Artificial intelligence and corporate innovation: A review and research agenda

Artificial Intelligence and Corporate Innovation: A Review and Research Agenda

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Abstract:

Artificial Intelligence (AI) induce corporates to re-design their innovation process. Due to rapid technological development, synchronization of information systems, and industrialization, corporate managers increasingly adopt AI in innovation. In response, scholars are interested in the idea of creating and mapping the intersection of AI in corporate innovation, which resulted in massive literature during the past decades. To critically analyze the phenomena of AI in corporate innovation, we conducted a hybrid review of published literature (364 articles) for the last 56 years (1996 to July 2022). We present taxonomy, outline AI phases, AI large scope definition, and link with innovation. We identify eight focal fields in the intersection of AI in corporate innovation, such as AI and business models (BM), AI and product innovation, AI and open innovation, AI and innovation process, AI and firm's innovation structure, AI, firm's knowledge and innovation, and AI, innovation and firm market performance, and AI and innovativeness of supply chain management. We outline a framework encompassing the role of AI in corporate innovation. We conclude this study by identifying influential aspects of literature and presenting future research agendas.

GEL Code: L1; L2; Q55; M1; F33

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1. INTRODUCTION

Artificial intelligence (AI) is the system's ability to interpret data and leverages computers and machines to enhance humans' decision-making, problem-solving capabilities, and technology-driven innovativeness (Haenlein & Kaplan, 2019; Mishra et al., 2020; Mustak et al., 2021). Emergent growth of technology innovation, synchronization of information systems, and industrialization made adopting AI technologies unavoidable in firms (Ferrario et al., 2019; Mishra et al., 2020). The AI technologies of machine learning (ML), algorithm, internet of things (IoT), automation, intelligence-driven robotics, etc., are transforming and re-designing the corporate structures and innovation process (Bocquet et al., 2007; Morley et al., 2019; Ferrario et al., 2019).

Nowadays, corporate management and executives are applying AI-based business process engineering, influencing their innovation process globally (Burgess, 2018). Firms are learning to blend their innovation process with AI technologies to enhance capabilities and achieve competitive advantage (Porter, 1985; Musiolik et al., 2020; Bai & Li, 2020). In response, scholars are interested in the idea of creating and mapping the intersection of AI in corporate innovation, which resulted in massive but scattered literature during the past decades (Beilin et al., 2019; Kim et al., 2015; Mahmood & Mubarik, 2020). Figure 1 shows the massive growth of literature.

We conduct a hybrid literature review to capture the richness of massive and scattered literature on the intersection of AI in corporate innovation (Bahoo, 2020; Paltrinieri et al., 2019; Oyna & Alon, 2018). This hybrid literature review consists of quali-quantitative methods such as bibliometrics citation analysis and content analysis (Fetscherin et al., 2010; Bahoo et al., 2020a). In this unique and comprehensive review, 366 articles during the last 56 years (1966 to July 2022) are accessed, critically analyzed, and mapped through quali-quantitative methods (Bahoo et al., 2020b; Alon et al., 2018). This review explores the following research questions to map the implications of AI in corporate innovation; **(1)** What is the taxonomy of artificial intelligence (AI) in corporate innovation? **(2)** What are the literature's leading research streams and future research agenda? **(3)** What is the framework for encompassing the role of AI in corporate innovation? **(4)** What are the influential aspects of literature such as key AI technologies, journals, articles, types of firms, industries, countries, data sources, and methods?

This study made the following contributions to the literature on AI in corporate innovation based on an in-depth quali-quantitative review (Iddy & Alon, 2019). *First*, we provide the taxonomy, discussing the AI phases (1940 to July 2022), AI's large scope definition, and its link with corporate innovation. We conceptualize AI's large scope definition as consisting of three main categories; AI-based methods (machine learning, deep learning, etc.), AI-based industry applications (Industrial internet of things (IIoT), industry 4.0, etc.), and AI-based system software (internet of things (IoT), cloud computing, automation, etc.). *Second*, we identify eight focal research streams in the literature on AI in corporate innovation; (1) AI and business models (BMs) (which consists of four sub-streams); (i) AI impact on BMs, (ii) AI-based BMs, (iii) AI and business model innovation (BMI), and (iv) IoT-based business models and corporate innovation, (2) AI and product innovation, (3) AI and open innovation, (4) AI and innovation process, (5) AI adoption and firm's innovation structure, (6) AI firm's knowledge, and innovation, (7) AI impact on firms innovation and market performance, and (8) AI and innovativeness of supply chains management (SCM). *Third,* we develop a research agenda consisting of 28 future research questions under eight research streams. *Fourth,* we contribute to the literature by developing an interpretive framework encompassing the role of AI in corporate innovation. *Finally,* we present the influential aspects of literature that uncover the seminal papers, journals, AI technologies, firms, industries, countries, and methods studied in the past literature.

This article is structured as follows. Section 2 presents the taxonomy of AI in corporate innovation. Section 3 discusses methodology. Further, Section 4 shows the results, such as research streams and future research agenda (Section 4.1), framework (Section 4.2), and influential aspects of literature (Section 4.3). Finally, the conclusion is presented in Section 5.

(Insert Figure 1 here)

2. TAXONOMY OF ARTIFICIAL INTELLIGENCE IN CORPORATE INNOVATION

2.1 Conceptualization of Artificial intelligence

In the 1950s, Artificial intelligence (AI) was established as an academic discipline because of the rise of big data and complex computations (Turing, 1950). AI entered human lives and the social and business environment through machine learning logarithms (Newell et al., 1955). The history and development of AI are divided into the following three main phases (Anyoha, 2017; Haenlein & Kaplan, 2019): (i) Phase I - Spring (1940-1979): AI birth, enthusiasm, and golden years, (ii) Phase II - Summer and Winter (1980-2010): AI boom and emergence of intelligent agents, and (iii) Phase III – Present of AI (2011- 2022): AI, deep learning, and big data. Figure 2 shows the events and developments of AI in each phase.

Social and technological development is not achievable without the application of AI technologies. It has become essential to the business environment to bring social changes and innovation (Frankenfiel, 2021) after passing throw several evolutionary stages in the last 70 years (1950 to 2020). The advancement of AI is classified into three main evolutionary stages (Kaplan & Haenlein, 2019; Wamba-Taguimdje et al., 2020): (i) artificial narrow intelligence (ANI) or weak AI, (ii) artificial general intelligence (AGI) or strong AI and (iii) artificial super intelligence (ASI) (see Figure 2). The ANI, or weak AI, is goal-oriented and performs a single task, i.e., driving a car (Tesla Cars) and facial and speech recognition (Facebook). The ANI is a first-generation AI that simulates human behavior and cannot mimic or replicate human intelligence. The AGI, or strong AI, is the second-generation AI, able to mimic human intelligence and behavior and learn and apply intelligence to solve problems like humans, i.e., IMB Waston Supercomputer, self-driving cars, and expert systems. In the future, we might see the third generation, called the ASI, where machines become self-aware and surpass the capacity of human intelligence and ability, capable also of scientific creativity, social skills, and general wisdom. Some ASI applications are Rainbrain from Google and Alexa from Amazon.

(Insert Figure 2 about here)

AI was defined as the problem of "making a machine behave in ways that would be called intelligent if a human were so behaving" (McCarthy et al., 1995). However, it is used as a buzzword in the business world due to the steady growth of its application in human lives and corporates (Sestino & De Mauro, 2021). AI terminology is widely used and loosely defined in academia (Kanal & Lemmer, 2014). Academic experts in multiple fields have different opinions on what AI is and how to standardize AI concepts that integrate with technological development (Müller & Bostrom, 2016).

The scientist Marvin Minsky explained AI as "a science of making machines do things that would require intelligence if done by men" (Minsky, 1968, p.v). AI is also defined as a "simulation of human intelligence in machines that are programmed to think like humans and mimic their actions" (Frankenfield, 2021). Thus, a common way to define AI is to reference "Human Intelligence." Recently, Haenlein and Kaplan (2019) defined AI as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (p.5).

We consider the large scope of AI definition for this review because the term AI has been loosely utilized in the past literature (Kanal & Lemmer, 2014; Frankenfiel, 2021). We divide and cover the definition of AI based on three categories: (i) AI based on method (machine learning, deep learning, natural language processing, artificial neural network, text mining, data mining, algorithmic trading, fuzzy logic analysis), and (ii) AI based on industry applications (Industry 4.0, industrial internet of things (IIoT), robotics, wearable technologies, smart products), and (iii) AI based on system applications (Automation, internet of things (IoT), soft computing, cloud computing, biometrics, geotagging, digital technologies, information and communication technologies) (Wamba-Taguimdje et al., 2020; Weking et al. 2020; Kahle et al. 2020; Xu et al. 2020; Lichtenthaler, 2020). Based on three categories of AI, we can define AI technologies as the artifacts made through AI methods, AI industry applications, and AI systems and software used to achieve practical goals. The definition and concepts of AI technologies are explained in Figure 3. The AI technologies individually identified under three main categories are linked with each other for example, the IIoT is part of industry 4.0 (Tay et al., 2018). However, in this review, the purpose of explicitly identifying each technology is to search and cover complete literature on the subject of AI in corporate innovation.

(Insert Figure 03 about here)

2.2 Conceptualization of Corporate innovation

Innovation is defined as “the process of bringing into being something novel and useful” (Sternberg & O’Hara, 1999, p.251). Innovation was considered a fluid, whimsical process associated with a trait of individuals and corporates (Rampersad, 2020). It consists of a full spectrum of activities, from idea generation through creative thinking to commercializing products and services that will benefit the end user.

In the modern and digitalized world, innovation is regarded as a learnable process based on factors such as human capital, technologies, economic aspects, and competitive advantages in corporates (Haefner et al., 2021). The innovation range from incremental to radical and transformative changes in firms. However, the degree of innovation depends on the close eye of the holder and technologies used in that specific industry. For example, by applying AI technology to rotating paint applications, crops can be cultivated without pesticides, and air-conditioning unit efficiency can be enhanced, which is considered radical innovation.

Therefore, corporate innovation plays a significant and critical role in the survival and achieving competitive advantage in a specific industry (Kijkuit & van den Ende, 2007). For this review, we adopt the following definition of corporate innovation as “the process of enterprises implementing innovation opportunities into existing business models and modifying them according to industry requirements” (Burgelman & Sayles, 1988). The corporate innovation process consists of three main stages (Kijkuit & van den Ende, 2007; Haefner et al., 2021); (i) idea generation-creation, discovery, and generation of ideas, and (ii) idea generation-exploitation of various ideas, opportunities, and solutions, and (iii) idea implementation -the evaluation and selection of ideas to offer a product or service which may modify the business model of a corporate (Kijkuit & van den Ende, 2007).

2.3 Leveraging Artificial Intelligence in Corporate Innovation

The AI’s augmentation in corporate innovation can be understandable by analyzing its leveraging role in the corporate innovation process (Haefner et al., 2021). It can be argued that AI plays a significant role in the innovation process by supporting creativity and out-of-box thinking (Martin & Wilson, 2016). AI influences the innovation process due to technology adoption, electronic services, automation, and digital transformation of corporates (Haefner et al., 2021). AI technology is transforming the corporate innovation process in the following three stages (Arrow, 1962, Nelson, 1959; Eggers & Kaplan, 2009).

First, information processing has a core value for the idea generation stage of corporate innovation (Nelson & Winter, 1982). Managers without technology may face constraints in collecting and analyzing the adequate amount of information essential for new opportunities or finding solutions for the firms (Williams & Mitchell, 2004). The information processing constraints of a human being to process a large amount of data leads to the adoption and implementation of general-purpose technology based on AI in the firm. As a result, AI technology transforms idea generation techniques and research methods in corporate innovation (David, 1990).

Second, the effective search for new opportunities and solutions to the problem is the second and most crucial stage for idea development in corporate innovation (Eggers & Kaplan, 2009). The manager's knowledge based on their and firm experience is limited because of human constraints; therefore, the opportunities and solutions they find lead to incremental innovation (Gavetti & Levinthal, 2000). Thus, to generate radical innovation expertise in the corporate innovation process, the managers adopt AI-based advanced technologies such as automation, networks, and machine learning which extend their existing knowledge domain to create a new field (Posen et al., 2018).

The idea evaluation and implementation are the third vital stage in corporate innovation (Kijkuit & van den Ende, 2007). At this stage, the managers must evaluate and implement the best opportunity or solution to the problem. A firm lacking the adoption of AI-based technology usually cannot produce a valuable incremental innovative solution or option for their business. Therefore, the evaluation and implementation are more successful by adopting AI-based technologies (Bresnahan & Trajtenberg 1995). Summing up, AI technology is leveraging corporate innovation by transforming it because AI drives technological and organizational changes across many applications in firms. The AI-based general-purpose technologies have the potential to shift the corporate innovation process toward radical inventions which significantly enhance quality and firm productivity across many fields or sectors (David 1990; Bresnahan & Trajtenberg 1995).

3. METHODOLOGY

We adopted a hybrid review methodology to establish a literature review foundation on the topic (Paul & Criado, 2020; Bahoo et al., 2020a; Bahoo & Alon, 2020; Bahoo et al., 2019). The method consists of two critical techniques; (i) systematic review through content analysis (Danneels, 2004; Appio et al., 2021) and (ii) bibliometric citation analysis (Randhawa et al., 2016; Bahoo, 2020; Paltrinieri et al., 2019; Khan et al., 2020).

Content analysis is a widely used traditional methodology for conducting systematic reviews (Gaur & Kumar, 2018). Bibliometrics citation analysis was introduced by Price (1965) to explore the relationship between articles based on citations by considering articles as a unit of analysis (Kim & McMillan, 2008). The method adopted in this study consists of the following three essential parts (Bahoo et al., 2020a): (a) sample selection and data collection, (b) analysis, and (c) results. We summarize these essential three parts of the method in Figure 4. Further, we present methodological terms, concepts, and software in Table 1.

(Insert Figure 4 about here)

(Insert Table 1 here)

3.1 Sample Selection and Data Collection Process

The first part of the method consists of the *sample selection and data collection* for the literature review (Bahoo et al., 2020a) and entails three sequential stages (see Figure 4-Methodology). It consists of three stages. *In the first stage*, to avoid selection bias in selecting articles from only top-ranked journals or some specific field of journals like innovation and management, we searched all the journals and articles indexed in the Web of Science (WoS) database (Alon et al., 2018). The WoS covers a wide range of 3300 scientific publishers and 12000 high-ranked journals, has five databases, and provides citation data of articles dating back to 1950 (Oyna & Alon, 2018).

The second stage is selecting keywords to cover the entire literature on the subject. We adopted the large scope definition of AI to assign keywords (see Section 2.1 and Figure 3), which consist of three main categories such as (i) AI based on method, (ii) AI based on industry applications, and (iii) AI based on software/system applications. Based on the extensive scope of AI, we used the following 18 keywords to capture complete literature on the subject;

"Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Neural Networks*" OR "Natural Language Processing*" OR "Algorithmic Trading*" OR "Artificial Neural Network" OR "Robot*" OR "Automation" OR "Text Mining" OR "Data Mining" OR "Soft Computing" OR "Fuzzy Logic Analysis" OR "Biometrics*" OR "Geotagging" OR "Wearable*" OR "IoT" OR "Internet of Thing*" OR "digitalization" OR "Artificial Neutral Networks" OR "Big Data" OR "Industry 4.0" OR "Smart products*" OR Cloud Computing" OR "Digital Technologies*."

The selection of a large number of keywords for AI helps to avoid the error of missing relevant literature on the subject (Bahoo, 2020). But it may increase the chance of including irrelevant technology papers in the review that are irrelevant to AI. To avoid the error of having irrelevant technology papers, we used the methodology of Bahoo et al. (2020a) and searched these keywords in a combination of the word Artificial Intelligence. For example, the term digital technologies searched in the database with the following combination;

"Digital Technologies" AND "Artificial Intelligence" AND "Innovation" AND "Firm*" OR "Enterprise*" OR "Multinational" OR "Company" OR "MNE*" OR "MNC*" OR "Corporate."

This combination includes the papers that have at least once the word digital technologies, AI, innovation, and firm. For all 18 keywords, we followed the above mixture. Further, we searched the literature between 1950 to July 2022 and found 410 articles on the subject.

The third stage is related to confirming the final sample on the subject. By following the methodology of Wiegman et al. (2017) and Bahoo et al. (2020a), we established the following inclusion criteria for an article under this review; (i) an article must explicitly discuss or analyze the link between AI and corporate innovation, and (ii) and an article must address the topic in a non-trivial and non-marginal way. The criteria are based on the principles that an article must explore the relationship and impact of AI on corporate innovation. The two independent researchers reviewed and coded 410 articles found in the initial search and excluded irrelevant and marginal papers on the subject. This in-depth process resulted in a final sample of 364 articles. The year-wise division of articles is given in Figure 1.

3.2 Analysis

The analysis part consists of four stages in which the following complementary tests are applied (see Figure 4); (i) citation analysis, (ii) co-citation analysis, and (iii) content analysis (Alon et al., 2018). *In stage one*, we present the taxonomy of AI in corporate innovation through critical content analysis of literature (Thune & Mina, 2016). *In stage two*, we identified research streams and future research agendas through bibliometrics citation analysis coupled with content analysis (Fetscherin et al., 2010; Bahoo et al., 2020a). *In stage three*, the literature synthesis through content analysis (Alon et al., 2018; Bahoo et al., 2020b).

In the final stage, based on bibliometrics citations and content analyses, the influential aspects of literature are identified, such as AI categories based on large scope definition, methodologies, data sources and measurements, theories and frameworks, journals, top-cited and trending papers, industries and countries, and types of firms (Hall & Jaffe, 2018; Paltrinieri et al., 2019). The key findings of this quali-quantitative review (Bahoo, 2020) are discussed in detail, keeping the research objectives in the next section.

4. RESULTS

The following vital results are identified by applying quali-quantitative analysis (Bahoo, 2020). First, Section 4.1 identifies and discusses the research streams and future research agenda. The second is a framework encompassing AI's role in corporate innovation in Section 4.2. Finally, Section 4.3 identify and discuss the descriptive analysis of literature on the subject. The critical analysis of each section follows.

4.1. IDENTIFICATION OF RESEARCH STREAMS AND FUTURE RESEARCH AGENDA

The research stream in the literature is identified through bibliometrics citation analysis coupled with content analysis (Bahoo et al., 2020a). Co-citation cluster mapping was applied through CiteSpace software to identify streams. Cluster mapping is the idea that a paper cites other papers with similar content and topic (Alon et al., 2018). It shows network visualization, spectral clustering, automatic cluster labeling, and text summarization. Following this approach, we first identified clusters through co-citation, and second, we interpreted these clusters using content analysis to identify research streams (Mustak et al., 2021).

As a result of this quali- quantitative analysis (Alon et al., 2018; Bahoo et al., 2020a; Bahoo et al., 2020b), we identified the following eight distinct but interrelated research streams in Figure 5: (1) AI and business models (BMs) (which consists of four sub-streams); (i) AI impact on BMs, (ii) AI-based BMs, (iii) AI and business model innovation (BMI), and (iv) IoT-based business models and corporate innovation, (2) AI and product innovation, (3) AI and open innovation, (4) AI and innovation process, (5) AI adoption and firm's innovation structure, (6) AI firm's knowledge, and innovation, (7) AI impact on firms innovation and market performance, and (8) AI and innovativeness of supply chains management (SCM).

