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Artificial intelligence in supply chain management: A systematic literature review of empirical studies and research directions

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A R T I C L E I N F O

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A B S T R A C T

This article presents a systematic literature review (SLR) of empirical studies concerning Artificial Intelligence (AI) in the field of Supply Chain Management (SCM). Over the past decade, technologies belonging to AI have developed rapidly, reaching a sufficient level of maturity to catalyze transformative changes in business and society. Within the SCM community, there are high expectations about disruptive impacts on current practices. However, this is not the first instance where AI has sparked business excitement, often falling short of the hype. It is thus important to examine both opportunities and challenges emerging from its actual implementation. Our analysis clarifies the current technological approaches and application areas, while expounding research themes around four key categories: data and system requirements, technology deployment processes, (inter)organizational integration, and performance implications. We also present the contextual factors identified in the literature. This review lays a solid foundation for future research on AI in SCM. By exclusively considering empirical contributions, our analysis minimizes the current buzz and underscores relevant opportunities for future studies intersecting AI, organizations, and supply chains (SCs). Our effort is also meant to consolidate existing research insights for a managerial audience.

1. Introduction

The last couple of years have been characterized by mounting expectations around AI across sectors, industries, and domains (Dwivedi et al., 2023; Mariani et al., 2023). The scope of the technology is very broad, and generally refers to the "[…] *mechanisms underlying thought and intelligent behavior and their embodiment in machines*" (definition of the Association for the Advancement of Artificial Intelligence, as reported by Helo and Hao, 2022, p. 2). Since the concept first hit the public in the 1950s, its history has been characterized by waves of excitement and phases of disillusionment (Manyika and Bughin, 2018). Starting from early 2010s and even more since late 2022, after the release of generative AI solutions for non-technical users (e.g., Chat GPT), there has been a further surge of interest among researchers and practitioners alike.

Whereas there is little doubt that the technology has taken a great leap forward thanks to hardware innovation and cloud-based access (OECD, 2017), it is also true that introducing AI in real-life contexts is still challenging with implications that are still largely unknown. This is not only because of unsolved technical issues, but also due to the complexities of socio-technical systems requiring alignment of practices and process innovation. When considering SCM applications, such complexities are even more daunting due to (inter)functional and (inter) organizational dependencies coupled with cross-level integration within inherently open systems (Durach et al., 2017; Wieland, 2021). In this sense, whereas the future speaks of autonomy and data-driven optimization of production and buyer-supplier processes (Calatayud et al., 2019; Dolgui and Ivanov, 2022), reality is that companies today are just experimenting with and mostly piloting AI amid the confusion and roadblocks that have been documented by recent surveys (e.g., WEF, 2023; McKinsey, 2023). Similar messages come from empirical AI-related research in other disciplines (Brynjolfsson et al., 2021; McElheran et al., 2021).

Against growing calls on theorizing on the disruptive impact of AI in SCM (e.g., Hendriksen, 2023; Richey et al., 2023), the purpose of this paper is to tamper potentially inflated expectations around the technology while still highlighting major discontinuities that are emerging. Indeed, a solid understanding of the current state of AI in SCM is

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important to develop and elaborate theory in a context that is likely characterized by fashion waves and managerial hypes (Culot et al., 2024; Hanelt et al., 2021). To this end, the article presents a systematic literature review of empirical studies published in peer-reviewed journals. The choice was motivated by the need to exclude unsubstantiated narratives, anecdotical evidence, and ensure that the insights were derived from studies developed under rigorous standards. In selecting the scope of our review, we embraced a broad definition of SCM, encompassing the management of flows within a firm (i.e., production and related operations) and between independent organizations (i.e., suppliers, buyers, final customers) (Stock and Boyer, 2009). This rather ample angle was balanced with a focus on the manufacturing industry, so that we could report findings from a literature developed in contexts characterized by similar challenges and opportunities. Indeed, prior studies underline significant differences—for example—in healthcare, humanitarian, and energy SCs (Abidi et al., 2014; van Donk, 2003; Sarkar and Seo, 2021).

A total of 123 studies were analyzed to answer the following research questions (RQ):

(RQ1) What are the key messages of extant empirical studies on AI in SCM?

(RQ2) What research directions should be pursued for a better understanding of AI in SCM?

SLRs are crucial steps for advancing knowledge and are even more important for topics at the intersection between academic domains in order to enable distinct scholarly communities to converge on topics and concepts (Durach et al., 2017; Webster and Watson, 2002). In this perspective, our work enhances prior literature reviews in several respects. First, it provides an updated picture including works published until early 2024, whereas most previous reviews cover the period until 2020 (e.g., Toorajipour et al., 2021; Pournader et al., 2021). It also provides deeper insights through full-text coding rather than bibliometric approaches (e.g., Dhamija and Bag, 2020). Second, our SLR focuses on AI only, and not on clusters of technologies normally subsumed under the umbrella terms of "digital transformation" or "Industry 4.0" (e.g., Culot et al., 2020; Dalenogare et al., 2018; Perano et al. 2023; Pozzi et al., 2023; Rußmann et al., 2015; Yavuz et al., 2023). Indeed, AI might be implemented as a standalone solution not requiring integration with sensors and network connectivity (e.g., Brintrup et al., 2023). Moreover, several reviews on Industry 4.0 and related phenomena did not specifically mentioned AI, as data could be potentially processed through other (algorithmic) approaches (e.g., Rad et al., 2022; Lagorio et al., 2022; Fatorachian and Kazemi, 2021; Raut et al., 2020; Ardito et al., 2019). Third, the analysis includes studies concerning different AI techniques and applications. Differently than reviews on specific solutions (e.g., reinforcement learning – Rolf et al., 2023) or functional subdomains (e.g., predictive maintenance, procurement, SC resilience, sustainable SCM – Carvalho et al., 2019; Dalzochio et al., 2020; Deiva and Kalpana, 2022a; Zamani et al., 2023; Naz et al., 2022), this choice allows to clarify common topics in SCM. At the same time, by focusing on AI in manufacturing SCs, we could ensure a greater specificity than cross-sector studies (e.g., retail – Sharma et al., 2022). The selection of empirical contributions and not conceptual, simulated, or lab-based experiments, is a further differentiating element.

Our analysis uncovered four main research themes—data and system requirements, technology deployment processes, (inter)organizational integration, and performance implications—in addition to some contextual dimensions. Based on a close examination of extant research, we identify future directions and the potential need of new theoretical perspectives as opposed to established ones in SCM. The resulting research agenda contributes to the literature by providing a systematic overview of opportunities based on the current state and understanding of AI in SCM.

The rest of the paper is structured as follows. The next section illustrates the methodology. Then, we present descriptive and thematic findings. The Discussion identifies the core messages from extant literature and outlines future research directions. Finally, we conclude with the contributions of our study.

2. Methodology

The research question was approached through a SLR to ensure transparency and objectivity in the process while minimizing the implicit bias of researchers (Webster and Watson, 2002). We built on the methodological guidelines of Sauer and Seuring (2023), Seuring and Gold (2012), Rousseau et al. (2008), and Tranfield et al. (2003), which are widely recognized in managerial disciplines and specifically in SCM. Fig. 1 summarizes the review process.

