if CSR and corporates' environmental concerns are driving investment in AI. More specifically, studies quantifying the pace and size of investments in AI to support sustainable innovation complying with sustainability goals are virtually missing. Therefore, an important question for future research is:

(RQ4) *To what extent do managers' ecological concerns and corporate social responsibility influence investment in AI (compared to other digital technologies) to assist innovation decisions?*

Fifth, research has shown that firms of different type, size and age have different motivations and ways to engage with innovation. On one hand it has been found that the adoption and use of AI allows also small- and medium-sized enterprises (SMEs) to create new business opportunities, improving manufacturing capacity and profits. On other hand, smaller firms face more challenges in adopting, adapting, modifying, implementing and creating new AI-based capabilities for innovation. However, other studies have found that what matters is not always firm size but rather the technological resources and capabilities that a firm can rely on. Furthermore, arguably firms with different ownership structure (private vs public), family involvement (family/nonfamily firms) and business scope could have different attitudes towards adopting AI for innovation purposes. Therefore, an important question for future research is:

(RQ5) *In what ways do organizational contextual characteristics (*e.g.*, size, geographic location, diversity of business divisions) shape AI adoption decisions in innovation?*

Regarding the **impact of AI adoption on innovation consequences**, we have found that the impact of AI adoption has been investigated in relation to product/ service innovation, process innovation, business model innovation and social innovation. First, a number of studies have focused on the impact of AI adoption on product/service innovation through digital experimentation and online product/service testing (Mariani & Fosso Wamba, 2020; Thomke, 2020). This allows supporting firms to "listen to the voice of the customers" (Mariani & Nambisan, 2021) and anticipate customers' preferences and needs through predictive analytics (Lee et al., 2019, Singh et al., 2021; Akter et al., 2021, Mariani & Nambisan, 2021). That said, so far most of the research done has focused on analytics in a relatively static way, without considering that predictive analytics entail flows and not stocks of customer data and that digital experimentation is not a one-shot activity but currently is being embedded into agile lean thinking and lean innovation practices whereby validation occurs over time and bring about business idea and business model pivoting. Therefore, and beyond innovation studies that have focused on product innovation as a consequence of AI adoption (Chaudhuri, Chatterjee et al 2021; Borges et al. 2021, more emphasis should be given to the analysis of the seizing and transforming dynamic capabilities that are involved in product innovation. Therefore, an important question for future research is: (RQ6) *How does the extent of firm's engagement with AI technologies influence the development of new products and services? What is the role of dynamic capabilities in helping companies derive more from their AI investments in innovation?*

Second, AI capabilities have been both conceptualized and examined empirically (Mikalef et al., 2021; Sjödin et al., 2021). However, it is not clear how and to what extent these capabilities interact with other innovation capabilities such as big data analytics capabilities. Indeed, it might be that the combination of AI capabilities might generate synergies that yield more than the mere sum of individual capabilities and AI capabilities might indeed amplify and strengthen other innovation capabilities. Therefore, an important question for future research is:

(RQ7) *What are the interaction effects between AI capabilities and other innovation capabilities on innovation consequences?*

Third, recent research has investigated how digitial tecnhologies – including AI - can help firms rebuild and reorganise their adaptive capabilities in emergency situations that are far from normal. The COVID-19 pandemic is rather paradigmatic of an abnormal and unusual event – indeed a global crisis – that has affected businesses of all sizes and types. While certain firms have been able to leverage AI-led innovaton to overcome some of the challenges posed by the pandemic crisis (Wamba et al., 2021), others are discontinuing several digital innovation projects as they do not have enough financial resources. What seems missing is research showing that AI adoption can help not only mitigate crises and become resilient, but also innovate during crises. This implies exmaining how adopting AI can allow firms to inovate in periods of crisis. Therefore, an important question for future research is:

(RQ8) *What is the influence of AI adoption on shaping novel business opportunities in normal times* vs *periods of crisis?*

Fourth, our review has revealed that the impact of AI adoption on innovation consequences was investigated in relation to the use of AI to tackle social and environmental challenges with the ultimate aim of achieving sustainability. Firms embracing AI have been found to lower the ecological footprint of production (Chasin et al., 2020; De Bernardi and Azucar, 2020; Del Vecchio et al., 2021b; Fernandes and Castela, 2019; Weiss et al., 2019). As consumers seem to trust firms aiming at sustainable development and social value creation (Faludi, 2020) through AI, there seems to be a paucity of studies analysing in depth how firms that adopted AI are also making sure that they create green and sustainable products/services that align with the SDGs and are perceived as innovative by potential customers. Therefore, an important question for future research is:

(RQ9) *How do organizations that have embraced AI respond/create needs for green and sustainable products/services also in relation to the Sustainable Development Goals (SDGs)?*

6. Limitations

There are a few limitations to this study. First, we decided to focus on specific forms of innovation, including product innovation, process innovation, business model innovation, incremental innovation, radical innovation, digital innovation, social innovation, sustainable innovation, open innovation, service innovation, disruptive innovation, market innovation, and organizational innovation. Future research might take int consideration more holistically innovation so that it could cover potentially all the forms and types of innovation. Second, we chose specific databases indexing research. While Scopus and WOS are the most widely used databases in SQLRs (Zupic and Cater, 2015), scholars might also collect data from other databases such as Google Scholar. Third, the software deployed for bibliometric analysis (VOSviewer) might be juxtaposed by and combined with other different bibliometric software. Building on this SQLR, we identified a number of research gaps and research directions. Table 4 provided an illustration of research directions and developed unanswered research questions in the domain of AI and innovation.

Scholars interested in answering those questions will undoubtedly face some challenges. Firstly, given that technological adoption of AI happens over time, and that antecedents and consequences would be better captured in a processual way, a dynamic perspective is needed; therefore we call for more longitudinal studies, be them qualitative or quantitative. Experiments may also aid in understanding the cognitive foundations of innovation managers' activities and decision-making processes. Secondly, it appears that researchers could use mixed methodologies, such as sequential exploratory approaches, to more thoroughly answer some of the questions listed in Table 4. Third, we encourage scholars to undertake inter- and multi-disciplinary research incorporating constructs and concepts from innovation management, computer science, data science, and information systems, to produce more comprehensive answers.

CRediT authorship contribution

Marcello M. Mariani: Conceptualization, Writing – original draft, Writing – review & editing, Investigation, Validation, Formal analysis, Methodology, Supervision, Resources, Project administration. **Isa Machado:** Conceptualization, Data curation, Writing – original draft, Writing – review & editing, Formal analysis, Methodology. **Satish Nambisan:** Conceptualization, Writing – original draft, Writing – review & editing, Investigation, Validation, Supervision.

Declaration of Competing Interest

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

Appendix A

See the Tables A1 and A2.

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