Table 2 presents exemplary research studies that create citation mapping and research streams in the literature. These exemplary research articles are top-cited and appeared in the cluster analysis. In particular, we summarize the idea, content, and main topic of interest of these critical articles having top-citation as part of cluster analysis in Table 3.

The literature on the subject is at the maturation stage and covers multiple research areas. However, there are still numerous areas related to AI and corporate innovation which are essential to explore in the future. We recommend the future research agenda under each stream by adopting a four-step methodology based on quali-quantitative analysis (Bahoo, 2020; Bahoo et al., 2020a). First, identify the influential and top-cited articles which create co-citation cluster mapping (see Figure 5) through software. Second, we analyzed and summarized each influential paper in research streams through content analysis to determine the potential for future research agendas. Third, we critically examined the content of the remaining articles in our sample to avoid the idea of selection bias. Finally, we converted the potential future research directions into noticeable and trending research questions. However, we excluded those research questions already explored and analyzed by researchers. This multi-step process allows us to present 31 future research questions to extend research on the subject; of AI and corporate innovation. Table 4 shows future research questions. The critical review of each stream is discussed in the next section.

(Insert Figure 5 about here)

(Insert Table 2 here)

(Insert Table 3 here)

(Insert Table 4 here)

4.1.1 Stream 1: AI and Business Models (BMs)

AI refers to a set of technologies (the internet of things (IoT), robotics, etc.) and techniques (machine learning, artificial neural networks (ANN), automation, etc.) learned or applied to improve business performance through algorithms and machines (Hahn et al., 2020). The proliferation of AI technologies holds out the prospect of enabling radical changes in corporates' business models (BM) through production, servitization, and process (Sjödin et al., 2021). This research stream interprets AI's critical role in evolving business models in the intelligence era and is divided into the following four sub-streams; (i) the AI impact on business models, (ii) the AI-based business models, (iii) the AI, business models, and innovation ecosystem, and (iv) AI, IoT, and business models.

Sub-Stream 1.1: AI Impact on Business Models

This stream of research focuses on the role and impact of AI technologies and techniques on corporate business models (Laudien & Daxböck, 2016; Kiel et al., 2017; Paiola & Gebauer, 2020). A business model (BM) refers to a "description of the roles and relationships among a firm's consumers, customers, allies, and suppliers that identifies the major flows of product, information, and money, and the major benefits to participants" (Weill & Vitale, 2001, p. 34). BMs are evolving in the intelligence era because AI is modifying corporates' ideas, innovations, and inventions (Sjödin et al., 2021). The corporates have to overthink their BM due to AI technologies, their application, and the growing utilization of big data and information in many industries and almost every nation worldwide (Kiel et al., 2017). The intelligence era for businesses and firms is highly focused on applying AI technologies and techniques such as the internet of things (IoT), robotics, automation, and machine learning tools through big data (Iansiti & Lakhani, 2020). For example, corporates are adding precise, low-cost, and always connected IoT and robotics devices in their servitization and production, such as Airbus (factory for future), Boeing (IoT-based manufacturing), Facebook (automation, machine learning), and Amazon (reinventing warehousing). The phenomenon that corporates radically change their BM because advance AI descriptive technologies is explored by researchers. Laudien and Daxböck (2016) examined how the industrial internet of things (IIoT) influences the BM designs of manufacturing firms. They applied multiple case study methodology for analyzing the impact of IIoT on German firms' BM. Based on the analysis, they presented three archetypes of BM's designs for implementing IIoT;(i) technology adoption BM (ii) virtual diversification BMs, and (iii) IIoT business models. In a similar direction, the impact of IIoT on BM component changes due to AI technologies is studied for German firms (Kiel et al., 2017). The study confirms that IIoT influences and modifies the BM components, value proposition, internal infrastructure management, and customer relationship. AI triggers corporate BMs to focus on production and process optimization. The effect of IoT on service-oriented business models in manufacturing firms has been studied by Paiola and Gebauer (2020). They found that the firm's sale mode was a strategic factor in shaping its digital servitization strategy and presented three progressive digital servitization levels: product-process-and-outcome oriented (Paiola and Gebauer, 2020).

Further, in this stream, the primary concern of managers and academic scholars is to analyze how AI impacts the business models of corporates. Therefore, *the future potential research area* is to explore the impact of customer and industry-specific factors on digital servitization strategies based on AI-related technologies (IoT) in SMEs and large firms (Paiola & Gebauer, 2020). Further, the researchers should analyze the effect of AI-related technologies (IIoT) on BM component changes while considering firms' national, cultural, and organizational differences (Kiel et al., 2017). The intelligence era is changing the BMs of corporates because of the extreme utilization of small, medium, and large firms. These phenomena directly or indirectly influence the firm value. Thus, there is a need to explore the impact of change in BMI due to adopting new technologies (AI) on firm market growth (Yun et al., 2016). These research recommendations are converted and presented in the research questions in Table 4.

Sub-Stream 1.2: AI-based Business Models

This second sub-stream focuses on the characteristics and critical analysis of AI-based business models in firms. AI aims to provide innovative and intelligent products, services, and experiences through digitalization, information sharing, and utilization of technologies (IoT, robotics) and techniques (big data, machine learning) for corporates and create optimal business efficiency (Gretzel et al., 2015). Therefore, corporates continuously try to build intelligent systems based on AI technologies and techniques that faithfully reproduce human behaviors with social, cognitive, and emotional intelligence (Haenlein & Kaplan, 2019). AI technologies and techniques have penetrated various industries and strongly affected business models

(Brandenburger & Nalebuff, 2011). A-based business models are competitive and provide opportunities, resulting in reduced resource utilization (Maedche et el., 2019). For instance, IBM and Google use chatbots that can help customers and lower the cost of customer service by 30%.

The researcher argues that AI-based BM reduces firm costs, grows the firm, sets the right direction, and retains business value (Chen & Peng, 2018; Chen et al., 2018; Weking et al., 2020). Guo et al. (2017) examined the impact of e-business model selections (novelty, efficiency, lock-in, and complementarities) on IoT mobile application valuation creation and retention through moderating effect of investment from venture capitalists. They confirm that the efficiency and complementariness-centered e-business model increase, and the lock-in-centered e-business model reduce IoT App's value retention. And the involvement of venture capitalists does not help the e-business models.

Specifically, Cheah and Wang (2017) presented an integrated framework that AI-based BM consists of three elements: (i) data-driven BM, (ii) perspective, and (iii) BM processes. Chen & Peng (2018) explored manufacturing firms' digitalization-based Equipment Maintenance Business Models (EMBMs) taxonomy. They proposed two types of digitalization-based EMBMs; (i) efficient digitalization-based EMBMs and (ii) novel digitalization-based EMBMs. Leminen et al. (2020) also presented the IIoT-based BMs for the machine-to-machine context. Their framework presented four AI-based BM types; company-specific BM systemic, BM value designs, and Industry 4.0 (I4.0) BM. Further, Weking et al. (2020) presented the following three super-patterns for AI-based BMs; (i) integration (BM with new process and integration of parts of the supply chain), (ii) servitization (BM through new products and services), and (iii) expertization (BM through the hybrid of product-and-process-focused). However, AI-based BMs are very complex. Analyzing the theoretical base of AI-based business models and their impact on corporate is essential. Thus, *the researchers can explore* AI technologies and techniques (Industry 4.0) and their taxonomies and typologies for theory building to explain AI-based BMs in firms (Weking et al., 2020). Moreover, it will be interesting to analyze the impact of e-business models (efficiency and complementary-centered) based on AI technologies (IoT, mobile applications, etc.) on firm value creation (Guo et al., 2017).

Sub-Stream 1.3: AI and Business Models Innovation

This sub-stream of research explores how AI technologies and capabilities influence business model innovation (BMI) and create value. Value creation through BMI is dominant and central in the digital era (Lee et al., 2019; Reim et al., 2020; Sjödin et al., 2020). The innovation ecosystem plays a key role in business model innovation through AI technologies (Radziwon et al., 2017; Lim et al., 2018).

The innovation ecosystems "are collaborative networks focused on the co-creation of value" (Russell & Smorodinskaya, 2018). It creates an active flow of information among the corporates to create new digital ideas based on AI (Lee et al., 2019). The researchers explained that AI capabilities influence the BMI, impacting corporates' value-creation process. Radziwon et al. (2017) argue that AI capabilities and SME innovation ecosystem impact their business model innovation and create value. The AI technologies (IoT) in startups play a significant role in BMI in startup firms and help in technology convergence in the ecosystem (Lim et al., 2018). Similarly, Kahel et al. (2020) confirm that AI capabilities and technologies (IoT and Industry 4.0) are essential for BMI in the innovation ecosystem.

Further, AI technologies-based ecosystem (IoT) plays s significant role in the BMI of firms (Rocha et al., 2019). They confirm that AI improves decision-making in firms and modifies business models, which leads to value creation. AI (IoT, Industry 4.0) results in value creation in firms by leading to BMI in the business-to-business (B2B) platform (Hein et al., 2019; Benitez et al., 2020). It is a dominant conclusion that AI impacts BMI. However, *it is essential to explore in the future* how the AI-based innovation ecosystem leads to the adaptation of intelligent products' BM in firms (Kahle et al., 2020). The platform business model innovation may affect AI implementation and adoption; a theoretical and empirical investigation is essential at the firm level (Hein et al., 2019).

Sub-Stream 1.4: IoT-Based Business Models and Corporate Innovation

This fourth sub-stream explores the role of the internet of things (IoT) as AI technology in the business model and its impact on corporate innovation. The IoT could be explained as objects that can be linked and equipped with digital technology and have networking capabilities (Fleisch et al., 2015). It connects things, technologies, and communication solutions to support business models in firms. The researchers and managers are concerned with the characteristics and role of IoT-based business models and their impact on corporate innovation and value creation (Hakanen & Rajala, 2018; Ruan et al., 2019; Le et al., 2019; Lichtenthaler, 2020; Balakrishnan & Das, 2020). The IoT has increased the complexity of manufacturing and operational process. It requires more relevant and adaptive technical solutions (Bucherer & Uckelmann, 2011). Therefore, corporates focus on developing IoT applications in their business models to create value. Lichtenthaler (2020) presented an IoT-based business model framework that leads to the digital transformation of firms, technology-oriented innovations (innovative solutions and integrated communication), and market-related (value generation and value appropriation) value creation in firms.

Similarly, Balakrishnan and Das (2020) explore firms' digital transformation through IoT-based business model strategies. They confirm that IoT technology supports firms' digital transformation in SMEs, medium and large firms and create value. SMEs use process innovation and medium and large firms use separate innovation tasks to implement IoT-based business models. Specifically, SMEs use IoT-based business models to achieve digitalization and innovative value co-creation (Riera & Iijima, 2019).

Notably, Saarikko et al. (2020) proposed five digital transformation strategies for the corporates which want to adopt IoT-based business models. These strategies include: start small and build on first-hand benefits, team up and create competitive advantage from brand recognition, engage in standardization efforts, take responsibility for data ownership and ethics, and own the change and ensure organization-wide commitment. However, Ceipek et al. (2020) presented some contradicting findings that managers avoid digital transformation based on explorative innovation by applying IoT-based business models. They believe that IoT-based business models have a high risk for their firm. Therefore, *future research must* analyze IoT-based business model frameworks and characteristics before implementing them in firms as a digital transformation tool. It is essential to explore the effect of firm ownership (public, private, and family-owned) and category (SME, medium, and large firms) on implementing IoT-based business models to achieve digital transformation (Ceipek et al., 2020). The IoT-based business models impact corporate innovation depending on the industry and location. It is essential to see the role of these characteristics before moving towards digital transformation through IoT-based BM (Riera & Iijima, 2019; Balakrishnan & Das, 2020). Further, a detailed framework is required which analyzes the threats and opportunities for IoT-bases BM in firms (Saarikko et al., 2020). Researchers should also extend the analysis by considering the impact of digital technologies on

BM's digital transformation in SMEs and large firms in multiple industries and economics (Balakrishnan & Das, 2020).

4.1.2. Stream 2: AI and Product Innovation

In the second stream of research, the scholars explore the role of AI in product innovation in firms (Chien et al., 2016; Shamsuzzoha et al., 2016; Johnson et al., 2017; Bhardwaj, 2020). Several products can be launched rapidly in multiple customer segments with the emergence of AI technologies and AI applications (Chien et al., 2016). Bhardwaj (2020) examines the effect of AI on knowledge management in product innovation. He confirms that AI-based techniques and processes enhance product design and allow efficient automation. Mariani and Wamba (2020) also studied the effect of AI-based big data analytics (BDA) companies on their customer product innovation, which are consumer goods companies (CGCs). They confirm that BDA plays a significant role in the product innovation of CGCs. Johnson et al. (2017) explored an exciting relationship between the characteristics of big data (volume, variety, and velocity) and new product development. Exploration orientation positively affects all three dimensions of a firm's extensive data usage, while exploitation orientation does not.

Wang et al. (2019) analyzed and confirmed through machine learning that companies could establish an AI-based evaluation system for binary new product development strategy (incremental VS radical) to avoid resource waste. Thus, machine learning confirms that content, contributor, and crowd are most helpful in generating ideas in a firm product innovation process (Hoornaert et al., 2017). Christensen et al. (2016) confirmed the importance of machine learning as an appropriate tool for forecasting new product ideas in the online community. Specifically, Chien et al. (2016) argue that data-driven product designs are most useful for product innovation, capturing product visual aesthetics, and satisfying consumers. However, the theoretical framework that AI technologies influence product innovation requires to be explored further. *Future researchers should* conceptualize the relationship between AI technologies and capabilities through the lens of resource-based theory and transaction costs theory, and service-dominant logic (Mariani & Wamba, 2020). Moreover, analyzing the role of AI and big data in the product innovation process for multiple industries and countries will be essential before generalizing this logical concept (Johnson et al., 2017).

4.1.3. Stream 3: AI and Open Innovation

The third stream in the literature consists of studies that explore the association between AI and open innovation in firms (Lee et al., 2018; Yoon & Song, 2014). Open innovation “emphasizes using the knowledge from inside and outside an organization as well " (Chesbrough, 2003, p.4). Technology has transformed open innovation in firms by analyzing massive outside digital data (internet) and linking it with firm international data (Chesbrough, 2003). Lee et al. (2018) confirmed that big data analysis and text mining techniques of AI help firms overcome information overload in an open innovation structure. They also presented an adoption model to analyze the term and non-term features of data which play an essential role in predicting and adopting the idea.

Furthermore, Ramos and Blind (2020) examined the role of data portability on data-driven open innovation for online platforms in Europe. They confirm that online platforms rely on two types of data-driven open innovation to overcome competition: exploitative and explorative. In a similar context, Yoon and Song (2014) demonstrated that the text mining technique of AI is an appropriate way of identifying potential partners for open innovation. Wu et al. (2019) confirmed that a decentralized innovation system is essential for adopting and implementing data-analysis technologies to improve firms' innovativeness and productivity. The conclusion can be drawn AI technologies add value to the open innovation capabilities of the firm. However, information overload is a critical problem in the open innovation process. *It is essential to explore in the future* that AI techniques such as machine learning and data analysis could minimize the problem of information (Lee et al., 2018). Further, the role of partnership among firms for open innovation structure with AI implementation is worth to be explored empirically (Yoon & Song, 2014).

4.1.4. Stream 4: AI and Innovation Process

The fourth stream of research explores AI's influence on firms' innovation process. The innovation process is described as the path of translating existing and new knowledge into marketable solutions (Lead, 2020). Paschen et al. (2020) argue that AI restructures the firm’s innovation process dimensions, such as the innovation boundaries (product-facing & process-facing innovation) and the firm’s competencies (firm's competency-enhancing or competency destroying).

Verganti et al. (2020) define design as the "decision-making side of the innovation process" (p.1) and explore the AI effect on designs in firms by applying a case study methodology. They proposed a framework that AI rewrote design in two directions; first, it reduces the limitation of the human-intensive design process by enhancing the design's scalability, scope, learning, and adaptability. Second, AI reinforces design thinking principles such as people-centered, abductive, and interactive.

Scholars also analyzed the role of AI in the innovation process of specific types of businesses, such as online platforms, online communities, service incumbent firms, and AI service providers. Hwang et al. (2019) analyzed and confirmed the positive role of data and information in improving the innovation process and idea generation in online crowdsourcing community platforms. Kim and Park (2017) also examined and confirmed that online user innovation communities refer to "'distributed groups of individuals focused on solving a general problem and developing a new solution supported by computer-mediated communication" (Dahlander & Wallin, 2006), enhancing the innovation process. Another example is Müller and Daschle (2018), who analyzed the effect of Industry 4.0 solution provider firms on the innovation process of their customers. They confirm that Industry 4.0 solution providers positively influence the innovativeness and productivity of their customers. Troilo et al. (2017) explored the influence of a data-rich environment at the service of the incumbent corporate innovation process. They developed the concept of data density as three distinct processes (spotting, real-timing decision, and synergistic exploration) that connect the service innovation opportunities with a data-rich environment.

Wang et al. (2020) studied the strategic role of IT-enabled automation, information, and transformation on explorative and exploitative innovation in Chinese firms. Their findings confirm that IT-enabled information positively affects exploration and exploitation innovation, but IT-enabled transformation positively influences firms' explorative innovation. However, IT-enabled automation negatively impacts exploration innovation in firms. Finally, Yu et al. (2016) studied the internet of things (IoT) capability on product and process innovation of Chinese high-tech IoT ventures. They found that IoT capabilities enhance the innovativeness of firms. AI adds value to the innovation process. However, the innovation process has changed from human-centered to technology-centered in firms with the adoption of AI and Industry 4.0 (Paschen et al., 2020). Therefore, *an inquiry is essential to explore* the process or factors that lead the firms to transfer their innovation process and design from human-intensive to AI-centric innovation (Verganti et al., 2020). Furthermore, a particular business firm provides Industry 4.0 solutions to customers (individuals and firms). It is timely to explore their role in the innovation process of their customers in multiple countries, industries, and types of business (SMEs, platforms, and MNEs) (Muller & Daschle, 2018).

4.1.5. Stream 5: AI Adoption and Firm's Innovation Structure

In this stream of research, the scholars examine factors and capabilities which lead the firms to adopt AI in their organizational innovation structure (Chen & Cheng, 2010; Kromann & Sorensen, 2019; Matthyssesn, 2019; Ghobakhloo & Ching, 2019). Matthyssesn (2019) identified the capabilities and factors needed for adopting AI technologies (industrial internet of things (IIoT), Industry 4.0) in organizational innovation structure. He argues that the following capabilities are essential for AI adoption; (i) marketing product-service systems, (ii) blending digital strategy and process, (iii) mobilizing the ecosystem, and (iv) integrating technological and value innovation approaches.

Similarly, Kromann and Sorensen (2019) studied the factors influencing the adoption of AI technologies in Danish firms. They confirm that international competition with industrial economies such as China is one of the main reasons for adopting AI in firm innovation and production. Additionally, SMEs' adoption of innovative manufacturing-related information and digital technologies (SMIDT) depends on technological, organizational, and environmental factors (Ghobakhloo & Ching, 2019). Trust, management style, technological innovation, risk analysis, and perceived IT security risk are the factor that leads firms to adopt AI in their innovation structure (Raut et al., 2018).