As a first step, we performed a formal keyword search in Scopus and Web of Science. These databases were selected as they represent the two most important repositories of academic research (Aria and Cuccurullo, 2017; Bretas and Alon, 2021; Kumar et al., 2021); many previous SLRs used these two sources for articles retrieval (e.g., Vishwakarma et al., 2023; Talwar et al., 2021; Mokhtar et al., 2019). Consistently with the recommendations of Rowley and Slack (2004), we devised the search string to guarantee that it accurately captured the entire scope of our investigation, while excluding any irrelevant elements. To achieve this result, we referred to previous studies on AI and SCM (e.g., Toorajipour et al., 2021; Riahi et al., 2021; Guida et al., 2023a) and performed some pilot searches. The resulting search string comprised two set of keywords: one pertaining to AI and the other to SCM interconnected with an AND operator (see Fig. 1 for the list). To ensure a good balance between the breadth of data collection and the depth of analysis (Seuring and Gold, 2012), the search targeted articles' titles, abstracts, and keywords. The time span was from 2010 to April 2024 (the date the search was conducted); the starting year is justified considering when AI applications reached sufficient maturity for industry use (Babina et al., 2024; Hendriksen, 2023; Manyika and Bughin, 2018). For what concerns the inclusion criteria, we considered only articles in English published in peer-reviewed Business, Management and Accounting (Scopus) and Management and Business (Web of Science) journals listed in the Association of Business Schools Academic Journal Guide (2021). This list is a widely recognized indicator of journal quality (e.g., Johnsen, 2009), being based on a combination of citation metrics and scholarly evaluation. This allowed us to build our review on highly reputed sources. Duplicate contributions were identified with the help of the software Zotero. The process yielded to pre-selecting 3,173 articles.

In the second step, two authors independently reviewed the titles, abstracts, and keywords of the papers to ensure alignment with our study's aim. The exclusion criteria were defined to remove from our sample:

- *Articles on non-manufacturing SCs*, namely studies on other sectors such as retail, healthcare, construction, and energy.
- *Conceptual articles*, such as purely theoretical papers, literature reviews, and editorial commentaries.
- *Articles superficially mentioning AI* without structured analysis/discussion.
- *Articles presenting AI applications outside SCM*, focusing on areas such as new product development, venture financing, and business model innovation.
- *Articles not using real-world data*, namely studies that relied on synthetic datasets, simulations, or laboratory experiments which do not accurately represent the complexities and unpredictable nature of real-world SC environments.

In this way, 262 articles were pre-selected. Their full text was read in light of the abovementioned exclusion criteria. Their references were checked for additional pertinent works via forward/backward citation analysis (Webster and Watson, 2002), resulting in a final list of 123

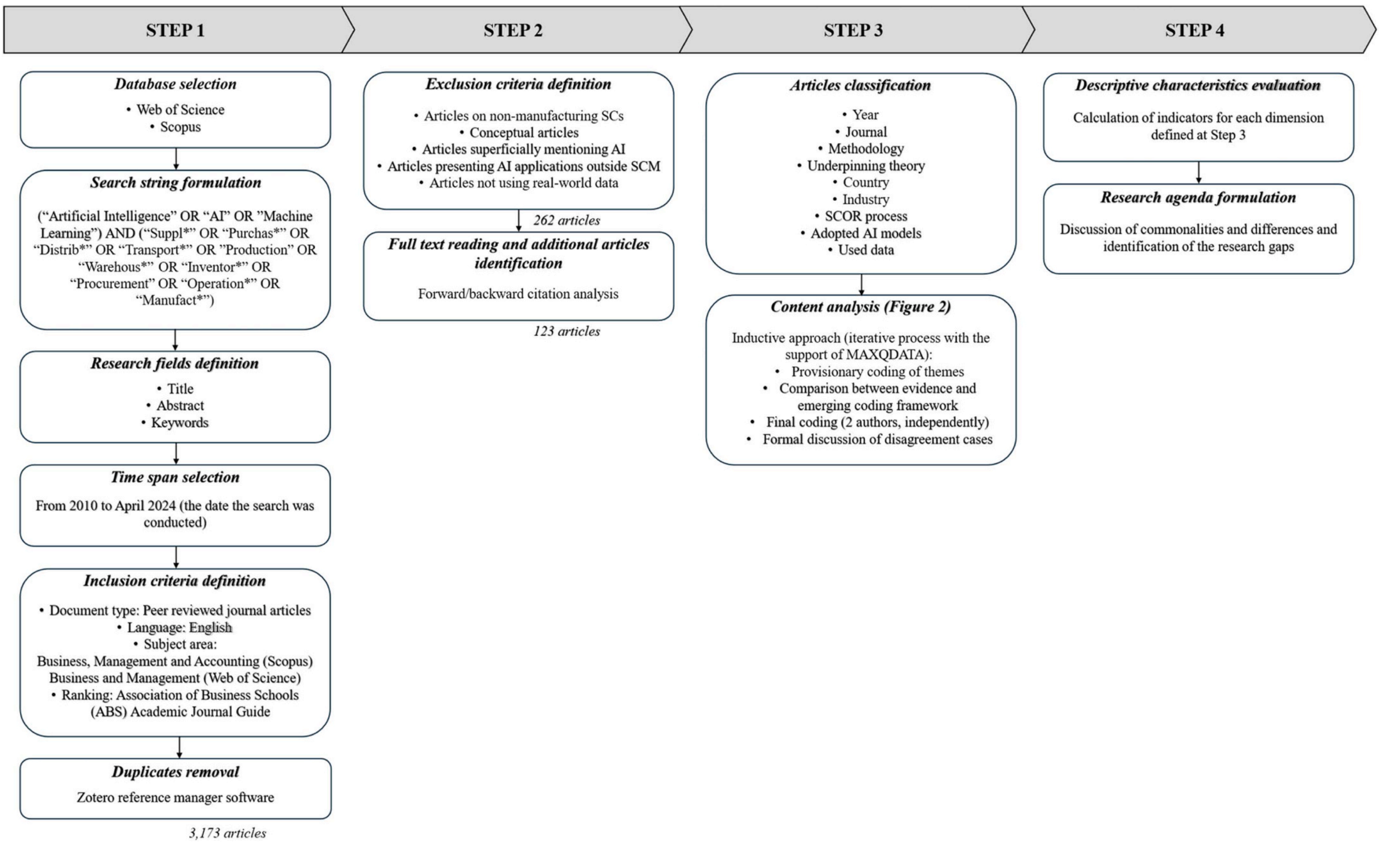

Fig. 1. Review process.

articles (see the Online Appendix).

The third phase consisted in the analysis. Each article was classified by year, journal, methodology, underpinning theory, country, industry, Supply Chain Operations Reference (SCOR) process, adopted AI models, and used data. Subsequently, we performed a content analysis using an inductive approach. Namely, after a provisionary coding of themes, categories were derived through an iterative process of comparison between materials and the emerging coding framework (Seuring and Gold, 2012). The result is presented in Fig. 2. We identified four main cross-cutting themes, with the addition of a series of contextual factors affecting them all. All the articles were then coded again independently by two researchers (Duriau et al., 2007). To facilitate the comparison and retrieval of text passages and support manual coding, the software MAXQDATA was used. The few cases of inter-coder disagreement were resolved through formal discussion.

Finally, we analyzed the results, calculating indicators for the descriptive characteristics of the articles and the proportion of studies covering each theme and category. Moreover, the research team

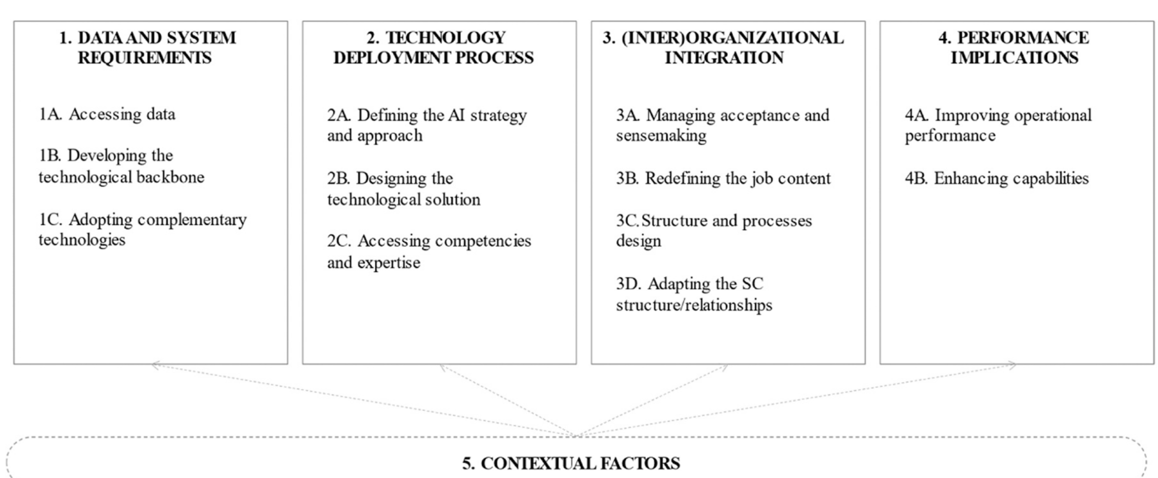

Fig. 2. Coding framework.

discussed commonalities and differences to formulate a future research agenda.

3. Findings

3.1. Descriptive findings

The characteristics of the 123 journal articles included in the review have been analyzed to clarify the evolution of the empirical research on AI in SCM (Fig. 3 and Online Appendix – Tables A1-A6). Given the aim of the review, three aspects appear particularly relevant: 1) *methodology* and *empirical context (country and industry)*, 2) *SCOR process*, and 3) *AI approach*, *purpose*, *technique,* and *analyzed data*.

First, for what concerns the *methodology*, most articles built on single case study analyses either quantitative (e.g., using company data) or qualitative (e.g., based on interviews). Several contributions also relied on survey-based approaches. A small number of studies adopted mixed qualitative/quantitative methods (e.g., Bodendorf et al., 2023). As for the *empirical context*, the prevalent focus was on European and Asian companies with some studies covering multiple countries (e.g., "industrialized countries" – Kinkel et al., 2023) or regions (e.g., Middle East and North Africa – Al-Surmi et al., 2022). In terms of industry, most of the contributions referred to the automotive sector, followed by electronics, metalworking, food, and machinery. Some studies examined more than one industry (e.g., automotive and telecommunications – Meyer and Henke, 2023; aerospace and electronics – Usuga-Cadavid et al., 2022) or generally considered manufacturing firms (e.g., Leoni et al., 2022).

Second, in terms of the *SCOR process* considered in the articles, many studies revolve around the "Make" and "Enable" phases, investigating the use of AI to optimize production activities (e.g., quality control, predictive maintenance, cost reduction and time saving, resource use optimization), improve the performance of the SC (e.g., flexibility/agility, innovation), or shed light on the factors affecting AI adoption. Additionally, significant attention is directed towards the "Plan" (e.g., demand forecasting, inventory level definition) and "Source" (e.g., suppliers scouting and selection, purchasing cost analysis) phases. Conversely, the "Return" (e.g., warranty claims forecasting) and "Deliver" (e.g., logistic management) processes represent rather peripheral areas of research. Interestingly, some studies consider more phases together like "Source-Deliver" (e.g., overall SC resilience), "Source-Make-Deliver", "Source-Make", and the whole processes of "Plan-Source-Make-Deliver-Return" (e.g., Manimuthu et al., 2022a; Cannas et al., 2023).

Finally, with respect to the *AI approach*, most studies present Machine Learning (ML) solutions. Several contributions (42) engage with supervised learning, 5 with unsupervised learning, 1 with semi-supervised learning, and 10 with a combination of supervised and unsupervised learning. The *purpose* was mainly regression (26 contributions) and classification (15) or a combination of both (6). Other relevant applications referred to clustering (2) and anomaly detection (2). For what concerns the specific *techniques*, the most common were Random Forest (18 contributions), Artificial Neural Network (12), Linear Regression (12), Support Vector Machine (10), Extreme Gradient Boosting (8), K-nearest Neighbors (7), and Support Vector Regression (7). To conclude, in terms of *analyzed data*, inputs were related to production and related activities (e.g., process parameters, production schedule – 30 contributions), product features (e.g., transportation/manufacturing costs, relevance for the company – 21), demand (e.g., orders, discounts – 17), sourcing metrics (number of transactions, lead times, order volume – 14), machine statistics (maintenance frequency, number of failures – 8), after-sales (e.g., number of warranty requests – 3), as well as macroeconomic indicators (e.g., exchange rates – 3) and social media trends (e.g., number of tweets – 2). In most cases, these data have been used in combination.

3.2. Thematic findings

This section presents the results of the coding process and the key messages from the papers. Each subsection corresponds to a theme of the