The scholars conclude that AI adoption in firm innovation depends on several organizational, individual, and natural factors. However, *it is essential to explore in the future* the determinants of AI adoption in manufacturing and service firms (SMEs and large) in multiple industries and economies (Ghobakhloo & Ching, 2019; Raut et al., 2018). The adoption of AI in manufacturing firms is higher due to Industry 4.0. Therefore, it is relevant to critically analyze the impact of digital artifacts (factory installation layouts or digital visualizations) on industrial co-creation projects in different industries (Kostis & Ritala, 2020).

4.1.6. Stream 6: AI, Firm's Knowledge, and Innovation

In the six streams of research, the scholars study the relationship between AI, firm knowledge, and innovation. Viberg and Eslami (2020) analyzed the impact of utilizing machine learning (ML) on knowledge integration and innovativeness of Swedish technological firms. They confirm that ML enhances firms' tacit and explicit knowledge integration and improves innovativeness. Similarly, Liu et al. (2020) studied the effect of AI on the technological innovation of Chinese firms through firm knowledge. They confirm that AI promotes technological innovation by accelerating knowledge creation, technology spillover, learning, and absorptive capacity. García-Álvarez (2015) demonstrated the positive impact of utilizing information and communication technologies (ICTs) on knowledge management, co-learning, and innovativeness in the Zara textile group.

Further, Ballestar et al. (2021) analyzed the impact of industrial robotics (AI) on knowledge and labor productivity in Spanish SMEs. They confirm that industrial robotics positively impacts SME performance, high labor productivity, and knowledge-intensive value processes. Lee et al. (2016) analyzed the impact of a firm's knowledge management on the technological innovation of Malaysian SMEs by applying artificial neural network techniques. As a result, they confirm that a firm's knowledge enhances SMEs' technological innovation and competitive advantage.

In another study, Lee et al. (2013) demonstrated the positive impact of knowledge management practices on technological innovation (product and process) through AI technologies. It can be concluded that AI positively affects innovation capabilities by increasing firm knowledge. However, *we believe that future researchers should conduct* an empirical investigation is necessary to explore the impact of robotics density and multiple types of robots on SMEs' knowledge, productivity, and innovativeness by considering various industries and countries (Ballestar et al., 2020). Adopting new information and communication technologies (ICTs) is vital for SMEs and large firms in the era of digitalization and Industry 4.0. Thus, it is necessary to examine how ICTs affect the firm innovative profile through knowledge management (García-Álvarez, 2015). Further, researchers should explore the impact of a firm's knowledge management on technological innovation across multiple industries and countries while considering cultural variables (Lee et al., 2016).

4.1.7. Stream 7: AI impact on Firm Innovation and Market Performance

This stream of research analyzes the impact of AI technologies on firm innovation and market performance. Innovation capabilities are referred to a firm's ability to generate a new idea and convert it into a successful product and service that benefit the firm market performance (Aas & Breunig, 2017). And market performance can be defined as a firm's value creation, productivity, and profitability (Aas & Breunig, 2017). MacPherson (1994) analyzed the impact of new technologies on the market performance of SMEs and confirmed that it enhances their process innovation, unique product development ability, and market performance. In similar directions, Christensen et al. (2018) investigated the impact of AI techniques such as machine learning, data mining, and text mining on firms' automatic idea detection systems and innovation. They confirm that an AI-based automated idea detection system improves firm knowledge, innovativeness, and value.

Furthermore, Wu, Hitt, & Lou (2020) studied the impact of data analytics capabilities on the innovation and productivity of firms. They confirm that data analytics capabilities complement innovation because it improves knowledge by linking it with information. Camina et al. (2020) empirically analyzed the effect of automation technologies on Spanish firms' productivity and employment in the long run. Their analysis confirmed that automation technologies such as robotics, computer-aided design, and data-driven control enhance productivity and employment. The researcher concludes that AI technologies positively impact a firm's performance through innovation. However, *we suggest future research directions* to confirm the role of AI in innovation and a firm's performance. AI influences both manufacturing and services firms. Thus, it could be relevant to analyze the impact of AI-based intelligent manufacturing systems on manufacturing firms' performance (financial and innovation) in multiple economies (developing, emerging, and developed) (Yang, Ying, & Gao, 2020). Furthermore, automatic idea detection based on AI is increasing in SMEs and large firms, and it is timely to explore its impact on the firm's innovativeness (Christensen et al., 2018).

4.1. 8. Stream 8: AI and Innovativeness of Supply Chain Management

The eight streams of research explore the association and impact of AI technologies on a firm's supply chain management and innovativeness. Supply chain management (SCM) is a complex network consisting of several entities, including business partners to end customers (Khatua et al., 2021). Researchers mainly focus on the innovativeness and effectiveness of SCM (Niseen & Sengupta, 2006; Papert & Pflaum, 2017; Gravili et al., 2018; Chen, 2019; Bottoni et al., 2020; Kadiyonol et al., 2020; Khatua et al., 2021; Mendonça et al., 2021). Battoni et al. (2020) explored the role of AI technologies-based smart contracts in managing firms' supply chains. They confirm that AI smart utilization in firms improves the innovativeness of the supply chain and results in high performance. Further, in an in-depth systematic review, Mendonça et al. (2021) confirm the AI's impact on SCM, improving its innovativeness. Additionally, the automation of supply chain management has a positive effect on the innovativeness of SCM.

Furthermore, Papert and Pflaum (2017) investigated the role of Internet of Things (IoT) ecosystems in SCM. Using case study grounded theory methodology, they provided a framework for firms to establish their IoT ecosystem based on a solution integrator as a central role, smart product sub-ecosystem, and application of sub-ecosystem. Notably, Niseen and Sengupta (2006) studied utilizing intelligent software agents in the supply chain management decision-making based on computer aid in firms. They confirm that computer-based decisions through intelligent software agents positively impact the supply chain decision of firms.

Similarly, Gravili et al. (2018) examined the impact of big data on supply chain management decision-making. They found that the application and utilization of big data for the decision-making process of supply chains in firms depend on the opportunity costs between automation and decision-making relying on human factors. Finally, Chen (2019) studied integrating technologies and IoT with industrial supply chains in the industry 4.0 revolution. By applying the case study for Taiwanese SMEs, he argues that SMEs can connect with global supply chains through the IoT ecosystem, improve firm productivity, negotiate, and create novel customer service experiences. However, *it is essential to analyze* the role of the IoT ecosystem in improving the SCM system in firms in different industries (Papert & Pflaum, 2017). Furthermore, it is crucial to examine the impact of AI technologies (automation, IoT, ML, and Industry 4.0) on the ecosystem of global value chains (Chen, 2019).

4.2 FRAMEWORK ENCOMPASSING THE ROLE OF AI IN CORPORATE INNOVATION

Through our in-depth quali-quantitative review of the literature (Bahoo et al., 2020a), we present the framework encompassing the role and effect of AI technologies adoption in corporate innovation. Figure 6 depicts the framework, which consists of two parts; (i) corporate innovation before AI technologies adoption and (ii) corporate innovation after AI technologies adoption (Haefner et al., 2021; Mishra et al., 2020). This framework critically analyzes the impact of AI adoption on the following elements of corporate innovation; (i) business model innovation (BMI), (ii) product innovation, and (iii) innovation outcome. We discuss the framework for ensuring subsections.

(Insert Figure 6 about here)

4.2.1 Business Model Innovation (BMI) Before VS After Adoption of AI Technologies

In industries around the globe, the corporates' BMI depends on the innovation process (Haefner et al., 2021). The innovation process is called the core of innovation structures in firms which consists of multiple stages such as identification and generation of an idea, exploration of various ideas, and evaluation and implementation (Kearney, 2002; Haefner et al., 2021). These innovation stages highly depend on information and data processing, which ultimately impacts the BMI in firms (Martin & Wilson, 2016; Shane, 2003). In traditional companies, innovation managers attempt to recognize and develop based on limited data and information (Eggers & Kaplan, 2009). Typically, the managers follow three stages of BMI; (i) strategy (limited data & information), (ii) structure (information processing), and (iii) process (implementation) (Kearney, 2002; Mishra et al., 2020). Traditional firms face the limitation of data & information processing because of cognitive limitations of manager ability. This limitation affects the firm's BMI and firm value as well.

Firms are adopting AI technologies around the globe to conduct great experiments and enhance their innovation process (Åström et al., 2022). As a result of AI technologies adoption, corporates have access to additional intelligence which links data & information with devices, social platforms, media platforms, industry platforms, and big data platforms, which overcome the cognitive limitation of humans (Agarwal et al., 2020; yoffie et al., 2016). AI-driven technologies advance the BMI transformation in firms through synchronizing the technology (Gentsch, 2019). Therefore, AI-driven firms adopt to BMI process consists of stages; (i) strategy (data & information, positioning, business segmentation), (ii) structure: architecture, event management, product portfolio, business partner network, capabilities), and (iii) process: Implementation of the idea, controlling.

4.2.2 Product Innovation Before VS After Adoption of AI Technologies

The decision-making side of innovation is called design which influences product innovation in firms (Auernhammer & Roth, 2020). Traditionally, firms use product design to innovate and produce new products and services (Bhardwaj, 2020). The decision-making and new product development innovation process consists of human-centric activities (Varganti et al., 2022). The companies face limitations in decision-making related to the product development innovation process because they rely on human cognitive decision-making. When corporates adopt AI technologies, the decision-making and problem-solving approach are replaced by algorithms and technology (Varganti et al., 2022). And the human role is to only sense which problem should be addressed through AI technologies. After adopting AI technologies, the product innovation process of firms consists of design thinking instead of product thinking, an AI-based design approach, and AI-based decision-making. Design thinking consists of principles of people-centered, abductive, and interactive. Significantly, AI does not change the product innovation process. However, reducing the human-centric approach makes it more efficient and reliable.

4.2.3 Technological Drivers of AI Adoption and Innovation outcome

The technological drivers play a significant role in firms adopting AI technologies in their innovation process (Blackburn et al., 2017). Prominently, three effective drivers are reported in the past literature such as (i) big data & information (Ciampi et al., 2021; Zhang et al., 2019), (ii) industry competition (Åström et al., 2022; Bhardwaj, 2020), and (iii) value creation in firms (Kostis & Ritala, 2020; Riera & Iijima, 2019). First, the big data & information internally and externally force firms to adopt AI technologies to identify new ideas and avail market opportunities (Zhang et al., 2019). Machine learning, big data, and IoT technologies help accelerate a firm’s ability to respond to market needs (Caputo et al., 2020). Second, the competitive industrial advantage force firms to implement AI technologies (Mariani & Borghi, 2020). Firms utilize AI technologies to create competitive advantage and capabilities in the industry to offer customized products and services (Caputo et al., 2020). Further, AI technologies are essential for firms to create value through standardized innovation (Kostis & Ritala, 2020).

Further, adopting AI technologies supports and aids the firm’s digitalization and technology development, innovation ecosystem, competitive advantage, and performance (Beilin et al., 2019; Radziwon et al., 2017; Lim et al., 2018). AI supports a firm's digitalization and new technology development, which help them to forecast, innovate, and develop new products and services (An & Ahn, 2016). Digitalization helps a firm's manufacturing and innovation process (Gavilane-Trapote et al., 2015). Using AI technologies, firms can connect and relate to other firms operating in the same industry (Lim et al., 2018). The scholars confirm the role of AI in creating an innovation ecosystem in firms (Radziwon et al., 2017; Lim et al., 2018). Finally, the adoption of AI technologies aid firm in creating a competitive advantage and improving their market performance (Beilin et al., 2019). AI support firms in achieving competitive advantage and creating standardized system, process, and operations which directly impact financial and non-financial performance (Yang et al., 2020; Wamba-Taguimdje et al., 2020).

4.3 DESCRIPTIVE ANALYSIS OF INFLUENTIAL ELEMENTS OF THE LITERATURE

The descriptive analysis of influential aspects of the literature is conducted based on bibliometrics citation analysis (Bahoo et al., 2021). We identified and discussed the following significant elements of literature, such as; (i) publication and citation structure, (ii) AI technologies studied in the literature, (iii) top publishing journals, (iv) top-cited and trending articles, (v) key measurements of variables, data sources, and methods used in literature (v) Key theories applied in the literature, and (vi) Key industries, regions, and type of firms studied in the literature.

4.3.1 Publication and Citation Structure

Table 5 shows the year-wise publication trend and citation structure of literature on the subject of AI in corporate innovation. The year-wise publication trend is graphed in Figure 1 to understand the publication phases in the literature. The literature on the subject is divided into three phases of AI utilization in social science research, organizations, and firm innovation. The phases-I (1956 to 1979) called the birth of AI in business and firms. During this initial phase, only 3 articles are published, having a 9.5 citation rate per year. These three papers marginally present the idea of AI utilization in firms, organization structure, and innovation (Meinhar, 1966; Chaitin et al., 1970; Dunca's, 1974). Phase II (1980 to 2010) shows the emergence and growth of the utilization of AI technologies in firm innovation. During the second phase, 42 articles having 1413 citations were published on the subject. The citation rate improved to 88 citations per year. The higher publication and citation rate shows the importance of AI technologies in firm innovation structure. Finally, Phase III (2011 to 2022-July) represents the book on utilizing AI technologies in corporate innovation. In total, 320 articles having 2391 citations are published during this phase. The citation rate per year increased to 217 per year. The publication and citation structure re-confirm our discussion that due to social and technological developments, the AI application in corporate innovation is non-avoidable. The findings provide vital insight for corporate managers to realize the timely application of AI technologies in their innovation process.

(Insert Table 5 here)

4.3.2 AI Technologies Studied in Literature

Section 2.1 defined AI technologies as artifacts made through AI methods, AI industry applications, and AI systems to achieve practical goals. Our large scope definition of AI consists of three categories discussed in detail in Section 2.1 for this review. It is vitally essential to explore and summarize which studies analyze the role of specific technologies in corporate innovation. Table 6 shows the list of crucial AI technologies whose role is explored. The findings show that AI, IoT, IIoT, industry 4.0, big data, and machine learning are prominent AI technologies that impact and role in corporate innovation analyzed. The results provide insights for the researcher and managers as well. The findings may be helpful for researchers in understanding which AI technology is given less importance to analyze its impact on corporate innovation. For example, the past literature gives less priority to the cloud computing and innovation relationship. Further, the results provide insights for firm managers into which technology and AI category is highly studied and essential for firm innovation. For example, the results show IoT significantly impacts firm innovation.

(Insert Table 6 here)

4.3.2 Top Publishing Journals in the Literature

Our sample of 364 articles on the subject is published by 177 journals having a total of 3454 citations. We classified the top publishing journals ranked by the Association of Business Schools (ABS) in Table 7. The results show that ABS-ranked journals publish 94 articles which are 25% of the total sample of 364. These ABS-ranked journals fall into business, management, strategy, innovation, and business categories. The *Journal of Product Innovation Management (ABS 4)* published 12 articles (11% of 94 articles), *Research Policy* (ABS 4) 7 articles (8% of 94), and the *Journal of Business Research* 9 articles (10% of 94 articles). Prominently, the *Technological Forecasting and Social Change* (ABS 3) published 22 articles which are 23% of 94 articles on AI and corporate innovation. The journal publishes high-quality papers which provide significant insights related to the subject, such as Haefner et al. (2021); Palmié et al. (2020); Shen et al. (2020), Ballestar et al. (2020), Haefner et al. (2021). The Technological Forecasting and Social Change journal could be a future target and reference for academic scholars and firm managers to explore the role of AI in corporate innovation.

(Insert Table 7 here)

4.3. 3 Top Cited and Trending Articles

We identify top-ten cited, and trending papers based on total global citation (TGC) and total local citations received in the recent period (TLCe) (see Table 1 for definitions). The HistCite software is used for this citation analysis. Table 8 lists the top 10 cited and trending studies (during 2018, 2019, 2020, 2021, and 2022). The most cited and trending articles are based on the number of citations. The most cited and trending research papers analyze and discuss the relationship between AI technologies and corporate innovation under the following research streams: AI and open innovation (Kostoff et al., 2004; Parthasarthy & Hammond, 2002; Yoon & Song, 2014; Johnson et al., 2017; Kong et al., 2017; Santoro et al., 2018; Mariani et al., 2020; Haefner et al., 2021; Leone et al., 2021), AI adoption and firm’s innovation structure (Wang & Chien, 2006; Li, 2009; Kim et al., 2015; Müller et al., 2018), AI and BMI (Ceipek et al., 2020; Hengstler et al., 2016; Kiel et al., 2017; Lalicic & Weismayer, 2021; Leone et al., 2021), and AI, firm’s knowledge and innovation (Athaide et al., 2003; Lee et al., 2013; Hoornaert et al., 2017; Troilo et al., 2017; Goduscheit & Faullant, 2018; Verganti et al., 2020), AI impact on firm’s innovation and market structure (Ballestar et al., 2020; Sjödin et al., 2020), AI and innovativness of supply chain (Toorajipour et al., 2021), and IoT-bases business models (Burström et al., 2021).

(Insert Table 8 here)

4.3.4. Key Types of Firms, Industries, and Countries Studied in the Literature

Table 9 lists firms based on the nature of their business, which has been studied in the past literature. We categorized them as manufacturing, service, and multiple types, such as IoT startups and IIoT solution providers. The categorization is helpful for firm managers to understand the role of AI technologies in specific types of firms. The relevant papers will help understand the essentials of AI in service (Balakrishnan & Das, 2020; Weking et al., 2020) and manufacturing firms (Golovina et al., 2020; Sjodin et al., 2020; Paiola & Gebauer, 2020; Aversa et al., 2020). It provides insights for academic scholars to understand and plan future research projects in multiple types of firms (Laudien & Daxböck, 2016; Shamsuzzoha et al., 2016). The research on the role of AI technologies in startups, platforms, and digital-born global firms is limited and could be a future unit analysis for the researchers (Müller, & Däschle, 2018).

Further, we categorized the industries and countries analyzed in the past literature on AI and corporate innovation in Table 10. The past literature studied the manufacturing, informational technology (IT), information and communication technology (ICT), IoT, cloud computing, big data, and service-providing industries. For example, the role of AI technologies in corporate innovation is explored in the automotive sector (Hein et al., 2019; Bhardwaj, 2020), IoT (Lim et al., 2018; Wamba-Taguimdje et al., 2020), and IT (Kiel et al., 2017; Ramos, & Blind, 2020). The findings are helpful for firm managers working in those industries to review the relevant studies to conclude.

Moreover, the role of AI technologies in corporate innovation depends on the country where a firm works. For example, Europe, America, and China are highly advanced and developed in applying AI technologies to companies (Guo et al., 2017). Therefore, we summarize the countries analyzed as the sample in the past literature. For example, prominently several studies have been conducted on Chines firms because of the country's industrialization (Yu et al., 2016; Guo et al., 2017; Zhang et al., 2018; Wang et al., 2019; Wang et al., 2020; Liu et al., 2020). In the second position, the academic scholars explored AI's role in German firms (Laudien & Daxböck, 2016; Kiel et al., 2017; Müller et al., 2018; Veile et al., 2019; Ceipek et al., 2020). The findings of industries and countries explored in the past literature show the technological advancement of nations.

(Insert Table 9 here)

(Insert Table 10 here)

4.3.5. Measurements, Data Sources, and Methods

Table 11 shows measurement and data sources for AI and corporate innovation, which the past researcher used. The researcher primarily measures the variable AI technologies through questionnaires and surveys (Leone et al., 2021; Lalicic & Weismayer, 2021). For example, IoT (Benitez et al., 2020; Kahle et al., 2020) and Industry 4.0 applications (Kahle et al., 2020; Benitez et al., 2020; Mahmood & Mubarik, 2020) is studied through survey and interviews. Similarly, the researchers analyze the firm innovation structure through surveys and interviews (Kostis & Ritala, 2020; Saarikko et al., 2020; Paiola & Gebauer, 2020; Mahmood & Mubarik, 2020; Sjodin et al., 2020; Mariani, & Wamba, 2020). The detailed content analysis of data sources and measurements reflects a solid need to conduct a firm-level survey by some public organizations at the country level. This public data at the firm level will help investigate the role of AI in corporate innovation.