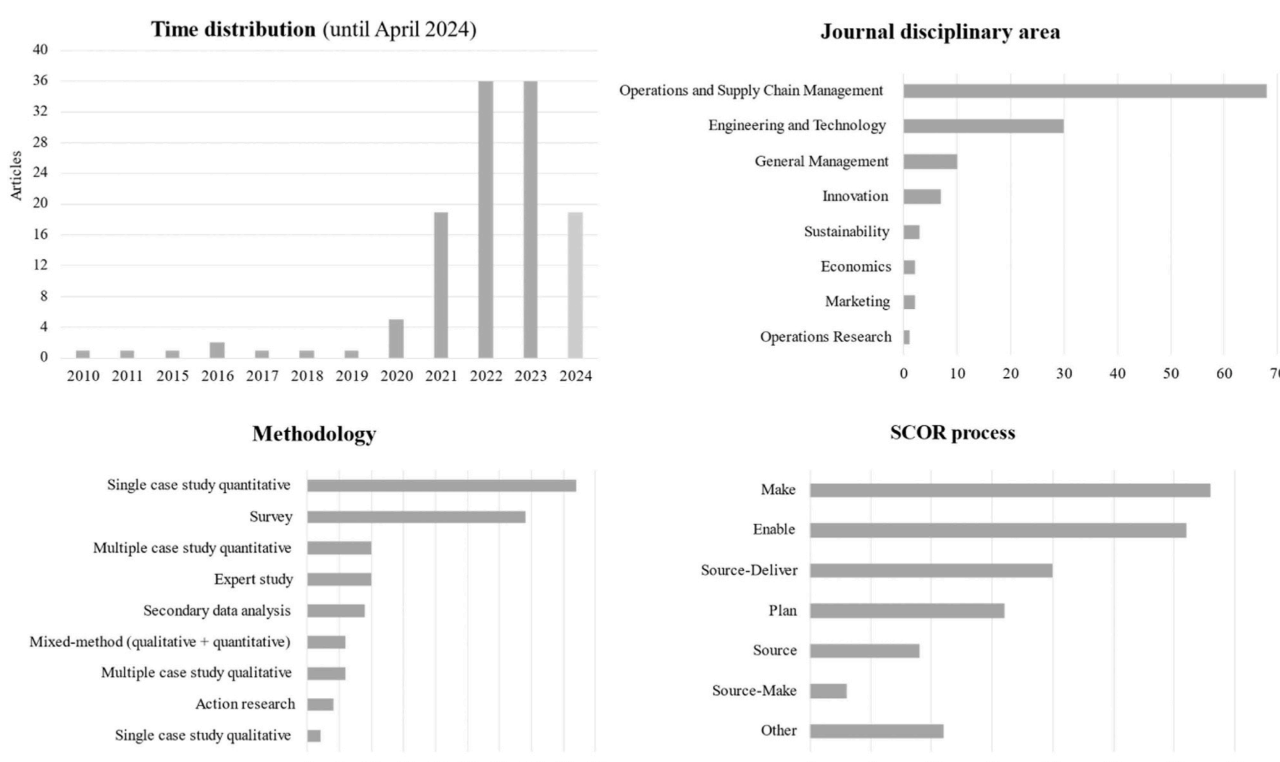

Fig. 3. Main characteristics of the articles included in the review.

coding framework (Fig. 2). See the Online Appendix for the full articles categorization.

3.2.1. Data and system requirements

The first theme (1. Data and system requirements) is covered by the majority of the articles (94, 76 %). This refers to data that are fed into AI and system/technological characteristics needed for this purpose; it is composed by three coding categories, which are illustrated in the following paragraphs.

1A. Accessing data (79 articles, 64%)– Several studies stress the importance of *data availability, quality, and volume* as AI effectiveness depends on what is fed into the model ('garbage in-garbage out' assumption; Brock and von Wangenheim, 2019; Demlehner et al., 2021). This is particularly relevant for ML solutions as training data in high-dimensional spaces are required to ensure adequate sampling combinations (Brintrup et al., 2020; El Garrab et al., 2023). Large datasets are indeed related to higher analytical accuracy (Ji et al., 2021). Whenever AI is used for autonomous decision-making and process implementation, large-scale real-time and historical data are required (Budak and Sarvari, 2021; Cadden et al., 2022; Hu et al., 2023). Notably, data volume doesn't compensate for quality whenever large datasets present missing/incomplete values (Loyer et al., 2016; Perno et al., 2023; Sen et al., 2023). AI has the ability to deal with incomplete datasets and adapt to different levels of data availability (Msakni et al., 2023; Senoner et al., 2022; Takeda-Berger and Frazzon, 2024). However, this requires shaping the approach upfront and choosing simpler techniques whenever the data amount/quality is suboptimal (Sohrabpour et al., 2021; Vanderschueren et al., 2023). Moreover, limited data availability might often require human intervention (Burger et al., 2023; Oberdorf et al., 2021).

Firms lacking confidence in data quality might be reluctant to implement AI (Meyer and Henke, 2023; Nayal et al., 2022). Companies that have built data management capabilities are better positioned (Brock and Von Wangenheim, 2019). Significant challenges come in fact from setting up extensive data collection (Ko et al., 2017; Kosasih et al., 2022), while poor data quality might lead to costly mistakes, particularly in buyer-supplier relationships (Cannas et al., 2023). In this regard, Bodendorf et al. (2022a) indicate three major issues in (inter)organizational settings, namely data availability, trustworthiness, and normalization; noting that 50–80 % of project time is dedicated to data collection and cleaning. Similarly, Hasija and Esper (2022) stress that in large organizations data reside across several functions, making it necessary to network and build data pipelines. As highlighted by Bokrantz et al. (2023) and Manimuthu et al. (2022b), data quality needs to be reassessed over time because information used for training might no longer correspond to reality; for instance, due to data corruption (e.g., error in data capturing/transfer) or stochastic changes in system behavior.

Another aspect to consider concerns *data security and confidentiality*. Security involves protecting data and networks from harm, while confidentiality is the right of protecting personal/organizational information. Effective management of these aspects—often addressed through formal policies and definition of tasks and responsibilities (Chatterjee et al., 2023; Leberruyer et al., 2023)—is critical for technology adoption (e.g., Sodhi et al., 2022; Yadav et al., 2020).

Related to previous points, researchers explicitly flag issues related *to (inter)organizational data-sharing*. This is a long-lived issue in SCM (Kembro and Näslund, 2014) and several roadblocks persist today in terms of limited trust issues and the size of the investment (Bodendorf et al., 2022b; Cannas et al., 2023). These barriers can be overcome through long-term relationships and by sharing the benefits with the involved partners (Cadden et al., 2022; Chatterjee et al., 2023). Similarly, it appears more likely for AI to be introduced in SCs already characterized by data integration (Nayal et al., 2022; Yadav et al., 2020). Novel forms of (inter)organizational data-sharing are also reported. Guida et al. (2023b) mention that buyers and suppliers share procurement-related data via third-party intermediaries (e.g., digital platforms) ensuring restricted access.

The last coding category concerns *new data sources and methods to reduce data dependency*. AI can in fact process unstructured data (e.g., from the web) (Bodendorf et al., 2022b; Brintrup et al., 2023; Chatterjee et al., 2023). This can alleviate the need for (inter)organizational data-sharing by inference from alternative sources (e.g., supplier-related newsfeeds – Pessot et al., 2022). The approach appears viable for planning, demand forecasting, and risk management (Chuang et al., 2021; Modgil et al., 2022). Moreover, AI can create synthetic/semi-synthetic data to mimic real datasets, allowing algorithm training before formal data collection (Vanderschueren et al., 2023). Finally, Zheng et al. (2023) and Manimuthu et al. (2022a) testified the application of federated learning approaches for risk prediction, namely applying edge devices on data servers for collaborative analysis on private data.

1B. Developing the technological backbone (25 articles, 20 %)– Extant research indicates that AI needs an adequate *technological infrastructure, computational resources, and information system integration*. Despite the low cost of computing power, AI still demands substantial resources (Bokrantz et al., 2023). Many companies lack hardware, software, and broadband connectivity (Bodendorf et al., 2022a; Cannas et al., 2023). Leberruyer et al. (2023) and Merhi and Harfouche (2023) argue that companies should reflect upfront on their technological infrastructure to ensure data flows. Helo and Hao (2022) and Xia et al. (2022) highlight two complementary aspects: infrastructures for data collection/storage and computing power. Firms need to implement and integrate manufacturing execution system (MES), supervisory control and data acquisition (SCADA) system, and programmable logic controller system (PLC) on individual machines (Oberdorf et al., 2021). However, there might be challenges in integrating legacy systems (Brock and Von Wangenheim, 2019; Zhu et al., 2021), which are more severe in (inter)organizational settings because of multi-party compatibility (Cadden et al., 2022; Cannas et al., 2023). Interoperability, standardization via common schema and data dictionaries, and semantic information exchange across organizational units and firms are preconditions along SCs (Ji et al., 2021; Kosasih et al., 2022; Pillai et al., 2022). Moreover, the importance of data makes the presence of *cybersecurity systems* crucial. It has been noted that, behind organizational measures, companies often adopt specific system solutions like intrusion detection and disaster recovery mechanisms (Allal-Chérif et al., 2021; Brock and Von Wangenheim, 2019).

1C. Adopting complementary technologies (45 articles, 37 %)– AI in manufacturing SCs is often associated with broader digital transformation initiatives and the Industry 4.0 phenomenon (e.g., Agrawal and Narain, 2023; Hopkins, 2021). Even if AI can be adopted as a standalone technology (Brintrup et al., 2023), many times it comes together with other technologies for data gathering/processing and automation. Most studies refer to the *Internet of Things* and machine connectivity, especially for applications related to quality management (e.g., Sen et al., 2023; Song et al., 2023), smart maintenance (e.g., Hoffmann et al., 2021; Kaparthi and Bumblauskas, 2020), and real-time logistics management (Chen et al., 2021). The second most mentioned technology is *cloud computing*, valued for its scalability and rapid deployment of computing power (Bodendorf et al., 2022a; Xia et al., 2022). It also facilitates data storage and processing, and collaboration among SC actors (Perno et al., 2023; Pessot et al., 2022). Another complementary technology is the *blockchain* in cross-organizational settings (Rodríguez-Espíndola et al., 2022; Yadav et al., 2020). Finally, studies report complementarities with technologies applied in factory and logistics operations, like *automation, robotics, and drones* (e.g., Pillai et al., 2022), *wearables and virtual/augmented reality* (e.g., Perno et al., 2023), and *additive manufacturing* (e.g., Song et al., 2023).

3.2.2. Technology deployment process

The second theme (2. Technology deployment process – 92 articles, 75%) addresses topics related to how AI is integrated in real-world SC environments through the development, testing, and monitoring of specific solutions. The following three categories emerge from the literature.

2A. Defining the AI strategy and approach (33 articles, 27 %)– One core issue concerns *investments and resource allocation*. The perceived cost (Pillai et al., 2022) and the lack of resources/financing appear among the main barriers to AI implementation (Mohiuddin et al., 2022; Sodhi et al., 2022). This is challenging especially for innovative and factory-wide applications (Demlehner et al., 2021; Gonçalves et al., 2021). Most resources are however not absorbed by AI itself, but rather in the development of the technological backbone and in the adoption of complementary technologies (Gupta et al., 2022; Hopkins., 2021).

Defining the AI strategy and approach depends on *business leaders' direct engagement and support*. Their role is crucial, for instance, in setting a vision for AI, allocating resources, and fostering a supportive organizational climate (Hasija and Esper, 2022; Merhi and Harfouche, 2023). Conversely, limited support is related to low adoption and assimilation (Meyer and Henke, 2023; Mohiuddin et al., 2022). There is moreover a need for a *strategic alignment with business requirements*. Brock and Von Wangenheim (2019), Merhi and Harfouche (2023), and Meyer and Henke (2023) underline the necessity of a digital strategy over unplanned or tactical approaches. In this respect, firms structure their approach to pursue competitive differentiation (Demlehner et al., 2021) and to address environmental uncertainties (Pillai et al., 2022; Zhu et al., 2021). Importantly, AI adoption can lead to strategic shifts, enabling new business and operating models (Chen et al., 2022). Early alignment of strategic vision, processes, and technology is thus important both within individual organizations (Sodhi et al., 2022) and among business partners (Bodendorf et al., 2022a; Pessot et al., 2022).

In this phase, *cost-benefit assessment* emerges as a necessary but daunting task. Managers seem to mostly base their judgment on perceptions (Dora et al., 2022; Merhi and Harfouche, 2023), only few develop structured business cases to justify investments and determine priorities (Manimuthu et al., 2022b; Mohiuddin et al., 2022). Considered metrics include operational costs, return on investment, net cash flow, payback periods, and qualitative indicators based on benchmarking (Meyer and Henke, 2023; Sodhi et al., 2022). Costs include not only AI acquisition/implementation but also information system integration and technical support (Zhu et al., 2021). Quantifying investments and estimating returns is difficult due to limited data from past projects (Bodendorf et al., 2022a; Cannas et al., 2023). Some studies suggest an *incremental roll-out* due to abovementioned uncertainties and potential changes required (Brock and Von Wangenheim, 2019; Meyer and Henke, 2023).

2B. Designing the technological solution (65 articles, 53 %)– Many studies address the *accuracy of the analytical approach*. Some researchers develop and compare different approaches to identify the most apt to the analytical challenge at hand (e.g., by assessing prediction accuracy – Abualsauod, 2023), while others confront firms' performance metrics prior to AI introduction (e.g., Perno et al., 2023) and across multiple case studies (e.g., Sen et al., 2023). The literature also shows activities of *tradeoff resolution* whereby desired accuracy levels need to be balanced with the required computational power (Gonçalves et al., 2021; Hasija and Esper, 2022). This is reflected in the algorithm semantics and the choice of measures, which should be considered early in the project (Bokrantz et al., 2023; Chuang et al., 2021). Other tradeoffs concern approaches to available data (e.g., balancing sample size/quality – Nikolopoulos et al., 2016) and error tolerance (e.g., the business cost of false positives/negatives – Flath and Stein, 2018).

Another core topic in technology design is *model update and maintenance*. Regular retraining and updates are necessary against changes in the real environment (Helo and Hao, 2022; Brock and Von Wangenheim, 2019) and maintenance costs are higher for complex models (Bodendorf et al., 2022a). Whereas model update and maintenance can go in parallel with AI usage (Burger et al., 2023; Gauder et al., 2023), Bokrantz et al. (2023) argue that maintenance should be a specific phase in AI projects; this is to avoid the risk of overlooking important tasks such as monitoring input signals, notifying when changes have occurred, and retraining the model with new data. These activities should be performed regularly over time, preferably involving experts (Flath and Stein, 2018; Hasija and Esper, 2022). In some cases, however, the technology allows for *self-design and updating* as, for example, maintenance can be integrated into cloud platforms for automatic data extraction and retraining in the presence of process changes (Perno et al., 2023).

2C. Accessing competencies and expertise (45 articles, 37 %)– One core topic is the availability of *technical expertise* in data science and data engineering, the latter being relevant once the data pipeline is defined (Bodendorf et al., 2022a; Budak and Sarvari, 2021). Dedicated staff should be skilled in operating AI-enabled programs across implementation stages (Manimuthu et al., 2022b; Mohiuddin et al., 2022). The integration of technical experts within functional teams and the development of basic digital literacy across the workforce are also emphasized (Burger et al., 2023; Hasija and Esper, 2022). Moreover, companies need skills in cybersecurity, user experience, and hardware technologies (e.g., sensors and actuators – Kinkel et al., 2022; 2023). The availability of technical expertise is a critical aspect hindering AI adoption and successful implementation (Demlehner et al., 2021; Guida et al., 2023b), especially whenever firms lack the resources to attract talent (Babina et al., 2024; Dey et al., 2023; Hopkins, 2021).