Further, we summarized the critical methods used by the researcher in the past literature. Table 12 lists 21 different and unique methods used to study AI's role in corporate innovation. The most prominently applied methods in the literature are case studies (34 articles) (García-Álvarez, 2015; Laudien & Daxböck, 2016; Balakrishnan & Das, 2020; Ramos & Blind, 2020), machine learning (17 articles) (Jun & Sung 2013; Christensen et al., 2016; Paschen et al., 2020; Guerzoni et al., 2020), and neural network analysis (12 articles) (Kannebley, Porto, & Pazello, 2005; Chen & Chang, 2009; Wu et al., 2019; Xu et al. 2020). Some studies also applied more than one method. The findings are helpful for researchers who are working or planning to work on AI in the corporate innovation context.

(Insert Table 11 here)

(Insert Table 12 here)

4. CONCLUSION

This article reviews the literature quali-quantitatively on AI in corporate innovation between 1966 and July 2022. We conducted a hybrid review of 364 papers using bibliometric citation and content analyses. This study answered the following questions: (1) What is the taxonomy of artificial intelligence (AI) in corporate innovation? (2) What are the literature's leading research streams and future research agenda? (3) What is the framework for encompassing the role of AI in corporate innovation? (4) What are the influential aspects of literature?

By answering to questions mentioned above, this study portrays and enhances debate on the phenomena of AI in corporate innovation. This study made the following contributions to the literature. First, a detailed discussion of AI phases (see Figure 2), conceptualization, large scope definition (Figure 3), and role in corporate innovation is presented. Second, the eight research streams are identified (Figure 5, Table 2 & 3) ; (1) AI and business models (BMs) (which consists of four sub-streams); (i) AI impact on BMs, (ii) AI-based BMs, (iii) AI and business model innovation (BMI), and (iv) IoT-based business models and corporate innovation, (2) AI and product innovation, (3) AI and open innovation, (4) AI and innovation process, (5) AI adoption and firm's innovation structure, (6) AI firm's knowledge, and innovation, (7) AI impact on firms innovation and market performance, and (8) AI and innovativeness of supply chains management (SCM). Third, a framework encompassing the role of AI in corporate innovation is presented and discussed (Figure 6). Finally, the influential elements of literature are identified (Section 4).

Through this in-depth review, we identified novel research gaps and questions which will be fruitful for firm managers to understand the role of AI in corporate innovation. More specifically, we made key recommendations for firms. First, AI and industry 4.0 have transformed the business model innovation (BM) in all firms (SMEs and large). Thus, firms need to consider AI as part of their business strategy in the short and long run. Second, industrial manufacturing firms should adopt AI technologies in intelligent manufacturing to achieve a competitive advantage. Therefore, firms should establish an AI management division in their internal organization structure.

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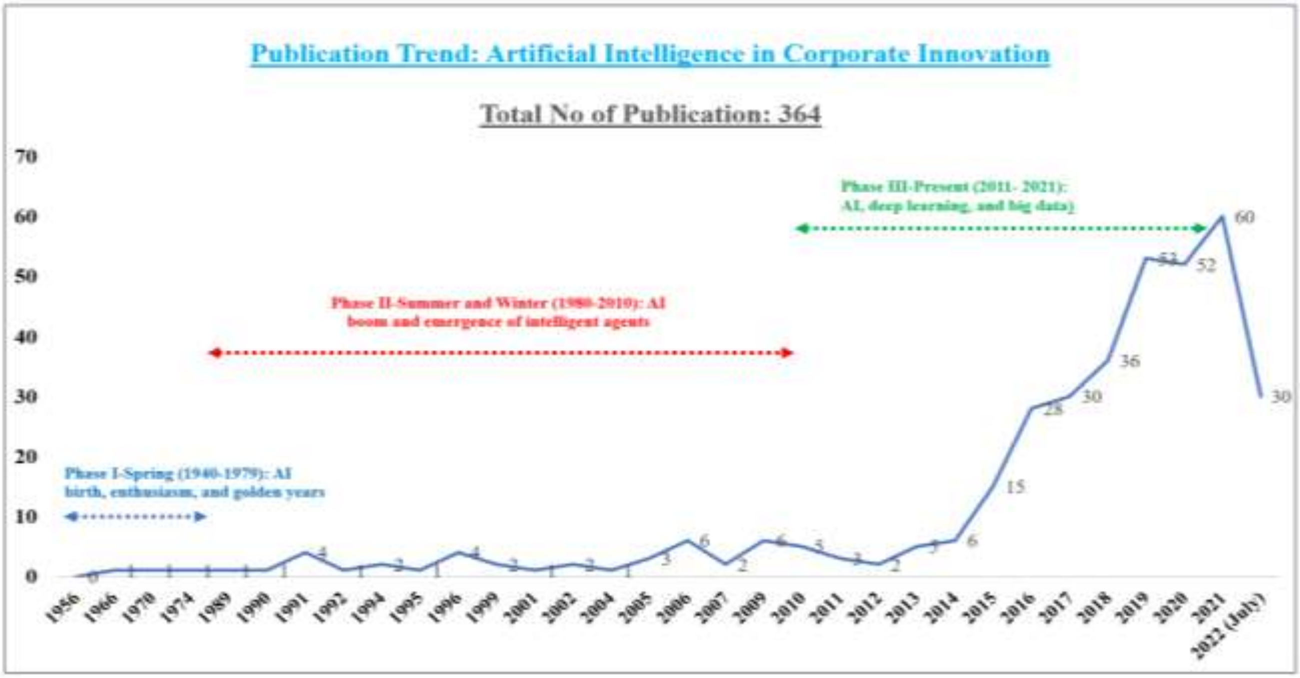

Figure 1. Publication Trends: AI and Corporate Innovation

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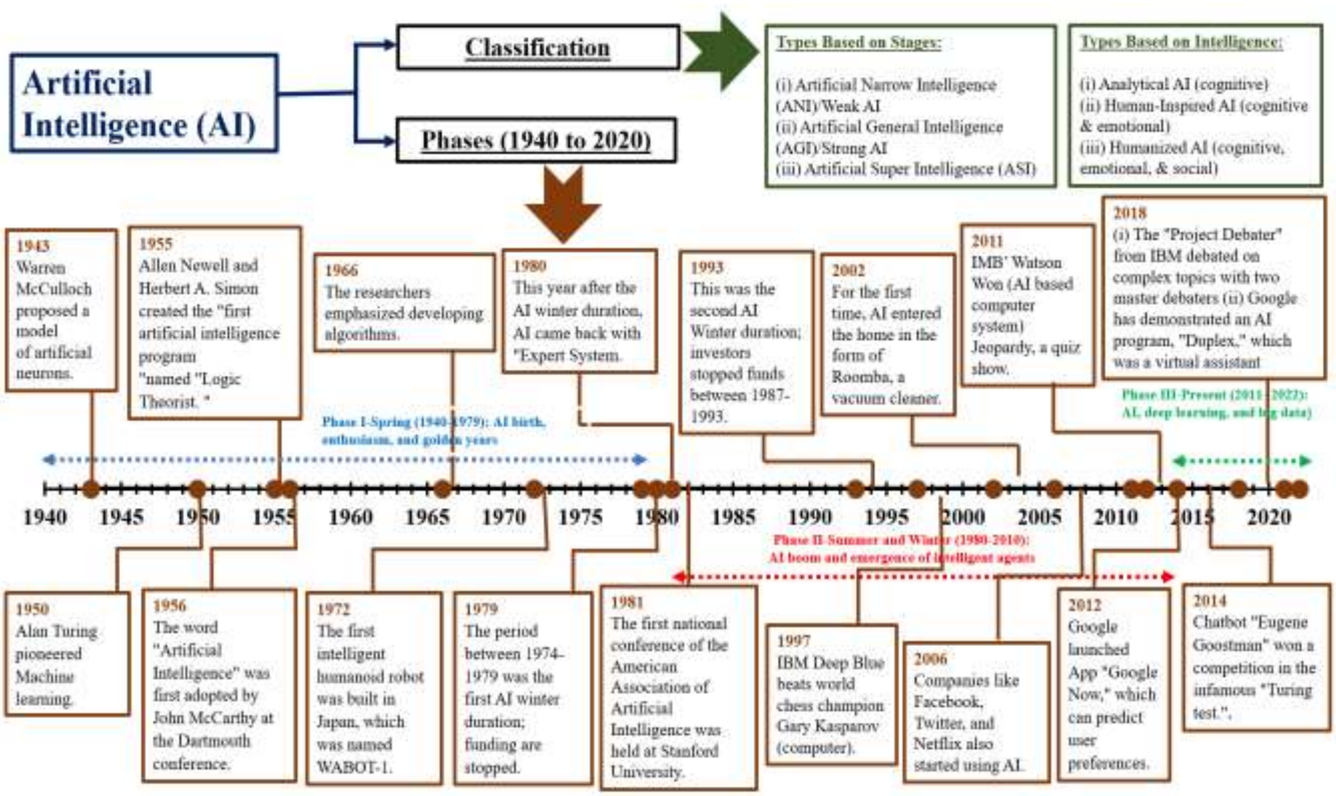

Figure 2: Artificial Intelligence (AI) History and Phases.

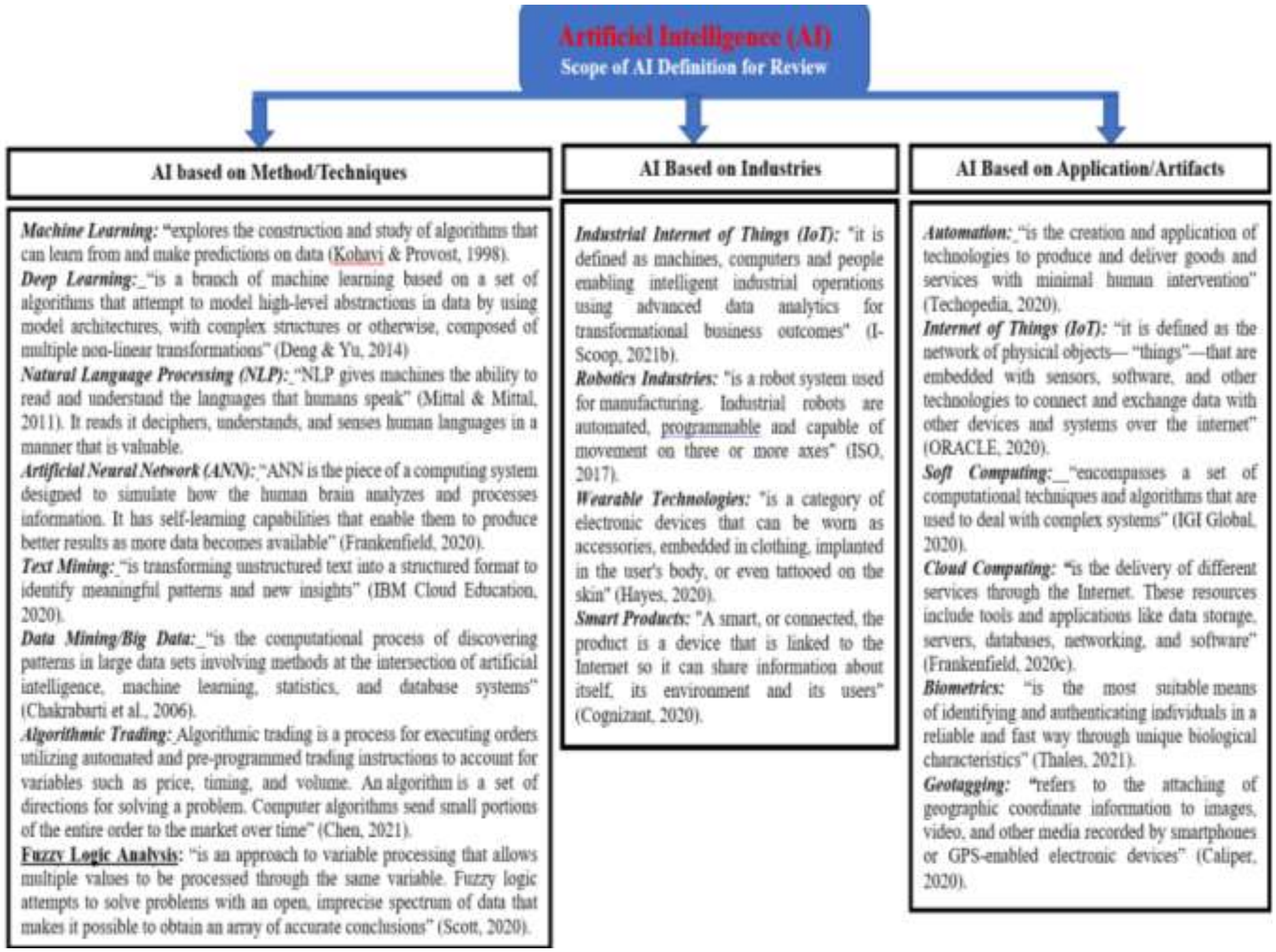

Figure 3. Concept of AI for this Review Study

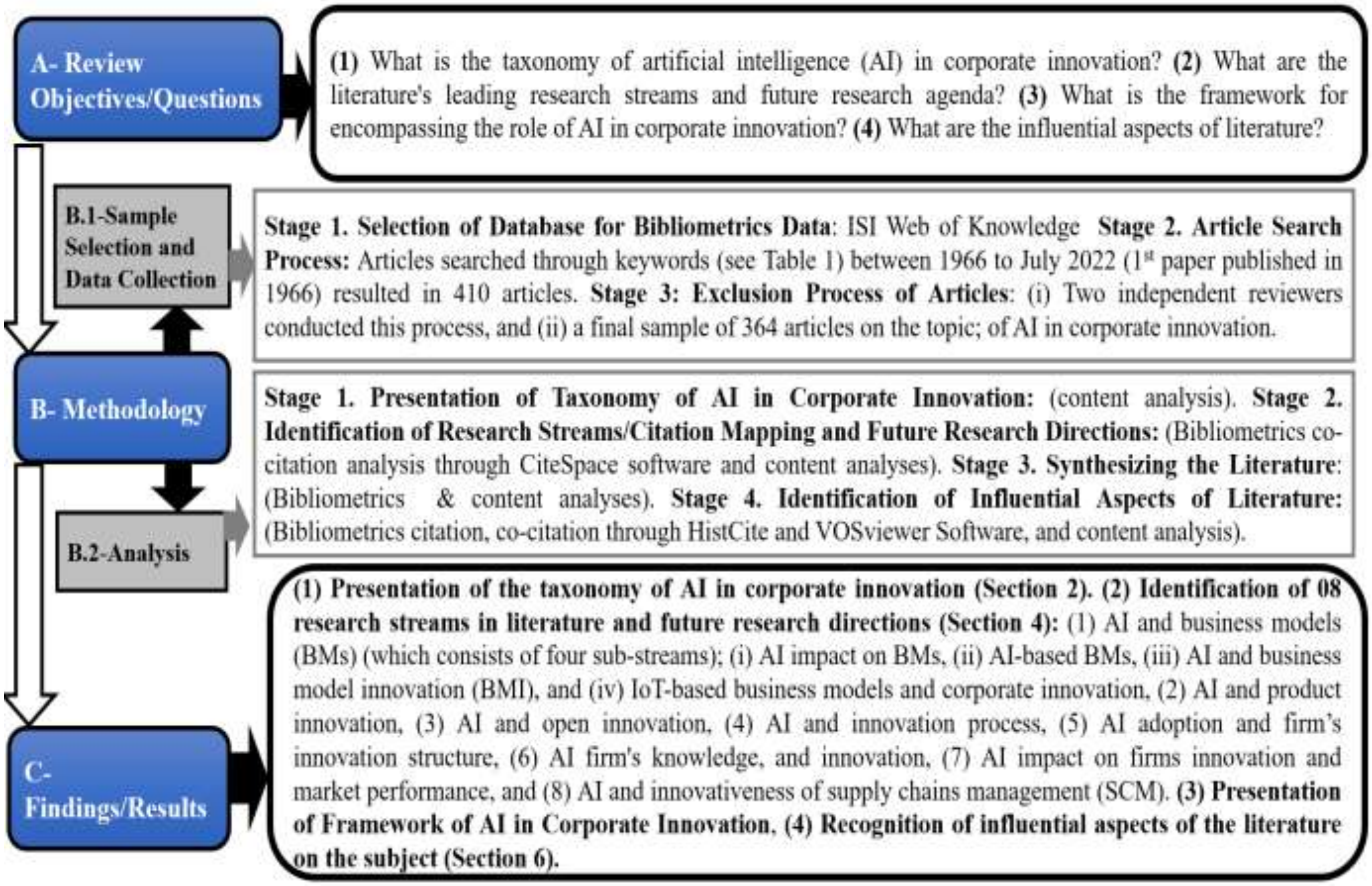

Figure 4. Methodology

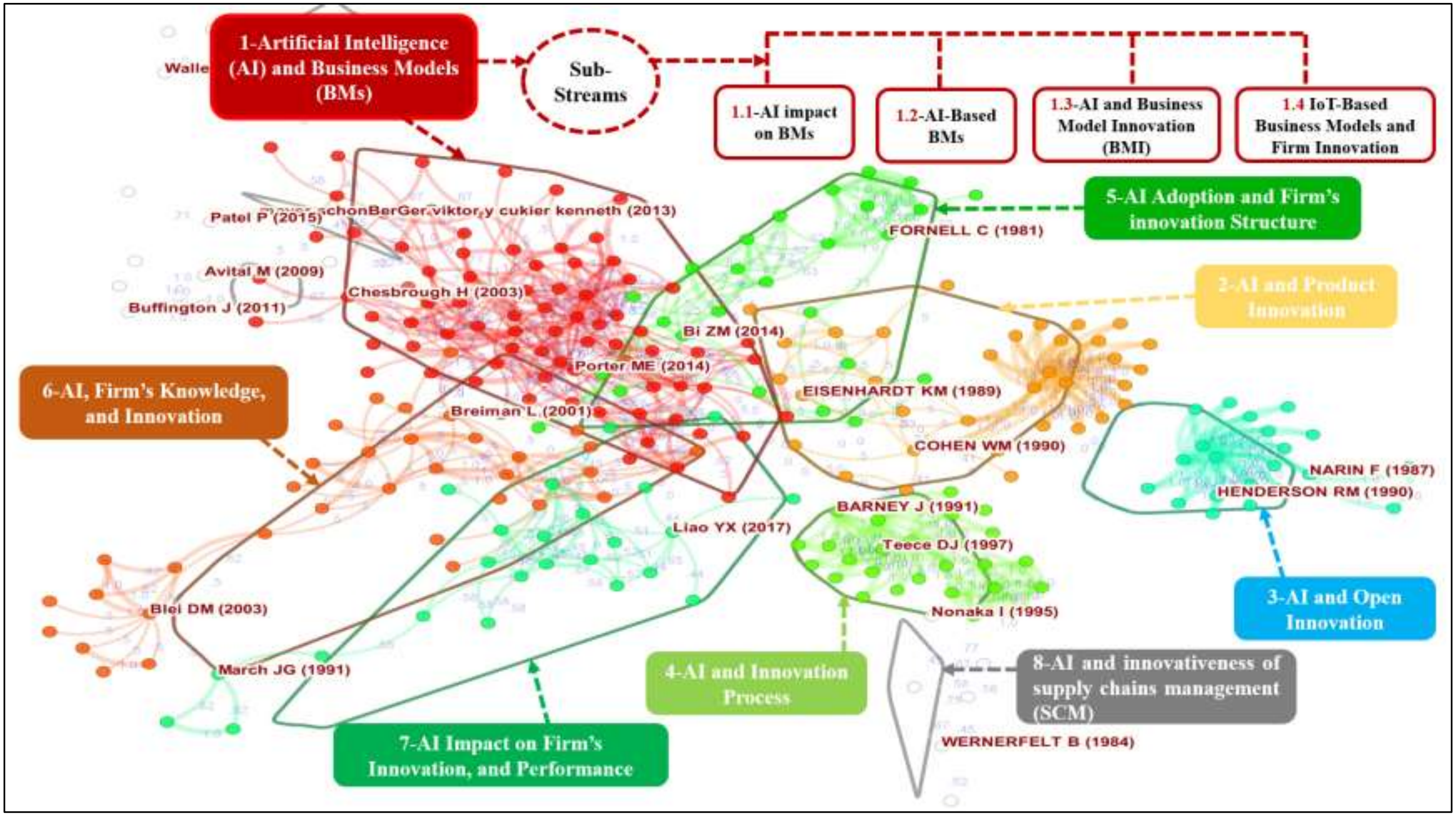

Figure 5. Citation Mapping: Co-Citation Analysis and Identification of Research Streams