Complementary, several studies highlight the need of *domain competence* (i.e., the specialized knowledge required for variable selection/feature engineering). Designing AI solutions requires interpreting data in light of the specific characteristics and properties of the phenomena under investigation (Brintrup et al., 2020; El Garrab et al., 2023; Kang and Kang, 2021). In this perspective, Chuang et al. (2021) note the value of academic knowledge in SCM to illuminate the implementation journey.

AI prompts firms to seek collaborations with technology providers and universities to gain *external expertise*. This is due to the novelty of the technology, the presence of specialized vendors, and opportunities arising from applying AI to data from multiple firms (Cannas et al., 2023; Meyer and Henke, 2023).

3.2.3. (Inter)organizational integration

One important theme is AI integration within organizations and along SCs (3. (Inter)organizational integration – 91 articles; 74%). It revolves around the interplay between the technology and (inter)organizational social systems, entailing the following categories.

3A. Managing acceptance and sensemaking (35 articles, 28 %)– As organizations are still experimenting with and adapting to AI (Sodhi et al., 2022), *organizational culture and change management* play a significant role forming a foundation of shared values and beliefs (Chatterjee et al., 2021; Merhi and Harfouche, 2023). Brock and Von Wangenheim (2019) and Meyer and Henke (2023) specify the need for a "failure culture" for experimentation and risk acceptance. Other works point to a "data-driven culture" whereby employees are used to managing and analyzing data (Dey et al., 2023; Oberdorf et al., 2021). Change management programs with incentives for new tools adoption and proactive communication are recommended (Dora et al., 2022; Leberruyer et al., 2023). Importantly, cultural elements are also reported for (inter)organizational AI applications which are easier in contexts characterized by stable relationships and trust (Cadden et al., 2022; Pessot et al., 2022).

Reliability perception and "black-box" issues emerge as key elements. Practitioners need to understand the workings of the specific AI solution in practice (Guida et al., 2023b; Nikolopoulos et al., 2016). Major issues emerge with black-box models, which, unlike white-box models, display more accurate results but lack transparency (Flath and Stein, 2018). Transparency, however, can increase acceptance and trust in the technology, especially in fully automated processes (Burger et al., 2023; Merhi and Harfouche, 2023). Potential mitigation actions relate to supplementing models with explanations (Kosasih et al., 2022), establishing clear responsibility for the results when AI makes incorrect decisions or predictions (Hasija and Esper, 2022), educating employees about AI mechanisms (Meyer and Henke, 2023), and involving future users in development and evaluation cycles (Oberdorf et al., 2021). At any rate, trust can develop naturally over time by experimenting with the technology (Bodendorf et al., 2022a).

Some contributions stress *workforce fears and job engagement*. There seems to be challenges whenever employees fear of being replaced by AI and in case the high number of automated decisions diminishes the job content (Cadden et al., 2022; Mohiuddin et al., 2022). Blue collars are the most susceptible to potential automation (Hasija and Esper, 2022), whereas individuals might experience lower job engagement (Braganza et al., 2022). This might negatively affect performance (Chatterjee et al., 2022b). *Managerial understanding of technology* potential/advantages emerges thus as key to stimulating AI adoption and guiding organizational change (Guida et al., 2023b; Rodríguez-Espíndola et al., 2022).

3B. Redefining the job content (26 articles, 21 %)–This category includes task/job automation, job redefinition, and workforce skills and retraining. *Task/job automation* refers to activities of data collection and analytics, as well as shopfloor and logistic operations (Brock and Von Wangenheim, 2019; Xia et al., 2022). For example, purchasing departments can automate analytics, supplier scouting, negotiation/contracting activities, and use voice-enabled cognitive assistants to answer questions asked by internal/external contacts (Cannas et al., 2023; Meyer and Henke, 2023). Several studies refer to automation of planning and forecasting (Nikolopoulos et al., 2016). Moreover, SC configuration decisions can be automatized to rapidly cope with potential disruptions (Hopkins, 2021; Modgil et al., 2022). While standard activities are more easily automated, human-in-the-loop solutions (i.e., systems where human judgment is integrated into automated processes) are necessary for processes with high variability (Mohiuddin et al., 2022; Oberdorf et al., 2021). Moreover, even when technically feasible, companies need to consider the risks of dehumanization (Allal-Chérif et al., 2021). Increasing automation naturally implies a *job redefinition* because employees leave behind purely operational tasks to focus on strategic matters (Bodendorf et al., 2022a; Nikolopoulos et al., 2016). AI can augment human capabilities, assisting in activities like dealing with suppliers in other languages, planning activities, and risk detection (Allal-Chérif et al., 2021; Modgil et al., 2022). This necessitates specific user interfaces (Hasija and Esper, 2022; Perno et al., 2023) and new job profiles (Hopkins, 2021; Mohiuddin et al., 2022), as humans and AI are integrated into "hybrid works" that take advantage of their respective strengths (Burger et al., 2023). In this perspective, organizations are increasingly embracing technology-human collaboration, including AI-enabled robots on shopfloors (Chen et al., 2022; Xia et al., 2022).

Consequently, *workforce upskilling and retraining* are needed. On a basic level, employees require training for each new tool adopted (Burger et al., 2023; Chatterjee et al., 2021). Beyond initial training, continuous education and systematic upskilling are essential to facilitate AI integration and promote data-driven environments (Dey et al., 2023; Hasija and Esper, 2022). Structured training can also improve acceptance and assimilation (Bag et al., 2021; Dora et al., 2022). However, challenges exist due to digital skills gaps which are higher in operations-related settings and the significant investment required (Mohiuddin et al., 2022; Sodhi et al., 2022).

3C. Structure and processes design (67 articles, 54 %)– One core implication of adopting AI appears related to *process digitalization and standardization*. On the one hand, previous studies indicate this to be a precondition for AI adoption (Bodendorf et al., 2022a). Companies leveraging digitalized interfaces, embracing management systems, and focusing on lean manufacturing can be facilitated (Leoni et al., 2022; Yadav et al., 2020). On the other hand, process digitalization and standardization are identified as consequences of AI adoption and a necessary complement to reap its benefits (Bokrantz et al., 2023). For example, Allal-Chérif et al. (2021) and Guida et al. (2023b) note that AI solutions in purchasing lead to practice homogenization, process standardization, and communication streamlining. Firms can also progressively redesign their processes, starting with specific phases until complete digitalization (Loyer et al., 2016; Mohan et al., 2023); the planning process is often one of the first to be reshaped (e.g., Takeda-Berger and Frazzon, 2024).

Several studies explicitly indicate the *integration of AI into decision-making processes.* These contributions often present AI as a tool enhancing managerial decisions through new analytical dimensions and faster (potentially real-time) data processing (e.g., Abualsauod, 2023; Paul et al., 2015). AI can offer managers new insights from previously unavailable data sources (e.g., Deiva and Kalpana, 2022b), advanced scenario analysis (Al-Surmi et al., 2022; Modgil et al., 2022), prioritization algorithms (e.g., Islam et al., 2021), adaptive models (e.g., Usuga-Cadavid et al., 2022), and consideration of more variables than it was possible in the past (e.g., Kim, 2023). These can be applied for internal operation as well as in sourcing and distribution (Hasija and Esper, 2022; Detwal et al., 2023). Moreover, AI can mimic decision-makers behavior (Belhadi et al., 2022). The literature also presents instances of firms adopting decision support tools offered by commercial vendors (e.g., in purchasing); alongside the benefits of a quicker turnaround of tasks, some limitations emerge concerning innovativeness (Allal-Chérif et al., 2021). At any rate, managers mostly remain responsible for enforcing decisions following firms' leadership guidance, building on previous know-how, and combining traditional methods with AI-based approaches (Bodendorf et al., 2022a; Burger et al., 2023; Leberruyer et al., 2023).

Another aspect concerns *organizational design*. Whereas AI appears more apt for flat organizations with highly decentralized decision-making (Xia et al., 2022), it is also true that decentralization might lead to conflicts and data silos, potentially limiting AI effectiveness (Guida et al., 2023b). When implementing AI, firms would often consider changing their organizational structure (Meyer and Henke, 2023) or implementing cross-functional/unit coordination mechanisms assisted by the technology itself (Bodendorf et al., 2022a; Sodhi et al., 2022). Moreover, new organizational units dedicated to digitalization might also be needed (Bokrantz et al., 2023; Leberruyer et al., 2023).

3D. Adapting the SC structure/relationships (24 articles, 20 %)– Effective AI applications in SCM often require data sharing and alignment of actions across organizations (Dora et al., 2022; Pessot et al., 2022), so that *(inter)organizational coordination mechanisms* with suppliers, competitors, and customers are needed. Here, success factors include early agreement on common objectives and benefits (Olan et al., 2022; Zhu et al., 2021) while maintaining open communication and feedback loops (Meyer and Henke, 2023). AI is also linked to a *redefinition of the SC structure* in terms of characteristics/number of suppliers and location of outsourced/insourced production. This can be explained considering that AI aids in identifying new suppliers beyond the usual network (Allal-Chérif et al., 2021), influences production geographies by detecting SC risks (Wong et al., 2022), and can lead to reshoring due to automation and the need of specific capabilities (Kinkel et al., 2023).

3.2.4. Performance implications

The literature extensively discusses the benefits of AI adoption (4. Performance implications – 89 articles, 72 %). Most articles report evidence from single applications (e.g., Kang and Kang, 2021; Senoner et al., 2022) and multiple case study analysis (e.g., Burger et al., 2023; Helo and Hao, 2022). Benefits are often reported as expectations or perceived outcomes. Empirical validation is limited, with surveys primarily gathering expert opinions rather than direct company experiences with AI (e.g., Cadden et al., 2022; Sodhi et al., 2022). Secondary data analyses are reported by Babina et al. (2024). Two ways of looking at performance implications emerge, which are summarized in the following categories.

4A. Improving operational performance (66 articles, 54 %)– Studies range from aggregated/generic operational performance measures (e.g., Chatterjee et al., 2022; Leoni et al., 2022) to specific aspects like *cost and efficiency* improvements. Enhancements are led by process optimization; for example, in production, it enables smart maintenance and real-time adjustments thus maximizing machine use (Mjimer et al., 2023; Msakni et al., 2023). Additionally, AI models can include targeted cost functions (Manimuthu et al., 2022a; 2022b) and help reduce defective products, leading to savings in logistics and disposal (Leberruyer et al., 2023). In planning, AI enhances prediction accuracy minimizing inventory requirements and improving stock rotation, with positive impacts on working capital and return on assets (Chuang et al., 2021; Gonçalves et al., 2021; Feizabadi, 2022). At strategic level, managers take more informed decisions proven to affect implementing firms' overall profitability (Budak and Sarvari, 2021; Senoner et al., 2022). Albeit to a lesser extent, the literature also mentions positive effects of AI-enabled automation (Hopkins, 2021; Sodhi et al., 2022). In production, this allows firms to shift their focus from labor-intensive activities and upgrade their operating model (Demlehner et al., 2021; Xia et al., 2022). In procurement, AI-based tools foster process digitalization reducing the costs of non-standard operations, for example by placing orders for families of items and simplifying the management of multiple suppliers (Allal-Chérif et al., 2021; Burger et al., 2023). Automatic systems remove the inefficiencies of looking for the right expertise within organizations (Oberdorf et al., 2021).

AI adoption is also associated with *time* improvements. This stems from the streamlining of internal processes, including supplier selection, cost analysis, bidding, and order management (e.g., Bodendorf et al., 2022c; Budak and Sarvari, 2021). Moreover, AI allows near real-time (inter)organizational coordination (Sodhi et al., 2022; Wong et al., 2022), particularly in logistics (Al-Hajj et al., 2020; Chen et al., 2021). These improvements result in reduced lead times and better on-time delivery rates (Bodendorf et al., 2022a; Burger et al., 2023). AI allows for the automatic adjustment of machine parameters (Hu et al., 2023; Xia et al., 2022) and provides functions for optimizing delivery times (El Garrab et al., 2023; Manimuthu et al., 2022a; 2022b). It also operates robots and assembly lines, saving time in the moving sequence (Cannas et al., 2023; Yang and Lu, 2010).

Benefits in terms of *quality and process reliability* are highlighted. AI-based methods are proposed for detecting defective products (e.g., Msakni et al., 2023), identifying production line failures (e.g., Crespo et al., 2020), and analyzing the root-causes (e.g., Kang and Kang, 2021). Overall, automation reduces output deviation from the expected standard (Mohiuddin et al., 2022; Sodhi et al., 2022). In quality inspection, the main benefits are higher accuracy (Dengler et al., 2021; Song et al., 2023), adaptive quality management (Gauder et al., 2023), and the full automation of activities allowing the shift from sampled quality control to full inspection (Helo and Hao, 2022). Moreover, AI tools can be used for defect classification and analysis, so that initiatives aimed at process improvements are prioritized (Senoner et al., 2022; Xia et al., 2022). Although most studies focus on quality in production, this is also experienced in documental management (Helo and Hao, 2022) and procurement activities (Burger et al., 2023) due to predictive purchasing anticipating potential supplier failures (Allal-Chérif et al., 2021).

In terms of *flexibility*, namely the ability to quickly adapt to supply and demand changes, it is enabled by the joint application of AI and automation technologies, like robots and drones (Demlehner et al., 2021; Enrique et al., 2022). Along SCs, the use of AI-based tools simplifies supplier switching (Burger et al., 2023) and allows to predict supplier capacity to promptly allocate orders (Brintrup et al., 2020; Dey et al., 2023). Similarly, AI helps companies to anticipate and adapt to changes like regulatory shifts and demand fluctuations (Gupta et al., 2023; Wong et al., 2022).