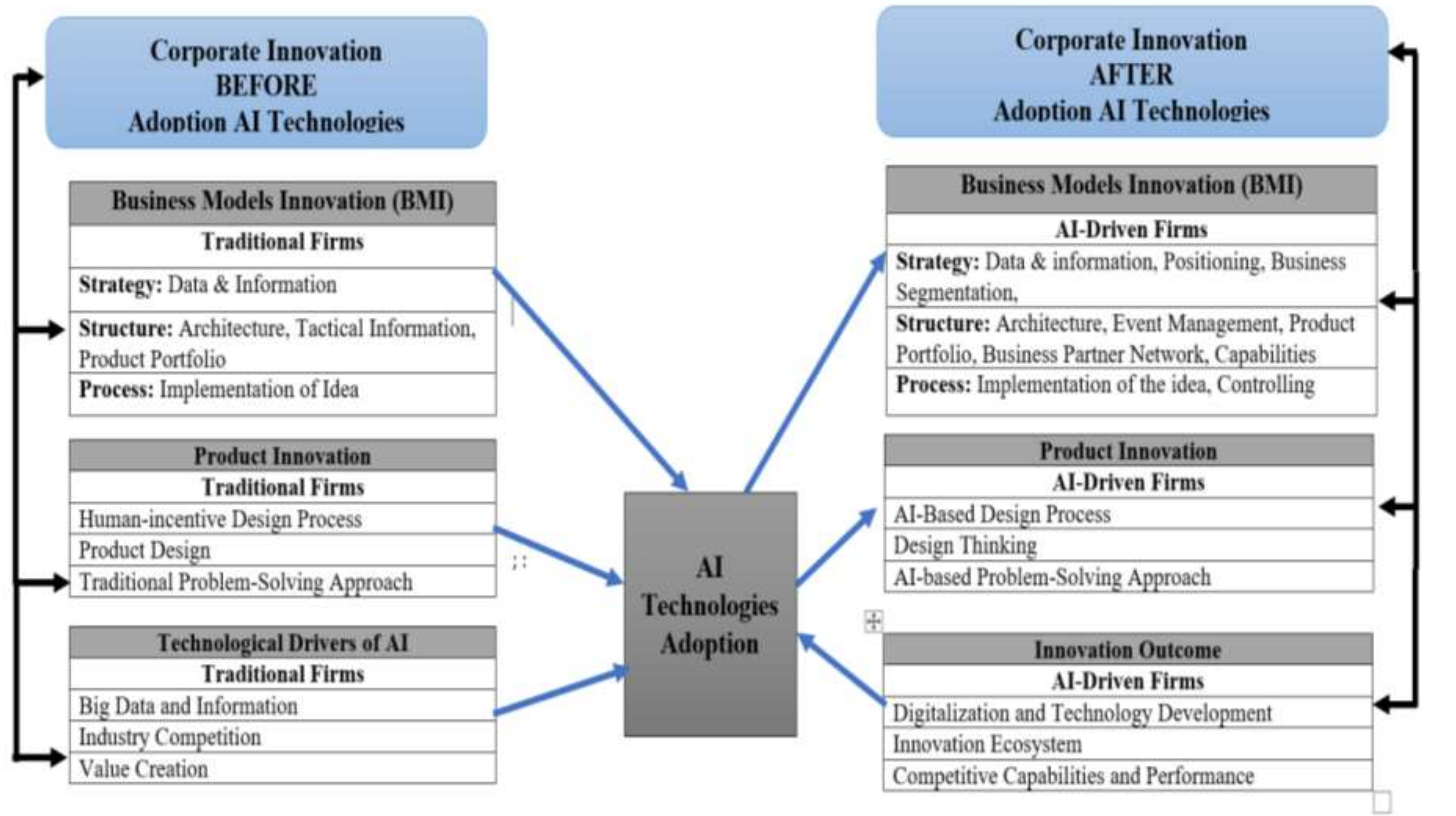

Figure 6. Framework Encompassing Role of AI in Corporate Innovation

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Table 1. Key Methodological Concepts

A- Sample Selection and Data Collection Process			
Stage 1*: Selection of database for articles bibliometrics data*			
Database for citation data:	(i) ISI Web of Knowledge (WoS) has been available since 1950, and the top 12000 journals are listed on it.		
Stage 2*: Articles search technique from database*			
Period of search:	1950 to July 2022.		
Keyword selection for literature search:	(i) The keywords are selected by analyzing the key papers on AI and corporate innovation. (ii) The large scope definition of AI covers the whole literature on the subject, as discussed in **Section 2 and Figure 03**. (iii) 18 AI, 01 innovation, and 06 keywords for the firm are combined in the search to cover the entire literature. The list is given below—the Asterisks (*) are used to capture plural forms. The example of a combination is given below; the same process is adopted for each word. (iv) The search yielded 410 articles on the topic: of AI and corporate innovation.		
List of keywords used in combination:	Keywords for AI (18) (Vlačić et al., 2021)	Keywords for innovation (02)	Keywords for the firm (06)
	"Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Neural Networks*" OR "Natural Language Processing*" OR "Algorithmic Trading*" OR "Artificial Neural Network" OR "Robot*" OR "Automation" OR "Text Mining" OR "Data Mining" OR "Soft Computing" OR "Fuzzy Logic Analysis" OR "Biometrics*" OR "Geotagging" OR "Wearable*" OR "IoT" OR "Internet of Thing*" OR “digitalization” OR “Artificial Neutral Networks” OR “Big Data” OR “Industry 4.0” OR “Smart products*” OR Cloud Computing” OR “Digital Technologies*.”	"Innovation*"	"Firm*" OR "Enterprise*" OR "Multinational" OR "Company" OR "MNE*" OR "MNC*" OR “Corporate.”
Example of Combination:	“Digital Technologies” AND *“Artificial Intelligence”* AND "Innovation" AND "Firm*" OR "Enterprise*" OR "Multinational" OR "Company" OR "MNE*" OR "MNC*" OR “Corporate.”		
Applied filters/field Tags:	(i) Topic filter: The topic filter, which searches keywords in the Title, Abstract, and Author Keywords of the article, is used for AI and firm keywords (Analytics, 2021). For innovation, the Title Filter is used. (ii) Language Filter: English (iii) Categories: All (iv) Document types: Only Article		
Initial sample:	By following the above process of article search, 410 articles were found on the topic.		
Stage 3: *Exclusion of irrelevant articles*			
Criteria and process of exclusion	(i) Two independent researchers critically reviewed the initial sample of **410** articles. (i) An article must explicitly discuss or analyze the link between AI and corporate innovation. (iii) The article must address the topic in a non-trivial and nonmarginal way-the—in-depth reading and coding of articles done. (iv) As a result, the final sample was reduced to **364** articles.		

B- Analysis			
***(i)** Key analytical methods applied*			
Name of analytical method	Software	Explanation/definition/purpose	Results found through analysis
Bibliometric citation analysis	HistCite	The term citation means an article refers to another article or book due to its relevant content and topic.	(i) Top cited and trending articles identified **(Table 7).** (ii) Identification of 364 articles in the sample.
Bibliometric cartography analysis	VOSviewer	This analysis is to identify a network among keywords-based co-occurrence of these words in the literature.	(i) Keyword's network **(Figure 05).**
Bibliometric Co-Citation Analysis	VOSviewer	The purpose of this analysis is to identify a network among journals that researchers cite due to the common topic.	(i) Top journals **(Table 6).**
Bibliometric Co-Citation Cluster	CiteSpace	This analysis aims to identify the literature clusters on AI and corporate innovation based on bibliometric co-citation analysis.	(i) Identification of co-citation mapping: Research streams in the literature **(Figure 6 & Table 11).**
Content Analysis	NA	It is a technique to analyze both the manifest and latent content of a study qualitatively.	Content analysis is combined with bibliometrics analysis to find all results.

***(ii)** Bibliometrics terms and software are used in the method*

Detail of term/software	Definition/explanation/details
Total Global Citation (TGC)	"It denotes citation of an article received based on the full database of ISI WOS" (HistCite - Glossary, 2018).
Total Local Citation Per Year (TLC)	"It denotes the number of times others cite an article in the sample literature (i.e., our 322 articles) (HistCite - Glossary, 2018).
No of Article Published = (P_{AI-CI})	"It shows the number of articles published on AI and corporate innovation" (HistCite - Glossary, 2018).
Total Local Citations Received in Recent Period = (TLCe)	"It denotes TLC citations an article received during last three years between 2018, 2019, and 2020" (HistCite - Glossary, 2018).
HistCite Software	It is a bibliometrics software designed to explore and analyze the citation data of WoS. It has several features, including citation analysis, co-citation analysis, and histography analysis (HistCite-Glossary, 2018).
VOSviewer Software	It is bibliometrics software that accepts the citation data from WoS and Scopus both for analysis. It can conduct investigations such as citation, co-citation, bibliometric coupling, etc. (VOSviewer, 2021).
CiteSpace Software	CiteSpace is also a bibliometric software that accepts data from WoS and creates co-citation clusters and identification of research streams.

Note: The table presents a detailed method, terms, methods, analysis, and sample selection process.

Table 2. Research Streams in the Literature.

Research streams	Exemplary research studies
***Stream 1*: AI and Business Models (BMs)**	
***(i) Sub-stream*: AI impact on BMs**	Laudien & Daxböck, 2016 ; Kiel et al., 2017 ; Paiola & Gebauer, 2020 ; Sjödin et al., 2021 ; Di Vaio et al., 2021.
(ii) Sub-stream: AI-Based BMs	Guo et al., 2017; Cheah & Wang, 2017; Chen et al., 2018; Weking et al., 2020; Leminen et al., 2020.
(iii) *Sub-stream:* AI and Business Model Innovation (BMI)	Radziwon et al., 2017; Lim et al., 2018; Rocha et al., 2019; Hein et al. 2019; Benitez et al. 2020; Kahle et al. 2020; Leone et al., 2021 ; Lalicic, & Weismayer, 2021.
(iv) *Sub-stream:* IoT-Based Business Models and Firm's Innovation	Riera & Iijima, 2019; Lichtenthaler, 2020; Ceipek et al. 2020; Balakrishnan & Das, 2020; Saarikko et al., 2020; Golovina et al., 2020; Burström et al., 2021; lshawaaf & Lee, 2021.
***Stream 2*: AI and Product Innovation**	Tidd, 1995; Shamsuzzoha et al., 2016; Chien et al., 2016; Christensen et al., 2016; Hoornaert et al., 2017; Johnson et al., 2017; Bhardwaj, 2020; Mariani & Wamba, 2020; Wang et al., 2020.
***Stream 3*: AI and Open Innovation**	Yoon & Song 2014; Lee et al., 2018; Nylund et al., 2018; Wu et al., 2019; Ramos, & Blind, 2020; Mariani & Wamba, 2020; Haefner et al., 2021.
***Stream 4*: AI and Innovation Process**	Yu et al., 2016; Kim & Park, 2017; Troilo et al., 2017; Goduscheit, & Faullant, 2018; Müller, & Däschle, 2018; Hwang et al., 2019; Wang et al., 2019; Verganti et al., 2020; Paschen et al., 2020.
***Stream 5*: AI Adoption and Firm's Innovation Structure**	Raut et al., 2018; Ghobakhloo & Ching, 2019; Kromann & Sorensen, 2019; Matthyssens, 2019; Kostis & Ritala, 2020; Lee, & Shin, 2020; Guerzoni et al., 2020.
***Stream 6*: AI Firm's Knowledge and Innovation**	García-Álvarez, 2015; Lee et al., 2016; Lee et al., 2013; Mahmood & Mubarik 2020; Liu et al., 2020; Viberg, & Eslami, 2020; Ballestar et al., 2020.
***Stream 7*: AI Impact on Firm's Innovation and Market Performance**	MacPherson,1994; Neubert & Krogt, 2018; Christensen et al., 2018; Wu et al., 2020; Aversa et al., 2020; Yang et al., 2020; Wamba-Taguimdje et al., 2020; Camina et al., 2020' Cappa et al., 2020; Ballestar et al., 2020 ; Sjödin et al., 2020.
***Stream 8*: AI and innovativeness of supply chains management (SCM)**	Nissen & Sengupta, 2006; Papert, & Pflaum, 2017; Gravili et al., 2018; Chen, 2019; Toorajipour et al., 2021.

Notes: The table shows the research streams identified based on citation mapping (Figure 05).

Table 3. Summary of Key Papers

Article reference	Purpose/research question	Sample/method/AI aspects/period	Key Findings/conclusions
Stream 1: AI and Business Models (BMs)			
	(i) Sub-stream: AI impact on BMs		
Laudien & Daxböck, 2016	How do IIoT-related technologies affect BM design?	i. Manufacturing firms, ii. Multiple Case study, iii. IIoT	i. Presented three archetypes of BMs for a manufacturing firm that implemented IIoT; (i) technology adoption BM, (ii) virtual diversification BM, and (iii) IIoT business model.
Kiel et al., 2017	How do IIoT* technologies affect BMs component changes?	i. German manufacturing firms, ii. Case study, iii. IIoT	i. The IIoT impacts BM components, value proposition, internal infrastructure management, and customer relationship. ii. IIoT-triggered business models are focused on production and process optimization within customers' production systems.
Paiola & Gebauer, 2020	How do service-oriented IoT technologies impact a firm's BMs?	i. B2B manufacturing firms, ii. Case Study, iii. IoT technologies	i. The study presents a digital servitization map that helps understand the firm's strategic transitions caused by technologies. ii. the firm's sales model as a strategic factor in shaping the firm's digital servitization strategies. iii. Three progressive levels of digital servitization BMs are presented, namely, product-process and outcome-oriented.
	(ii) Sub-stream: AI-Based BMs		
Cheah & Wang, 2017	Which business model innovation is progressive and dynamic among; perspectives, business model processes, and big data-driven business model innovations?	i. China, ii. Case Study	i. The study presents an integrated framework for BMI, which consists of three elements: (i) data-driven business model innovation, (ii) perspective, and (iii) business model processes. (ii) The findings confirm that BM based on big data is the more progressive and dynamic innovation process.
Guo et al., 2017	How do e-business model selections of an IoT mobile application impact value retention for a startup?	i. China, ii. Regression, iii IoT (mobile application)	i. The study analyzed the four characteristics of e-business model selection (novelty, efficiency, lock-in, and complementarity). ii They confirm that efficiency and complementarities-centered e-business model increase and lock-in-centered e-business model reduces IoT App's value retention. Iii, the involvement of venture capitalists, does not help all types of e-business model value retention.
Chen et al., 2018	The study presents a digitalization-based equipment maintenance business model (EMBM).	i. China, ii. SEM, iii. Digitalization (IoT, big data, Cloud Computing), iv. Period: December 2017 to April 2018	i. The study proposes two types of digitalization-based EMBM; (i) Efficient digitalization-based EMBM to monitor equipment operating conditions, and abnormal data, predict equipment life cycle, achieve efficient service transactions, and expand the existing market. (ii) Novel digitalization-based EMBM monitors operating conditions, analyzes customers' preferences, predicts customers' needs, provides new solutions, and covers new markets.

Weking et al., 2020	The study presents Industry 4.0 (I4.0) based business models (BMs)	i. Cases Study, ii I.40 BM.	i. The study presents a taxonomy related to I4.0 BMs and 13 patterns of I4.0 BMs. ii Three super-patterns are identified, such (i) Integration (BMI with new process and integration of parts of the supply chain management), (ii) servitization (MBI through new products and services), and (iii) expertization (BMI through the hybrid of product-and-process-focused).
Leminen et al., 2020	The study presents the IIoT-based BMs for machine-to-machine context (M2M)	i. Multiple, ii Case Study, iii. IIoT, iv. M2M	i. The study presents a framework related to IIoT-based BMs for M2M. ii Based on their framework, they present four distinct types of IIoT BMs; Company-specific business models, systemic business models, value designs, and systemic value designs. iii. The study also presents the idea of value design for BMs.
	(iii) Sub-stream: AI and Business Model Innovation (BMI)		
Radziwon et al., 2017	How do SMEs engage in BM development in a regional innovation ecosystem?	i. Denmark, ii. Case study, iii. Automation	i. The SMEs create value in the regional innovation ecosystem through shared goals and financial support by matching their core capabilities with others. ii. Ecosystem development depends on the value-capture process at the inter-organizational level. iii. The innovation ecosystem led to business model development and value creation in automation projects.
Lim et al., 2018	What factor results in technology convergence in the IoT startup ecosystem?	i. Network Analysis & Co-occurrence, ii. IoT	i. The study used the knowledge-sharing topology to confirm that investors play a crucial role in connecting IoT ecosystems. ii. IoT systems have many investors and connections and more chances of technology convergence.
Hein et al., 2019	How business to business IoT platform BM ecosystem add value to co-creation practices?	i. Multiple, ii. Case study, iii. IoT	i. IoT B2B platforms follow three value co-creation practices for their BMs; (1) integration of complementary assets, the demand-side through (2) ensuring platform readiness and connecting both processes by (3) servitization through application enablement.
Rocha et al., 2019	How can the IoT ecosystem influence decision-making and BMs through the International of Management Artifact (IoMA) framework?	i. IOT, ii. Theoretical study, iii. IOMA framework	i. The study presents an IOMA framework for how the IoT ecosystem impacts firms' business models. ii. The study proposes paradigm shifts from “things” centered to “information technology” architecture. iii. The results confirm that IoT architecture improves decision-making by providing rich, accurate, and relevant information to promote business models.
Benitez et al., 2020	How does the Industry 4.0 innovation ecosystem impacts the firm's BMs and value creation?	i. Brazil, ii. Case Study, iii. IoT	i. The study examines the effect of SMEs' Industry 4.0 innovation ecosystem on their value co-creation and retention. ii. the confirm that the ecosystem objective has shifted from innovation funds to industry 4.0 solutions and value creations in the firm through BMs. ii. With trust and commitment to I4.0 BMs, the power structure shifted from the centrality of business association towards a mechanism of neutral coordination of complex projects.
Kahle et al. 2020	What factors are essential for the innovation ecosystem to offer Smart products (IoT, I4.0) through BMs?	i. Brazil, ii. Case Study, iii. Smart Products (IoT, I4.0)	i. The study presents the following capabilities essential innovation ecosystem for smart product’ BMs; hardware; IoT and sensors; cloud services; big data and analytics; and (v) system integration.
	(iv) Sub-stream: IoT-Based Business Models and Firm’s Innovation		

Riera & Iijima, 2019	How can SMEs implement digital technologies (AI) and achieve digital business value?	i. digital Technologies (AI), ii. Japan, iii. Period: 2016-2017	i. The studies show that SMEs can achieve digital business value through two types of organizational capabilities; ii. AI-based capabilities like risk management, business planning, international knowledge, dissemination, and continuous innovation positively affect digital business value. iii. IT and organizational capabilities leverage business value from implementing digital technologies (AI) models in SMEs.
Golovina et al., 2020	How do digital twin (IoT, predictive and system analytics) technology influence the business model and industrial enterprises?	i. Text mining, ii. Case study, iii. Semantic analysis	i. Digital twins (IoT predictive and system analytics) influence the product enterprise, business models, productivity, resources, energy intensity, and production costs at all product life cycle stages. ii. The study refined the business model of a new generation industrial economic system based on the functionality of digital twins, system parameters, systems parameters, and IoT.
Saarikko et al., 2020	What strategies are helpful for digital transformation for firms by considering IoT as a backdrop?	i. Case Study, ii. Digitalization (IoT)	i. The articles presents five strategies for digital transformation; start small and build on first-hand benefits; (2) team up and create competitive advantage from brand recognition; (3) engage in standardization efforts; (4) take responsibility for data ownership and ethics; and (5) own the change and ensure organization-wide commitment.
Balakrishnan & Das, 2020	How do digital technologies (AI) influence the digital transformation of firms' strategic and managerial actions?	i. Case Study, ii. Digital technologies (DT)	i. The study provides insights into how AI technologies influence firms' digital transformation strategies. ii. they confirm that medium and large-size firms handle innovation and operation separately, but small firms build innovation into operations by embedding skills in team members. ii. SMEs focus on process innovation, whereas others focus on process optimization for implementing digital transformation. iii. New managerial action is required for DT; employee engagement, technology-centric activities, and external stakeholder-centric activities.
Ceipek et al., 2020	How does the family management role impact the BMs' digital transformation through IoT innovation (from *exploratory to exploitative)*?	i. German, ii. Longitudinal analysis, iii Period: 2002-2013, iv. IoT	i. The study's findings confirm that family-managed firms do not welcome the risk of exploratory IoT innovation compared to exploitative innovation for the transformation of digital transformation. ii. The involvement of family managers constrains the digital transformation of BMs through exploratory IoT innovations.
Lichtenthaler, 2020	Which is the appropriate framework for the digital transformation of firms?	i. Theoretical study, ii. AI, iii. Digital Transformation	i. The study presents the framework as a building block of the digital transformation of firms’ BM due to AI implementation. The study discusses technology-related factors (innovative solutions and integrated communication) and market-related factors (value generation and value appropriation).
Stream 2: AI and Product Innovation			
Shamsuzzoha et al., 2016	How will information and communication technologies (ICTs) influence SMEs' collaboration, productivity, and product innovation?	i. theoretical paper/case study, ii. ICTs (AI), iii. ICTs platform for SMEs (Net-Challenge)	i. The study presents an ICTs network platform for SMEs in three industries: textile, machine tools, and footwear. ii. The study concludes that the ICTs network platform substantially positively influences SME productivity, collaboration, and product innovation.

Chien et al., 2016	Is data-driven product design for capturing product visual aesthetics and user experience efficient and valuable for innovation?	i. Machine Learning, ii. Case study, iii. Electronics Manufacturing Company	i. This study confirms that data-driven product design for capturing product visuals and user experience is efficient and valuable for product innovation. ii. The findings are confirmed that applying machine learning in electronics manufacturing service companies will improve productivity and performance.
Christensen et al., 2016	How could online community data be used to identify a product innovation idea through machine learning and text mining?	i. online community, ii. Machine Learning and Text Mining	i. The study proposes a model for using big data from the online community step-by-step and generating product innovation ideas. ii. it confirms that machine learning is a vital forecast tool for the online community to innovate.
Hoornaert et al., 2017	Which variables (corresponding to the 3Cs (Content, Contributor, Crowd)) are more helpful in generating ideas for product innovation through AI (Machine Learning, Automated information retrieval method)?	i. AI (Machine Learning) and Automated information retrieval method) ii. Crowdsourcing IT platform, iii Period; Since 2008	i. The results from machine learning show that crowd-based idea predictor is best, followed by idea content and contributor. ii Firms should implement two idea selection systems; (i) Rank and select product ideas based on content and contributor experience, and (ii) integrate them with the crowd's idea evaluation.
Wang et al., 2020	Which is an appropriate indicator system for the binary new product development (NPD) strategy (i.e., incremental NPD or radical NPD) based on machine learning?	i. machine learning, ii. Chinese firms, iii. Period: 2001-2014	i. The study confirms that RS-Multiboosting machine learning (AL) is an outstanding forecasting method while dealing with the small dataset and helpful for firms to decide about incremental and radical NPD strategies to avoid resource waste and improve performance.
Mariani & Wamba, 2020	How do AI-based big data analytics (BDA) companies impact consumer goods companies' (CGCs) product innovation?	i. the UK, ii. Case Study, iii Big data analytics (BDA)	i. The confirms that BDA enhances product innovation in CGCs. ii. It presents a framework for how BDA works in CGCs for product innovation. iii. The framework consists of the following factors: digital experimentation, firm capabilities, and the directional process of data.
Bhardwaj, 2020	How do SAAS software and cloud computing impact a firm's knowledge management (KM) in product innovation?	i. Case Study, ii. SAAS software and cloud computing	i. The study confirms that creative design based on consumer's study can lead to sustainable product development. ii. AI, techniques, and processes enhance the creative design of product innovation and APIs (Application Programming Interface), allowing efficient infrastructure orchestration and resource allocation.
Stream 3: AI and Open Innovation			
Nylund et al., 2018	How does automation impact the firm's turnover in open innovation environment?	i. Automation, ii. Spanish firms	i. The study explores the link between open innovation, automation, and firm turnover. ii. The study found that firms that innovate and suppliers and their suppliers possess the knowledge to invest more in automation. ii. Automation also has a positive impact on firm turnover through open innovation.

Johnson et al., 2017	How has big data transformed the product development process?	i. Survey, ii. big data, iii. USA firms, iv. Casual effect analysis	i. The study analyzed the influence of big data usage characteristics (volume, variety, and velocity) in the new product development model. ii. the study concludes that exploration orientation positively affects all three dimensions of a firm's big data usage, while exploitation orientation does not.
Yoon & Song, 2014	What is an appropriate technique to explore the potential partners for open innovation through text mining?	i. Text mining, ii. LED industry,	i. The text mining, morphology analysis (MA), and generative topology map (GTM) are appropriate techniques to discover technological opportunities, identify necessary technologies and explore potential partners.
Lee et al., 2018	How can data and text mining overcome information overload in an open innovation environment?	i. Open innovation community, ii. Data mining, text mining, and sentiment analysis	i. The study explores the role of data mining and text mining on overload data in an open innovation environment firm through the adoption probability of the idea model. ii. The study confirms that term and non-term features of the data play a vital role in predicting and adopting ideas through a hybrid classification model. iii. The hybrid models will help the firms identify non-helpful ideas and enhance their efficiency for open innovation.
Wu et al., 2019	How does AI (data analytics technologies) impact a firm's innovation process?	i. Machine Learning ii. Period: 1988-2013	i. The study confirms that the impact of data analytics technology on the corporate innovation process depends on the organization's structure. ii. the decentralized innovation structure is required for data-analytics technologies, which improve firm productivity and innovation.
Ramos, & Blind, 2020	How does data portability in the EU impacts data-driven innovation for online platforms?	i. Data-driven, ii. AI (Data Analysis), iii. Period; 2015-2018, iv. Case study	i. The study empirically examined the Spotify online platform and found that it will invest in two types of data-driven innovation: exploitation-innovation to enhance user engagement and exploration-innovation to develop new algorithms to include customer data. ii these two types of innovation will improve the firm's capacity to develop new technology for online platforms.
Stream 4: AI and Innovation Process			
Yu et al., 2016	How do IoT capability and alliance impact product and process innovation?	i. High-tech IoT Ventures, ii. China, iii. Structural Equation Modeling	i. The results confirm that the IoT capability individually enhances product innovation. ii. However, the IoT capability with alliance enhances product and process innovation in new high-tech ventures. iii. New ventures should focus on IoT capability and alliance.
Kim & Park, 2017	How do user innovation communities influence the product/service innovation process?	i. text-mining (AI) & case-based reasoning, ii. User innovation communities-Apple App Store.	i. The authors confirm that user innovation communities promote idea creation and product/service innovation by applying text-mining and case-based reasoning approaches.
Troilo et al., (2017)	How the data-rich environment influences the innovation process of service incumbent firms?	i. case study, ii. literature review, iii. Survey of firms.	i. By applying the case study methodology, identify the concepts of data density as three distinct processes (spotting, real-time decision, and synergistic exploration) that connect the service innovation opportunities with a data-rich environment. ii. the study identifies the organizational enablers that facilitate the link between technology, data density, and service innovation.

Goduscheit & Faullant, 2018	What factors influence radical service innovation in firms? What factors lead to this transition process?	i. Fuzzy set qualitative, ii. Danish SMEs, iii. Digitalization/big data	i. By applying Service- dominant logic (SDL), the study explores the factors that lead to radical service innovation in Danish firms. ii. They confirm that digitalization and big data are the main factors that lead to radical service innovation in manufacturing firms.
Müller & Däschle, 2018	How do industry 4.0 solution providers impact their customer process innovation?	i. Germany, ii. SMEs, iii. Industry 4.0 solution providers iv. Case Study	i. They study to explore the impact of industry 4.0 solution providers on the process innovation of their customers. ii. The results confirm that I4.0 solution providers positively impact customer innovation by reducing the cost of their production, inventory, and complexity during process innovation.
Hwang et al., 2019	How can information and data collected through individuals' networks in an online crowdsourcing platform influence a firm's innovation?	i. Natural Language Processing (AI), ii. Period: 2007	i. The study confirms that an online customer support crowdsourcing community is called the generalists (who help others generate ideas online) and performs better in creative novel ideas and products than non-generalists. ii. The generation of outperforming ideas to innovate depends on accumulated deep knowledge as well.
Wang et al., 2019	How do strategic roles of IT (automation, information, and transformation) influence explorative and exploitative innovation activities?	i. China, ii. Period: 2013-2014, iii. IT (AI.)	i. The study explores the strategic role of IT in explorative and exploitative innovation activities. ii. The IT-enabled transformation has a positive effect on exploration innovation. iii. IT-enabled information has a positive effect on exploration and exploitation innovation. iv. IT-enabled automation is negatively related to exploration.
Verganti et al., 2020	How Artificial Intelligence impacts the design and innovation process?	i. Case Study, ii. AI.	i. The study explores the impact of AI on the innovation process and design and presents a framework having two directions. First, AI reduces the limitation of human-intensive design processes by improving the scalability of the design, widening its scope, and enhancing its ability to learn and adapt. Second, AI reinforces design thinking principles: people-centered, abductive, abductive, and iterative. ii. AI-based created solutions are more user-centered than human-based approaches.
Paschen et al., 2020	How does AI influence the business and managers, and how does AI impact innovation?	i. theoretical paper, ii. Artificial Intelligence	i. The study provides a typology of how AI influences the innovation process with two dimensions; (i) the innovation boundaries (distinguish between product-facing & process-facing innovation), and (ii) their effects on organizational competencies (describe innovation as a firm's competency-enhancing or competency destroying).
Stream 5: AI Adoption and Firm's Innovation Structure			
Raut et al., 2018	What are the determinants of the implementation of Cloud Computing (AI)?	i. India, ii. Structural Equation Modeling (SEM), Artificial Neural Networks (ANN), Interpretive Structural Modeling (ISM), iii. Cloud Computing, iv. Period: January 2016 to July 2016	i. The following factors are determinants of cloud computing are identified. (1) through SEM, trust, management style, technology innovation, risk analysis, and perceived IT security risk, (2) the ANN identified the following factors as most important; IT security risk, trust, and management style. (3) ISM identified the factors: a decrease in internal systems availability, utilization of internal resources, assurance of data privacy, increased adoption rate, innovativeness, and previous experience. (ii) the study also suggests that utilizing the hybrid approach is the best guide for implementing and adopting cloud computing.

Ghobakhloo & Ching, 2019	What are Smart Manufacturing-related Information and Digital Technologies (SMIDT) determinants, such as artificial intelligence adoption within SMEs?	i. Malaysian and Iranian SMEs, ii. AI, iii. Case Study and regression	i. The study confirms that the technological, organizational, and environmental factors determine AI adoption in manufacturing SMEs. ii. The study presents a framework for how SMEs decide to adopt AI.
Kromann & Sorensen, 2019	What factors impact the adoption of automation technologies (AI), and how do automation technologies impact a firm's productivity?	i. Denmark, ii. automation (AI)	i. The study confirms that adopting new technologies is slow in manufacturing firms and relies on manual production. ii. The manufacturing sector is highly exposed to international competition related to automated manufacturing in China. iii. China's direct competition firm is adopting innovative automation in manufacturing faster than others. iv. Automation has a positive impact on a firm's productivity and innovativeness.
Matthyssens, 2019	What are the key drivers and barriers to implementing and adopting Industry 4.0 and IIoT which impact the value innovation?	i. Industry 4.0 and IIoT, ii. Literature Review	i. Industry 4.0 and IIoT have changed companies' business models, and value or strategic innovation is essential. ii. Five key capabilities are suggested for adoption and implementation of I4.0 and IIoT; capabilities for designing, adapting, and marketing product-service systems, capabilities for blending digital strategy, capabilities for designing and mobilizing ecosystems and integrating these into a value-based IIoT platform, capabilities for combining and integrating technological and value innovation approaches.
Kostis & Ritala, 2020	How does adopting Virtual Reality (VR)-enabled digital artifacts influence firms to adopt and implement tailor-made solutions in robotics and automation projects?	i. Robotics and Automation (AI), ii. Case study,	i. The adoption of new digital co-creation practices redefines the traditional customer-provider roles in industrial co-creation, increasing engagement reducing uncertainty, and improving project outcomes.
Lee, & Shin, 2020	How does machine learning influence the enterprise, and which types of ML are appropriate to apply in firms?	i. Machine learning (ML), ii. Theoretical Paper	i. ML influences product and service costs and speeds up business processes. ii. ML is implemented almost in all industries due to technological development and Industry 4.0. iii. The study presents ML usage, types of ML usage in firms, accuracy and interpretability of ML, and crucial consideration in selecting the resight algorithm for the task at hand.
Guerzoni et al., 2020	What is the effect of innovativeness on the survival of Italian startup firms, measured through machine learning?	i. Machine learning (ML), ii. Italy, iii. Period: 2008-2013	i. This study uses data science techniques such as machine learning to examine the impact of innovativeness on the survival of Italian startup firms. ii. The results confirm that applying the different ML techniques confirms that innovative firms survived the global crisis of 2008 compared to non-innovative firms.
Stream 6: AI Firm's Knowledge and Innovation			

García-Álvarez, 2015	How do information and communication technologies (ICTs) (AI) influence the knowledge management processes within organizations and their influence on innovation?	i. Information and communication technologies (AI). ii. Case Study	i. The study applies a case study on Zara textile group and found that this company uses different tools of ICTs, management systems based on electronic communication, or automation processes. ii. ICTs positively affect knowledge management's socialization, exteriorization, and interiorization processes. iii. Co-learning from ICTs favors the development of living fashion that designs new output lines in two weeks (product innovation).
Lee et al., 2016	How do a firm's knowledge management influence technological innovation and competitive advantage, analyzed through ANN?	i. Malaysia, ii. Artificial Neural Networks (AI), iii. SMEs	i. The firm's knowledge management directly impacts technological innovation and competitive advantage for SMEs. ii. And technological innovation influence positively a competitive advantage.
Lee et al., 2013	How the knowledge management (KM) impacts technological innovation? Are artificial neural networks the proper methodology to identify technological innovation?	i. Malaysia, ii. Artificial Neural Networks, iii. Russia	i. This study confirms that a firm's knowledge management practices (knowledge sharing application and storage) positively impact technological innovation (product and process innovation).
Mahmood & Mubarik, 2020	How do a firm's intellectual capital (IC) and technology absorptive capacity (TAC) balance the innovation and exploitation activities in Industry 4.0 revolution?	i. Pakistan, ii. SMEs, iii. SEM	i. Intellectual capital influences the firm's innovation and exploitation activities in the era of I4.0. ii. TAC also plays a mediating role between IC and organizational ambidexterity.
Liu et al., 2020	How does AI impact technological innovation through firm knowledge?	i. China, ii. AI, iii. Period: 2008-2017	i. AI promotes technological innovation by accelerating knowledge creation, technology spillover, learning, absorptive capacities, and increasing R & D investments. ii. By controlling multiple variables, AI significantly promotes technological innovation.
Viberg & Eslami, 2020	How does machine learning (ML) technology impact a firm's knowledge integration and innovativeness?	i. Sweden, ii. Machine Learning, iii. Technology Firm	i. The study confirms that a technological firm indicates that tacit and explicit knowledge integration can occur using ML. ii. Technology such as ML enhances corporate innovation and performance by integrating knowledge.
Ballestar et al., 202	How do industrial robotics (AI) influence knowledge and labor productivity?	i. Industrial robotics (AI), ii. SEM, iii. Spain	i. The study explores the link between industrial robotics, knowledge, and labor productivity. ii. Robotic devices are associated with better performance, high labor productivity, and improved knowledge-intensive value processes. iii. Robot improves labor productivity.
Stream 7: AI Impact on Firm's Innovation and Market Performance			
MacPherson,1994	How the adoption of new technology impacts the market performance of SMEs?	i. USA, ii. New technology (AI.)	i. The new technology adoption enhances the SME's ability to process innovation, new product development, and market performance. ii. The significant new technology adoption improves the SME's competitive advantage.

Neubert & Krogt, 2018	How does a business intelligence solution impacts the export performance of firms?	i. Case study ii. business intelligence solution (AI.)	i. The study confirms that business intelligence solution positively impacts the firms' export performance.
Christensen et al., 2018	How does AI (machine learning, data mining, text mining) influence automatic idea detection systems in firms by analyzing the big data in online communities?	i. Online communities for brewing, ii. Machine learning and text mining, iii. Automatic detection system.	i. In this study, the 200 posts are collected from the online community for brewing by an automatic idea detection system. ii. The study confirms that an automatic idea detection system is sufficiently valid to be deployed for harvesting and initial screening of ideas and the profile of the identified ideas (in terms of novelty, feasibility, and value).
Wu et al., 2020	How do data analytics capabilities (AI) impact innovation and firm productivity?	i. Firms, ii. Natural Language Processing,	i. The data analytics capabilities (AI) are more valuable in firms inclined to improve the process and create new technologies. ii. Data analytics capabilities complement certain types of innovation because they improve firm knowledge to combine new technologies. iii. Firms that focused on process innovation and innovation by diverse recombination received more benefits from data analytics capabilities, which enhance firm productivity.
Yang et al., 2020	How intelligent manufacturing (AI) impacts the firm's financial and innovation performance?	i. China, ii. Manufacturing firms, iii. Period: 2014-2019	i. The study confirms that intelligent manufacturing positively impacts manufacturing enterprises' financial and innovation performance. ii. The relationship between AI and financial performance and innovation performance is not apparent in labor-intensive industries.
Wamba-Taguimdje et al., 2020	How does AI impact the firm performance, notably the business value of AI-based projects?	i. Artificial Intelligence, ii. AI-based transformation projects, iii.	i. The results confirm that AI improves the existing processes, automation, information, and transformation effects and detects, predicts, and interacts with humans. ii. AI enhances the organization's performance (financial, marketing, and administrative) and process levels. iii. AI solution providers can enhance the business value of their transformed projects.
Camina et al., 2020	How do automation technologies (AI) impact the firm's productivity and employment in the long run?	i. Spanish firms, ii. Regression, iii. Manufacturing firms	i. Automation technologies (robotics, computer-aided design, data-driven control) boost a firm's sales, exports, innovation, and R & D. ii. Robotics and flexible technologies for production boost productivity. iii. Automation technologies also reduce labor costs. iv. Overall, automation increase the long-term trend in employment.
Aversa et al., 2020	How the digital machines influence the firm's manufacturing flexibility?	i. digitalization, ii. British and Italian firms, iii. Case study	i. The study presents the four fundamental mechanisms (1) the interactive space around the machine, (2) the innovation activities performed in the machine space, (3) the time within activities involving the machine, and (4) the time perception is reshaped which impacts the firm's manufacturing flexibility. ii. these machine factors influence the flexibility of manufacturing firms and improve their performance.
Cappa et al., 2020	How does the big data for creating a digitized environment and value impact the firm?	i. big data/digitalization, ii.	i. The study analyzes the value-creating and digitized environment through big data by using three dimensions of data; volume, variety, veracity, and how it impacts the firm performance. ii. The study confirms that big data has a negative impact on firm performance (volume has a negative impact, variety moderates the negative impact of volume, and veracity positively impacts big data via value creation).

Stream 8: AI and innovativeness of supply chains management (SCM)			
Chen, 2019	How does AI (technologies, IoT) integrate industrial supply chains in the industry 4.0 revolution?	i. Taiwan SMEs, ii. Case Study, iii. AI (IoT)	i. SMEs can connect to global supply chains by using IoT ecosystems (AI) in the context of Industry 4.0. ii. SMEs can partner with global supply chains through three roles; original manufacturer, brand clothing manufacturer, and intermediate trader. iii. The connection with global supply chains occurs with a focus on the following four value creation models; (1) increasing production efficiency, (2) improving negotiation skills for more extensive and more orders from international suppliers, (3) grasping channel needs and management, and (4) creating novel customer service experiences.
Gravili et al., 2018	How does Big Data (AI) influence the decision-making process of supply chain management (SCM)?	i. Literature Review and Case study, ii. AI (big data (BD), digital divide (DD), and digital alphabetization (DA)), iii. Europe	i. The authors examine the impact of DD and DA on the big data that influence firms' supply chain management decision-making (SCM). ii. The utilization of the BD for the decision-making of SCM depends on the quality of the human factor. iii. Applying the DA in the decision-making process of SCM is challenging. It is an ongoing process that depends on the opportunity cost between automation and decision-making or relying on human factors.
Nissen & Sengupta, 2006	How do intelligent software agents (AI) impact the firms' supply chain decision-making based on computer-aided?	i. intelligent software agents (AI), ii. Experimental Research	i. This study presents some new boundaries of computer-based decision-making quite broadly related to the firms' supply chain decisions (procurements). ii. It confirms that computer-based decisions through intelligent software agents (AI) positively impact firms' supply chain decisions.
Papert & Pflaum, 2017	How to develop an IoT ecosystem for firms involved in supply chain management (SCM) (like logistics)?	i. SCM, ii. Case Study, iii IoT ecosystem	i. The paper aims to provide a framework for SCM-involved firms to establish an IoT ecosystem. The paper provides a framework based on- a solution integrator as a central role, smart product sub-ecosystem, sub-ecosystem, related roles, and cooperation.

Note: The table summarizes the key papers under each research stream that create citation mapping in Figure 8.

Table 4. Future research Directions

Sr.#	Article/Reference Study	Future Research Questions/Directions
Stream 01: Artificial Intelligence (AI) and Business Model (BM)		
	Sub-Stream 1.1: AI Impact on Business Models	
1	Paiola & Gebauer, 2020	How do customer and industry-specific factors influence digital servitization strategies and business models (BM) based on AI- technologies (IoT)?
2	Kiel et al., 2017	How do AI technologies (IIoT) impact BM's components change while considering national, cultural, and organizational differences?
3	Yun et al., 2016	How does the change in business models based on AI technologies impact the firm value, growth, and value creation?
	Sub-Stream 1.2: AI-based Business Models	
4	Weking et al. 2020	What taxonomies and typologies help build a theoretical framework for creating and implementing AI-based BM in firms?
5	Guo et al., 2017	Which e-business models (efficiency-and complementary-centered) based on AI impact the value creation in firms?
	Sub-Stream 1.3: AI and Business Models Innovation	
6	Kahle et al. 2020	How does the AI-based innovation ecosystem adapt intelligent products' BM in firms?
7	Hein et al., 2019	How does the platform's BMs affect the implementation of AI technologies in the corporate innovation process?
	Sub-Stream 1.4: IoT-Based Business Models and Firm Innovation	
8	Ceipek et al. 2020	How do ownership (private, public, and family business) and types of firms (SMEs, medium, and large firms) influence the adoption of IoT-based business models (BM)?
9	Saarikko et al., 2020	What are the key threats and opportunities related adoption of IoT-based BM for firms (SMEs, medium, and large) in the era of industry 4.0?
10	Riera & Iijima, 2019; Balakrishnan, & Das, 2020	What is the role of multiple industries and locations in adopting IoT-based BM by SMEs and medium and large firms? How do the industries and locations (country) characteristics influence IoT in BM?
Stream 2: AI and Product Innovation		
11	Mariani & Wamba, 2020	How does resource-based theory conceptualize the big data analytics (BDA) capabilities to strengthen product innovation in firms?
12	Mariani & Wamba, 2020	How do transaction cost economics theory and service-dominant logic explain the implementation and reliance of companies on BDA for their product innovation?
13	Johnson et al., 2017	How does big data transform the new product development process using longitudinal data for multiple industries and countries?
Stream 3: A.I. and Open Innovation		
14	Lee et al., 2018	Is AI (data mining, text mining, sentiment analysis, etc.) valuable tools to overcome information overload for online communities to generate an idea with open innovation structure?
15	Yoon & Song, 2014	Is partnership essential for a firm's open innovation with the adoption and implementation of AI?
Stream 4: AI and Innovation Process		
16	Müller, & Däschle, 2018	How do industry 4.0 solution providers impact the innovation process of their customers (firms) in multiple industries, countries, and types of firms (SMEs, Platforms, and MNEs)?

17	Troilo et al.,2017	How does the data rice environment influence the innovation process in service firms from multiple industries and countries, and what role does the social processes and organization structure perform during it?
18	Verganti et al., 2020	How could organizations (SMEs, large companies) transform human-intensive to AI-centric innovation processes and design? What factors or characteristics (new skills and changes at R & D, manufacturing, and IT required) led to this transition?
19	Goduscheit, & Faullant, 2018	How do digitalization and big data influence the radical servitization innovation of manufacturing firms (large, medium, and SMEs) in multiple industries?
Stream 05: AI Adoption in Firm's Innovation Structure		
20	Ghobakhloo, & Ching, 2019; Raut et al., 2018	What are AI implementation and adoption determinants in manufacturing and service firms (SMEs and large) in multiple industries in developing, emerging, and developed countries?
21	Kostis & Ritala, 2020	How do digital artifacts (factory installation layouts or digital visualizations) impact industrial co-creation projects in different industries?
Stream 6: AI, Firm's Knowledge, and Innovation		
22	Ballestar et al., 2020	How do robotics density and different types of robots influence SMEs and large firms' knowledge, productivity, and innovativeness in multiple industries and countries?
23	Lee et al., 2016	How does a firm's knowledge management impact technological innovation across different industries and countries, and how do cultural variables affect this relationship?
24	García-Álvarez, 2015	How do Information and Communication Technologies (ICTs) impact the knowledge management and innovativeness of different firms (SMEs and large firms) in multiple industries?
Stream 7: AI impact on Firm's Innovation and Market Performance		
25	Yang et al., 2020	How do AI-based intelligent manufacturing systems impact multiple firms' financial and innovation performance (SMEs and large) involved in manufacturing business in several economies (developing, emerging, and developed)?
26	Christensen et al., 2018	How could AI (Machine learning, text mining, and data mining) enhance firm innovativeness by analyzing the ideas of automatic ideas detection systems for multiple industries (manufacturing, service) and multiple firm sizes (SMEs and large companies)?
27	Cappa et al., 2020	How the big data (digitalization) influence firm governance and ownership and firm performance for B2B and B2C firms in multiple industries?
Stream 8: AI and Innovativeness of Supply Chains Management (SCM)		
28	Chen, 2019	How do AI technologies (automation, IoT, ML, Industry 4.0) impact the ecosystem of global value chains for multiple types of firms (SMEs and large firms), industries, and economies?
29	Papert and Pflaum (2017)	How can an AI (IoT ecosystem) enhance the supply chain management systems in firms (SMEs and large firms) in different industries?

Note: The table lists the 29 future research questions on the topic.

Table 5. Publication and Citation Structure

Phases	Year	No of Publications	Citations
	1956	0	0
	1966	1	22
	1970	1	23
(1956 to 1979)	1974	1	185
	1989	1	21
	1990	1	32
	1991	4	76
	1992	1	121
	1994	2	10
	1995	1	80
	1996	4	83
	1999	2	25
	2001	1	21
	2002	2	102
	2004	1	162
	2005	3	74
	2006	6	199
	2007	2	52
	2009	6	320
(1980 to 2010)	2010	5	35
	2011	3	34
	2012	2	19
	2013	5	148
	2014	6	74
	2015	15	195
	2016	28	464
	2017	30	384
	2018	36	397
	2019	53	237
	2020	52	151
	2021	60	198
(2011 to 2022-July)	2022 (July)	30	90
Total		**364**	**4034**

Note: The Table shows the year-wise publication and citations.

Table 6. AI Technologies Studied in the Literature

Artificial intelligence aspects	Exemplary research studies
AI	MacPherson,1994; Kostoff et al., 2004; Radziwon et al., 2017; Hoornaert et al., 2017; Ma et al., 2017; Ghobakhloo, & Ching, 2019; Chen, 2019; Palmié et al., 2020; Mahmood & Mubarik, 2020; Yang et al., 2020; Sjodin et al., 2020; Mariani, & Wamba, 2020; Liu et al., 2020; Yang et al., 2020; Verganti et al., 2020; Wamba-Taguimdje et al., 2020; Paschen et al., 2020; Balakrishnan, & Das, 2020; Cetindamar et al., 2020; lshawaaf & Lee, 2021
Internet of Things (IoT)	Yu et al., 2016; Zdravković et al., 2017; Guo et al. 2017; Papert, & Pflaum, 2017; Kim et al., 2017; Lim et al., 2018; Hein et al. 2019; Matthyssens, 2019; Rocha et al., 2019; Ceipek et al., 2020; Saarikko et al., 2020; Benitez et al., 2020; Lichtenthaler, 2020; Yang et al., 2020; Golovina et al., 2020; Saarikko et al., 2020; Paiola & Gebauer, 2020; Kahle et al. 2020
Industry 4.0 (I.4.0)	Yoon & Song, 2014; Müller et al., 2018; Veile et al., 2019; Matthyssens, 2019; Weking et al., 2020; Benitez et al., 2020; Kahle et al., 2020; Müller & Däschle, 2018; Mahmood & Mubarik, 2020; Chen, 2019; Golovina et al., 2020
Industrial Internet of Things (IIoT)	Laudien & Daxböck, 2016; Kiel, Arnold & Voigt, 2017; Müller & Däschle, 2018; Lim, Kwon, & Lee, 2018; Butschan et al., 2019; Sivathanu, 2019; Arnold & Voigt, 2019; Matthyssens, 2019; Leminen et al., 2020
Big Data Analytics/Data Mining	Yeo et al, 2015; Altuntas, Dereli, & Kusiak, 2016; Christensen et al., 2016; Kong et al., 2017; Garechana et al., 2017; Cheah, & Wang, 2017; Chen et al., 2018; Lee et al., 2018; Raut et al., 2018; Wu et al., 2019; Cobo, Rocha, & Villamizar, 2019; Wu et al., 2020; Mariani & Wamba, 2020
Cloud Computing	Weking et al., 2020; Bhardwaj, 2020
Machine Learning (ML)	Jun & Sung, 2013; Altuntas, Dereli, & Kusiak, 2016; Chien et al., 2016; Christensen et al., 2016; Christensen et al., 2016; Suominen, Toivanen, & Seppänen, 2017; Hoornaert et al., 2017; Jin et al., 2017; Christensen et al., 2018; Coad & Grassano, 2019; Gandin & Cozza, 2019; Lee, & Shin, 2020; Guerzoni et al., 2020; Xu et al., 2020; Mariani, & Wamba, 2020; Viberg & Eslami, 2020; Wang et al., 2020
Digitalization Information and Digital Technologies /Digital Divide	Gravili et al., 2018; Riera, & Iijima, 2019; Ghobakhloo, & Ching, 2019; Saarikko et al., 2020; Balakrishnan, & Das, 2020; Lichtenthaler, 2020
Automation /Automation Technologies /Automated Idea Detection System	Hengstler, Enkel, & Duelli, 2016; Radziwon, Bogers, & Bilberg, 2017; Beltagui, 2018; Christensen et al., 2018; Kostis & Ritala, 2020; Kromann & Sorensen, 2019; Camina et al., 2020
Neural Networks/ Generalized Regression Neural Network (Deep Learning)	Bertels et al., 1999; Kannebley, Porto, & Pazello, 2005; Wang, & Chien, 2006; Chen & Chang, 2009; Chen & Chang, 2010; Lee et al., 2013; Lee et al., 2016; Zhang et al., 2018; Xu et al. 2020
Intelligent Manufacturing	Yang, Ying, & Gao, 2020

Data Analytics Capabilities, Data-Driven	Wu et al., 2019; Ramos & Blind, 2020; Troilo, De Luca, & Guenzi, 2017; Johnson et al., 2017
Natural Language Processing	Hwang et al., 2019
Robotics	Kostis & Ritala, 2020; Ballestar et al., 2020; Aversa et al., 2020
Information and Communication Technologies (ICT)	Bocquet et al., 2007; Spanos, & Voudouris, 2009; Lee et al., 2009; García-Álvarez, 2015; Shamsuzzoha et al., 2016; Wang et al., 2019

Note: This table shows the key AI technologies analyzed in the literature.

Table 7. Key Journal Published on Topic

#	Name of journal	ABS ranking	$P_{AI\text{-}CI}$	Exemplary research studies
1	Technological Forecasting and Social Change	3	22	Kostoff, Boylan, & Simons, 2004; Lee et al., 2009; Yeo et al, 2015; Yun et al., 2016; Hengstler, Enkel, & Duelli, 2016; Suominen et al., 2017; Ma et al., 2017; Kong et al., 2017; Raut et al., 2018; Santoro et al., 2018; Li et al., 2019; Klarin, 2019; Camina et al., 2020; Wang et al., 2020; Kahle et al., 2020; Mahmood & Mubarik 2020; Liu et al., 2020; Haefner et al., 2021; Palmié et al., 2020; Shen et al., 2020; Ballestar et al., 2020; Haefner et al., 2021
2	Journal of Product Innovation Management	4*	11	Tidd, 1995; Athaide et al., 2003; Hoornaert et al., 2017; Johnson, Friend, & Lee, 2017; Troilo, De Luca, & Guenzi, 2017; Chester Goduscheit, & Faullant, 2018; Ceipek et al. 2020; Verganti, Vendraminelli, & Iansiti, 2020; Aversa et al., 2020; Cappa et al., 2020
3	Research Policy	4*	7	Kannebley et al., 2005; Bocquet et al., 2007; Spanos, & Voudouris, 2009; Kim et al., 2015; Kim et al., 2017; Balsmeier, & Woerter, 2019; Buhr et al., 2021
4	Journal of Business Research	3	9	Ballestar et al., 2020; Sjodin et al. 2020; Mariani, & Wamba, 2020; Haenlein & Kaplan, 20191 ; Leone et al., 2021 ; Lalicic, & Weismayer, 2021 ; Toorajipour et al., 2021 ; Burström et al., 2021 ; Di Vaio et al., 2021 ;
5	Creativity and Innovation Management	3	2	Christensen et al., 2016; Christensen et al., 2018
6	Industry and Innovation	3	1	Coad & Grassano, 2019
7	R & D Management	3	1	Kim & Park, 2017
8	Technovation	3	1	Da Silveira, 2001; Wang, & Chien, 2006; Li, 2009; Bourke, & Roper, 2016; Kiel et al., 2017
9	Scientometrics	2	6	Chen & Chang, 2009; Chen & Chang, 2010; Garechana et al., 2017; Xu et al. 2020; Kong, Yang, & Li, 2020; Kinne, & Axenbeck, 2020
10	International Journal of Innovation Management	2	2	Laudien & Daxböck, 2016; Butschan et al., 2019
11	International Journal of Innovation and Technology Management	1	3	Arnold & Voigt, 2019; Rocha et al., 2019; Lichtenthaler, 2020
12	Strategic Change-Briefings in Entrepreneurial Finance	2	1	Balakrishnan, & Das, 2020
13	California Management Review	3	1	Kostis & Ritala, 2021

14	Business Horizons	2	3	Paschen et al., 2020; Lee, & Shin, 2020; Saarikko et al., 2020
15	Management Decision	2	1	Cobo, Rocha, & Villamizar, 2019
16	Thunderbird International Business Review	2	1	Cetindamar et al., 2020
17	Journal of Business & Industrial Marketing	2	1	Matthyssens, 2019;
18	Journal of Chinese Economic and Foreign Trade Studies	2	1	Cheah, & Wang, 2017
19	European Journal of Operational Research	4*	1	Bertels et al., 1999
20	Decision Sciences	2	1	Wang et al., 2019
21	International Journal of Production Economics	3	3	Guo et al., 2017; Benitez et al., 2020; Weking et al., 2020
22	Business Process Management Journal	2	1	Wamba-Taguimdje et al., 2020
23	International Journal of Technology	2	1	Radziwon et al., 2017
24	International Journal of Logistics Management	1	1	Gravili et al., 2018
25	Journal of Manufacturing Technology Management	1	1	Veile et al., 2019
26	Information Systems Research	4*	1	Hwang et al., 2019
27	Mis Quarterly	4*	1	Nissen & Sengupta, 2006
28	Industrial Management & Data Systems	2	3	Jun & Sung, 2013; Yoon & Song 2014; Lee et al., 2018
29	Pacific Asia Journal of The Association for Information Systems	2	1	Riera, & Iijima, 2019
30	Information Resources Management Journal	1	1	Sivathanu, 2019
31	Environment and Planning-A	1	1	MacPherson,1994
32	Telecommunications Policy	1	1	Ramos, & Blind, 2020
33	Economic Policy	3	1	Kromann & Sorensen, 2019
34	Economics of Innovation and New Technology	2	1	Guerzoni et al., 2020
Total			**94**	(25% of 364 articles published in ABS-ranked journals) Total Global Citations: 3454 Total Journal Published 364 articles=177

Note: The table presents key ABS-ranked journals published on the topic. P_{AI-CI} = No articles published on the subject.

Table 8. Top 10 Cited and Trending Articles in the Literature

	Top Cited Articles			Top Trending Articles		
Rank	Author (s) and Year	Journal	TGC*	Author (s) and Year	Journal	TLCe
1	Athaide et al., (2003)	Journal of Product Innovation Management	216	Goduscheit and Faullant, (2018)	Journal of Product Innovation Management	2
	Li (2009)	Technovation	123	Hengstler et al., (2016)	Technological Forecasting and Social Change	1.7
3	Lee et al. (2009)	Technological Forecasting and Social Change	122	Verganti et al., (2020)	Journal of Product Innovation Management	1.6
4	Santoro et al. (2018)	Technological Forecasting and Social Change	111	Kim et al. (2015)	Research Policy	1.5
5	Johnson et al. (2017)	Journal of Product Innovation Management	87	Ceipek et al. (2020)	Journal of Product Innovation Management	1
6	Hoornaert et al. 2017	Journal of Product Innovation Management	81	Wang and Chien (2006)	Technovation	1
7	Hengstler et al., (2016)	Technological Forecasting and Social Change	80	Ha, et al. (2015)	Technological Forecasting and Social Change	1
8	Kiel et al., (2017)	Technovation	56	Bourke and Roper (2016)	Technovation	1
9	Kim et al. (2015)	Research Policy	51	Kong et al. (2017)	Technological Forecasting and Social Change	1
10	Troilo et al., (2017)	Journal of Product Innovation Management	51	Yoon and Song (2014)	Industrial Management & Data Systems	1

Note: The table shows top-cited and trending articles. *TGC= Total global citations, TLCe=Total local citations received in the recent period (2018, 2019, 2020, 2021, 2022).

Table 9. Types of Firms Examined in Prior literature

#	Type of firms	P_{AI-CI}	Exemplary research studies
(i) Type of firms based on nature of business			
1	Manufacturing firms	23	Kannebley et al., 2005; Lee et al., 2013; Laudien & Daxböck, 2016; Altuntas, Dereli, & Kusiak, 2016; Kiel et al., 2017; Radziwon et al., 2017; Cheah, & Wang, 2017; Chen et al., 2018; Zhang et al., 2018; Müller et al., 2018; Kromann & Sorensen, 2019; Chen, 2019; Veile et al., 2019; Wang et al., 2019; Cobo et al., 2019; Ghobakhloo, & Ching, 2019; Mahmood & Mubarik 2020; Camina et al., 2020; Yang et al., 2020; Liu et al., 2020; Weking et al. 2020; Golovina et al., 2020 ; Sjodin et al., 2020; Paiola & Gebauer, 2020; Aversa et al., 2020
2	Service firms	03	Raut et al., 2018; Goduscheit, & Faullant, 2018; Balakrishnan, & Das, 2020; Weking et al., 2020
(iv) Special types of firms			
1	IIoT solution providers	01	Laudien & Daxböck, 2016
2	Machine-to-Machine application providers	01	Leminen et al. 2020
3	B2B platforms	01	Hein et al., 2019
4	IoT startups	01	Lim, Kwon, & Lee, 2018
5	Big data analytics firms	01	Mariani, & Wamba, 2020
6	Crowdsourcing platform	02	Hoornaert et al., 2017
7	Open Innovation Community (MyStarbucksIdea.com (MSI))	01	Lee et al., 2018
8	Industry 4.0 Solution Providers	01	Müller & Däschle, 2018
9	IoT ventures	01	Yu et al., 2016
10	ICTs network platform for SMEs	01	Shamsuzzoha et al., 2016
11	AI-based solution providers	01	Wamba-Taguimdje et al., 2020

Note: The table shows the types and nature of firms examined in the literature. P_{AI-CI} = No of articles published on the topic

Table 10. Industries and Countries Examined in the Literature

(i) Industries examined in the literature on AI in corporate innovation

#	Industry	Exemplary research studies
1	Energy & Utilities	Chen et al., 2018; Raut et al., 2018; Sjodin et al., 2020
2	Transportation	Chen et al., 2018; Leminen et al., 2020; Weking et al., 2020; Liu et al., 2020
3	Sportswear/Footwear	Shamsuzzoha et al., 2016; Weking et al. 2020
4	Construction	Bertels et al., 1999; Laudien & Daxböck, 2016; Weking et al. 2020; Sjodin et al. 2020
5	Machinery (agriculture, heavy tools)	Shamsuzzoha et al., 2016; Ma et al., 2017; Weking et al. 2020; Leminen et al. 2020; Liu et al., 2020; Saarikko et al., 2020
6	Vehicle Manufacturing (autonomous and non-autonomous)	Yun et al., 2016; Weking et al. 2020
7	Aero-Engines Manufacturer/Sector	Weking et al., 2020; Beltagui, 2018
8	Telecommunication (Service and Manufacturing)	Bertels et al., 1999; Suominen et al., 2017; Hwang et al., 2019; Saarikko et al., 2020; Sjodin et al. 2020
9	Food & beverages	Raut et al., 2018; Christensen et al., 2018; Bertels et al., 1999; Paiola & Gebauer, 2020; Liu et al., 2020
10	Paper & paper product industry	Raut et al., 2018; Liu et al., 2020; Palmié et al. 2020
11	Automotive Industry	Hengstler, Enkel, & Duelli, 2016; Yun et al., 2016; Kiel, Arnold & Voigt, 2017; Hein et al. 2019; Bhardwaj, 2020; Leminen et al. 2020; Kahle et al. 2020; Wang et al., 2020; Paiola & Gebauer, 2020; Aversa et al., 2020
12	Internet of Things (IoT and IIoT, AI solution provider)	Laudien & Daxböck, 2016; Lim et al., 2018; Wamba-Taguimdje et al., 2020
13	IT Software Industry (solution providers, engineering)	Jun & Sung, 2013; Guo et al. 2017
14	Health Care Industry	Paiola & Gebauer, 2020; Shen et al., 2020
15	Heating Industry	Paiola & Gebauer, 2020; Liu et al., 2020
16	Mechanical and plant engineering industry	Laudien & Daxböck, 2016; Kiel et al., 2017; Müller et al., 2018
17	Chemical and Plastics Industry	Müller et al., 2018; Liu et al., 2020
18	Electrical Engineering Industry	Müller et al., 2018; Kiel, Arnold & Voigt, 2017; Laudien & Daxböck, 2016; Kahle et al. 2020
19	Medical Engineering	Laudien & Daxböck, 2016; Kiel et al., 2017
20	Electronics Engineering Industry	Chien et al., 2016; Laudien & Daxböck, 2016; Kahle et al. 2020
21	Information Technology (Cloud-Platform, ICT, IT platform, Big Data Analytics, computer numerical control, IT service provider)	Kiel et al., 2017; Hein et al. 2019; lorez Ramos, & Blind, 2020; Viberg, & Eslami, 2020; Mariani, & Wamba, 2020; Ma et al., 2017; Balakrishnan, & Das, 2020
22	Textile industry	Chen, 2019; Liu et al., 2020; García-Álvarez, 2015; Shamsuzzoha et al., 2016
23	Intelligent robotics industry	Yun et al., 2016; Kong, Zhou, Liu, & Xue, 2017; Kostis & Ritala, 2020;
24	Pharmaceutical Industry	Chen & Chang, 2009; Chen & Chang, 2010; Liu et al., 2020

(ii) Countries examined in the literature on AI in corporate innovation

#	Country	Exemplary research studies
1	Denmark	Radziwon et al., 2017; Goduscheit, & Faullant, 2018; Kromann & Sorensen, 2019
2	China	Yu et al., 2016; Guo et al. 2017; Kong et al., 2017; Ma et al., 2017; Cheah, & Wang, 2017; Chen, Zhang & Wu, 2018; Zhang et al., 2018; Wang et al., 2019; Wang et al., 2020; Liu et al., 2020; Zheng et al., 2020; Yang et al., 2020
3	Italy	Gandin & Cozza, 2019; Paiola & Gebauer, 2020; Guerzoni et al., 2020; Aversa et al., 2020
4	Germany	Laudien & Daxböck, 2016; Kiel, Arnold & Voigt, 2017; Müller et al., 2018; Müller & Däschle, 2018; Veile et al., 2019; Ceipek et al. 2020
5	Taiwan	Chen, 2019
6	Brazil	Kannebley, Porto, & Pazello, 2005; Benitez et al. 2020; Kahle et al. 2020
7	USA	MacPherson,1994; Chen & Chang, 2009; Johnson, Friend, & Lee, 2017; Lim, Kwon, & Lee, 2018; Cappa et al., 2020
8	UK	Mariani, & Wamba, 2020; Aversa et al., 2020
9	Malaysia	Lee et al., 2013; Lee et al., 2016; Ghobakhloo, & Ching, 2019
10	Iran	Ghobakhloo, & Ching, 2019
11	India	Raut et al., 2018
12	Sweden	Viberg, & Eslami, 2020
13	Pakistan	Mahmood & Mubarik 2020
14	Spain	Garechana et al., 2017; Camina et al., 2020; Ballestar et al., 2020
15	Korea	Yun et al., 2016
16	European Union	Coad & Grassano, 2019
17	Sweden	Kostis & Ritala, 2020
18	Turkey	Altuntas et al., 2016
19	Russia	Golovina et al., 2020
20	Japan	Riera, & Iijima, 2019
21	Australia	Cetindamar et al., 2020

Note: The shows the list of industries and countries studied.

Table 11. Measurements and Data Source used in the Prior Research.

(i) Measurement of artificial intelligence and data sources		
Construct/aspect of AI measured.	Data source/measurement	Exemplary research studies
Artificial Intelligence (AI)	Interviews/questionnaires	MacPherson,1994; Ghobakhloo, & Ching, 2019; Sjodin et al. 2020; Mariani, & Wamba, 2020; Leone et al., 2021; Lalicic & Weismayer, 2021
IoT Technologies	Interviews/questionnaires	Yu et al., 2016; Santoro et al., 2018; Hein et al., 2019; Chen, 2019; Paiola & Gebauer, 2020; Benitez et al., 2020; Kahle et al., 2020
Industry 4.0-Implementation	Questionnaires	Müller & Däschle, 2018; Müller et al., 2018; Veile et al., 2019; Kahle et al., 2020; Benitez et al., 2020; Mahmood & Mubarik 2020
IIoT Technologies	Interviews	Laudien & Daxböck, 2016; Kiel et al., 2017; Saarikko et al., 2020
Industry 4.0-Business Models Innovation	Interviews	Weking et al., 2020
Digitalization Technologies (IoT, Big Data, and Cloud Computing)	Questionnaire/interviews	Chen et al., 2018; Troilo, De Luca, & Guenzi, 2017; Johnson et al., 2017; Goduscheit, & Faullant, 2018
IoT Mobile Application	Survey/questionnaire	Guo et al. 2017
IoT Innovativeness	Patent data- International Patent Classification (IPC) codes proposed by the UK IP Office.	Ceipek et al., 2020
Cloud Computing	Interviews/Questionnaires	Raut et al., 2018
Automation Technologies	0 when the firm does not use them, and take value 1 when a firm uses them: (1) robotization (R); (2) computer-aided design and manufacturing (CADM); (3) data-driven control (DDC); and (4) flexible production systems (FPS)	Camina et al., 2020
Robotics	Dummy variable- Encuesta sobre Estrategias Empresariales (Business Strategy Survey, ESEE).	Ballestar et al., 2020
Automation Technologies	Survey/interviews/ questionnaires	Hengstler et al., 2016; Kromann & Sorensen, 2019
Intelligent Manufacturing	Dummy variables created from reports of firms	Yang et al., 2020
AI Capabilities	Survey of firms	Wu et al., 2020
Information and Communication Technologies	Questionnaire/survey/interviews	García-Álvarez, 2015
AI-based Technologies	Websites of companies	Wamba-Taguimdje et al., 2020

AI digital technologies	Questionnaire/survey/interviews	Riera & Iijima, 2019
Intelligent Technologies	Patent analysis	Ma et al., 2017
AI-based knowledge	Web of Science database	Cetindamar et al., 2020
Industrial Robots	Number of industrial Robots (AI) data from the International Federation of Robotics (IFR)	Liu et al., 2020
(ii) Measurement of corporate innovation and data sources		
Innovation	Questionnaire/survey/interviews	MacPherson,1994; Lee et al., 2013; García-Álvarez, 2015; Lee et al., 2016; Yun et al., 2016; Altuntas, Dereli, & Kusiak, 2016; Yu et al., 2016; Cheah, & Wang, 2017; Jin et al., 2017; Radziwon et al., 2017; Lee et al., 2018; Santoro et al., 2018; Müller & Däschle, 2018; Beltagui, 2018; Wang et al., 2019; Ghobakhloo, & Ching, 2019; Kostis & Ritala, 2020; Saarikko et al., 2020; Paiola & Gebauer, 2020; Mahmood & Mubarik 2020; Sjodin et al. 2020; Mariani, & Wamba, 2020
Innovation quality	Quality of patent	Yang et al., 2020
Innovation Quantity	No patents registered	Yang et al., 2020
Innovation	Patent analysis- United States Patent and Trademark Office (USPTO)	Yoon & Song 2014; Wu et al., 2020
Innovation (Prospective)	Dummy variable (1 & 0)/Questionnaire/Survey	Goduscheit, & Faullant, 2018; Gandin & Cozza, 2019
Innovation (ideas)	Online Community	Christensen et al., 2016; Christensen et al., 2018;
Technological innovation	Patent granted data	Suominen et al., 2017; Liu et al., 2020
Innovation	Number of Industrial Patents-China's National Bureau of Statistics	Zhang et al., 2018
Innovation	Technological Innovation-Industrial Research on Technological Innovation (PINTEC)-2000	Kannebley et al., 2005
Innovation	Patent data-United States Patent and Trademark Office (USPTO)	Chen & Chang, 2009; Chen & Chang, 2010; James et al., 2015
Innovation	Dummy Variable-Encuesta sobre Estrategias Empresariales (Business Strategy Survey, ESEE).	Ballestar et al., 2020
Innovation	China's primary market used in this paper is obtained from Wind Database (Wind, www.wind.com.cn/	Zheng et al., 2020
Innovation Propensity Index	Consist of 16 variables	Cobo et al., 2019
Innovation	Crowdsourcing plateform (Mendeley)	Hoornaert et al., 2017
Innovation	Patent analysis	Wu et al., 2019

Innovation (idea)	Open innovation community (MyStarbucksIdea.com)	Lee et al., 2018

Note: This table presents AI and corporate innovation measurement and data sources.

Table 12. Key Methodologies in the Literature

#	Method	$P_{AI\text{-}CI}$	Exemplary research studies
1	Case Study	34	Tidd, 1995; García-Álvarez, 2015; Laudien & Daxböck, 2016; Yun et al., 2016; Shamsuzzoha et al., 2016; Hengstler et al., 2016; Troilo et al., 2017; Papert & Pflaum, 2017; Radziwon et al., 2017; Kiel et al., 2017; Cheah, & Wang, 2017; Müller & Däschle, 2018; Gravili et al., 2018; Goduscheit, & Faullant, 2018; Chen et al., 2018; Veile et al., 2019; Chen, 2019; Hein et al. 2019; Veile et al. 2019; Benitez et al., 2020; Leminen et al., 2020; Weking et al., 2020; Kahle et al., 2020; Saarikko et al., 2020; Sjodin et al., 2020; Palmié et al., 2020; Bhardwaj, 2020; Paiola & Gebauer, 2020; Mariani, & Wamba, 2020; Yang et al., 2020; Kostis & Ritala, 2020; Wamba-Taguimdje et al., 2020; Golovina et al., 2020; Balakrishnan, & Das, 2020; Ramos & Blind, 2020; Aversa et al., 2020; Leone et al., 2021
2	Structural Equation Modelling	07	Lee et al., 2016; Yu et al., 2016; Müller et al., 2018; Raut et al., 2018; Chen et al., 2018; Raut et al., 2018; Mahmood & Mubarik 2020; Bhardwaj, 2020
3	Theoretical Analysis	04	Rocha et al., 2019; Lichtenthaler, 2020; Paschen et al., 2020; Lee, & Shin, 2020
4	Literature Review	04	Kostoff et al., 2004; Chen, Zhang & Wu, 2018; Matthyssens, 2019; Klarin, 2019; Palmié et al. 2020
5	Logistic Regression/Regression/Correlation	09	Jun & Sung, 2013; Guo et al. 2017; Johnson et al., 2017; Gravili et al., 2018; Ghobakhloo, & Ching, 2019; Wu et al., 2019; Kromann & Sorensen, 2019; Wang et al., 2019; Zheng et al., 2020; Camina et al., 2020; Yang et al., 2020; Liu et al., 2020; Wu et al., 2020
8	Machine Learning	17	Jun & Sung, 2013; Christensen et al., 2016; Suominen et al., 2017; Jin et al., 2017; Kong et al., 2017; Hoornaert et al., 2017; Lee et al., 2018; Christensen et al., 2018; Gandin & Cozza, 2019; Wu et al., 2019; Coad & Grassano, 2019; Zheng et al., 2020; Xu et al. 2020; Wang et al., 2020; Paschen et al., 2020; Guerzoni et al., 2020
9	Patent Analysis	05	Kong et al., 2017; Suominen et al., 2017; Ma et al., 2017
10	Text Analysis/Mining	11	Kostoff et al., 2004; James et al., 2015; Christensen et al., 2016; Garechana et al., 2017; Kim & Park, 2017; Ma et al., 2017; Lee et al., 2018; Li et al., 2019; Shen et al., 2020; Golovina et al., 2020
11	Neural Network Analysis	12	Kannebley et al., 2005; Chen & Chang, 2009; Chen & Chang, 2010; Lee et al., 2013; Lee et al., 2016; Lim et al., 2018; Zhang et al., 2018; Raut et al., 2018; Wu, Lou, & Hitt, 2019; Xu et al., 2020
12	Data Mining	06	Yoon & Song, 2014; Yeo et al., 2015; Kong et al., 2017; Lee et al., 2018; Cobo et al., 2019; Golovina et al., 2020
13	Natural Language Processing	03	Hwang et al., 2019; Zheng et al., 2020; Wu et al., 2020
14	Bibliometrics Analysis	03	Yeo et al., 2015; James et al., 2015; Cetindamar et al., 2020
15	ANOVA	02	Camina et al., 2020; Ballestar et al., 2020
16	Sentiment Analysis	01	Lee et al., 2018

17	Vector autoregressive (VAR) approach	01	Gravili et al., 2018
18	Fuzzygrid based rule-mining algorithm (FGBRMA)	01	Altuntas et al., 2016
19	Fuzzy logic	01	Goduscheit, & Faullant, 2018; Cobo et al., 2019
20	Linear Discriminant Analysis (LDA	01	Hoornaert et al., 2017

Note: The table presents the critical mythologies used in the literature.