4B. Enhancing capabilities (58 articles, 47 %)– One key aspect refers to *risk management and resilience*. This can indeed be a driver for AI adoption (Chen et al., 2022) to augment the capabilities of organizations to deal with unexpected circumstances (Leoni et al., 2022). In manufacturing plants, AI helps avoiding risky situations through the timely identification of anomalies and accurate predictions on potential faults (Kaparthi and Bumblauskas, 2020; Leukel et al., 2023). AI-enabled planning also reduces the risks coming from high demand volatility (Gonçalves et al., 2021; Manimuthu et al., 2022a, 2022b). Considering logistics, AI facilitates real-time monitoring and automatic vehicle re-routing following unexpected events (Chen et al., 2021; Gupta et al., 2022). When dealing with first-tier suppliers, AI can process public and private information sources and automatize the enforcement of risk management policies (Allal-Chérif et al., 2021; Brintrup et al., 2020). This translates fewer blind spots and faster responses to disruptions (Burger et al., 2023; Nayal et al., 2022). Additionally, buyers can use AI to collaboratively assess risks by jointly processing supplier data (Kosasih and Brintrup, 2022; Zheng et al., 2023). In multi-tier supply networks, the technology can be used to manage disruptions and fraud (Deiva and Kalpana, 2022b; Hopkins, 2021), uncover hidden SC interdependencies (Kosasih et al., 2022), and formulate what-if scenarios and stress tests (Modgil et al., 2022). Moreover, AI can structure operating rules for SC reengineering (Belhadi et al., 2022) and support SCs' financial resilience (Gupta et al., 2023; Olan et al., 2022).

A second cluster of organizational capabilities concerns *innovation and customer relationships.* AI is associated with increased customer focus and sales (Cadden et al., 2022; Hopkins, 2021) because of its analytical strength in segmentation, targeting, and after-sales quality monitoring (Helo and Hao, 2022; Ko et al., 2017). AI aids in market insight acquisition and new product development (Babina et al., 2024; Mohiuddin et al., 2022; Pessot et al., 2022). The use of advanced analytics helps in defining optimal pricing strategies (Budak and Sarvari, 2021). Moreover, AI-based automation in relationships can reduce human error (Chatterjee et al., 2023). Integrating AI into requirements management and sales configurator tools increases accuracy and speeds up the quoting process (Helo and Hao, 2022). Chatbots and intelligent assistants enhance customer interfaces (Wong et al., 2022).

Finally, some papers underline that firms can increase their capability to manage *social and environmental sustainability*. In particular, the use of AI enhances environmental sustainability by improving recycling quality (Cannas et al., 2023), reducing waste (Demlehner et al., 2021), and incorporating energy controls to lower emissions (Manimuthu et al., 2022a). Similarly, supplier selection tools can incorporate 'green' criteria (Kuo et al., 2010). In terms of social sustainability, studies show that hazardous task automation and the use of co-bots enhance workers' safety (Cannas et al., 2023). More generally, surveys link AI data processing with circular economy practices, leading to sustainable manufacturing (Dey et al., 2023; Yadav et al., 2020).

3.2.5. Contextual factors

The last theme (5. Contextual factors – 40 articles, 3**3 %**) reflects the nature of the reviewed articles (i.e., a prevalence of single-case applications) resulting in a research that is inherently context specific. Under this premise, it is however important to underline some elements identified in prior studies that emerge across the themes presented in the prior subsections. First, the *competitive environment* emerges as a key factor. Industry-specific competitive pressures prompt firms to adopt AI. The choice of specific tools (Chatterjee et al., 2021; Dora et al., 2022) and approaches is often tailored to specific business goals (e.g., cost--based vs. quality competition) (Al-Surmi et al., 2022; Kinkel et al., 2022). Second, some papers relate AI to the *COVID-19* crisis. Companies leveraging AI proved to be more effective in managing business operations and SC finance (Gupta et al., 2022; Olan et al., 2022). In addition, AI-based solutions were specifically created/repurposed to tackle pandemic challenges (Raghuram et al., 2023; Zheng et al., 2023). Third, AI implementation is influenced by *institutional factors, policies, and regulations*. Institutions are related to cultural contexts that facilitate the experimentation/adoption of emerging technologies (Dey et al., 2023). Similarly, the existence of policies, incentives, and clear regulatory frameworks for AI and data handling (e.g., data residency) encourage firms' investments (Bag et al., 2021; Dora et al., 2022). Finally, firms' *size* represents an important contingency determining technological readiness and investment availability as well as talent attraction and performance (Babina et al., 2024).

4. Discussion and research agenda

The aim of this study was to investigate empirical studies of AI in SCM to provide a solid understanding of the current state and emerging discontinuities brought about by the technology (RQ1). In this section, we first discuss the results of the SLR in this respect and then move on in outlining a series of potential research directions (RQ2).

Regarding **RQ1**, the key messages from the SLR are summarized in Fig. 4. Here we reflect on the emerging elements for each theme and coding category to identify those elements that seem more specific to AI and that entail a potentially disruptive impact on the theory and practice of SCM (right-hand side). We also recap for each theme the messages that can be extended to the introduction of other technologies in SCs or to digital transformation/Industry 4.0 trends in general (left-hand side).

Four insights emerge from our analysis. These are:

1. AI needs to be fed with adequate data (quality/volume); there are emerging approaches to overcome ongoing limitations in data quality and (inter)organizational data sharing.
   Data access—especially in (inter)organizational contexts—represents a major challenge for the implementation of digital technologies in SCs (e.g., Culot et al., 2024; Kembro and Näslund, 2014). A major step change comes from the fact that AI can still operate with low-quality/volume data from internal operations, derive SC-specific insights from third-party sources, and analyze data in federated learning modes (e.g., Brintrup et al., 2023; Bodendorf et al., 2022b; Zheng et al., 2023).
2. AI is deployed through a structured process entailing strategic, business, and technological dimensions; these activities continue after AI introduction and can be partially automatized.
   Differently than other technologies, AI requires ongoing maintenance and adaptation while its value increases over time as more data inform learning processes towards ever more accurate results (Bokrantz et al., 2023; Hasija and Esper, 2022). There are opportunities to automatize AI design and updating through third-party services where, alongside potential benefits, risks also emerge (Perno et al., 2023).
3. AI is impacting (inter)organizational processes at multiple levels with technological agency being more complex to manage for black-box/automation approaches.
   AI is not the only technology implying some form of automation (Culot et al., 2020; Frank et al., 2019); however, it is the one that most of all implies humans to attribute not only tasks but also decision-making rights to technological agents (Belhadi et al., 2022; Hasija and Esper, 2022). This aspect becomes estremely complex for AI approaches that are more autonomous/less explicable (e.g., black-box approaches), especially in (inter)organizational settings (Guida et al., 2023b).
4. AI brings to the table new/enhanced/complementary capabilities.
   The range of capabilities impacted by AI is very broad, spanning from innovation to risk management (Babina et al., 2024). The impact on performance—both at organizational and SC level—might depend on how/where technology is integrated in existing activities and processes.

Overall, these insights point to the fact that AI has indeed several elements that develop in continuity with other SC technologies. Similarly, the SLR uncovered some dynamics that characterize the current wave of innovation in general, as previously illustrated in reviews on digital transformation and Industry 4.0 (e.g., Dalenogare et al., 2018; Perano et al. 2023; Pozzi et al., 2023). There are nevertheless some peculiarities that ought greater focus.

Based on these considerations and the SLR results, the following paragraphs provide an answer to **RQ2**. Aa highlighted by scholars in other managerial disciplines (e.g., Hanelt et al., 2021; Gama and Magistretti, 2023), any research on novel phenomena and potentially disruptive technologies needs to start from assessing whether and how a shift is required in the current thinking and in established theoretical

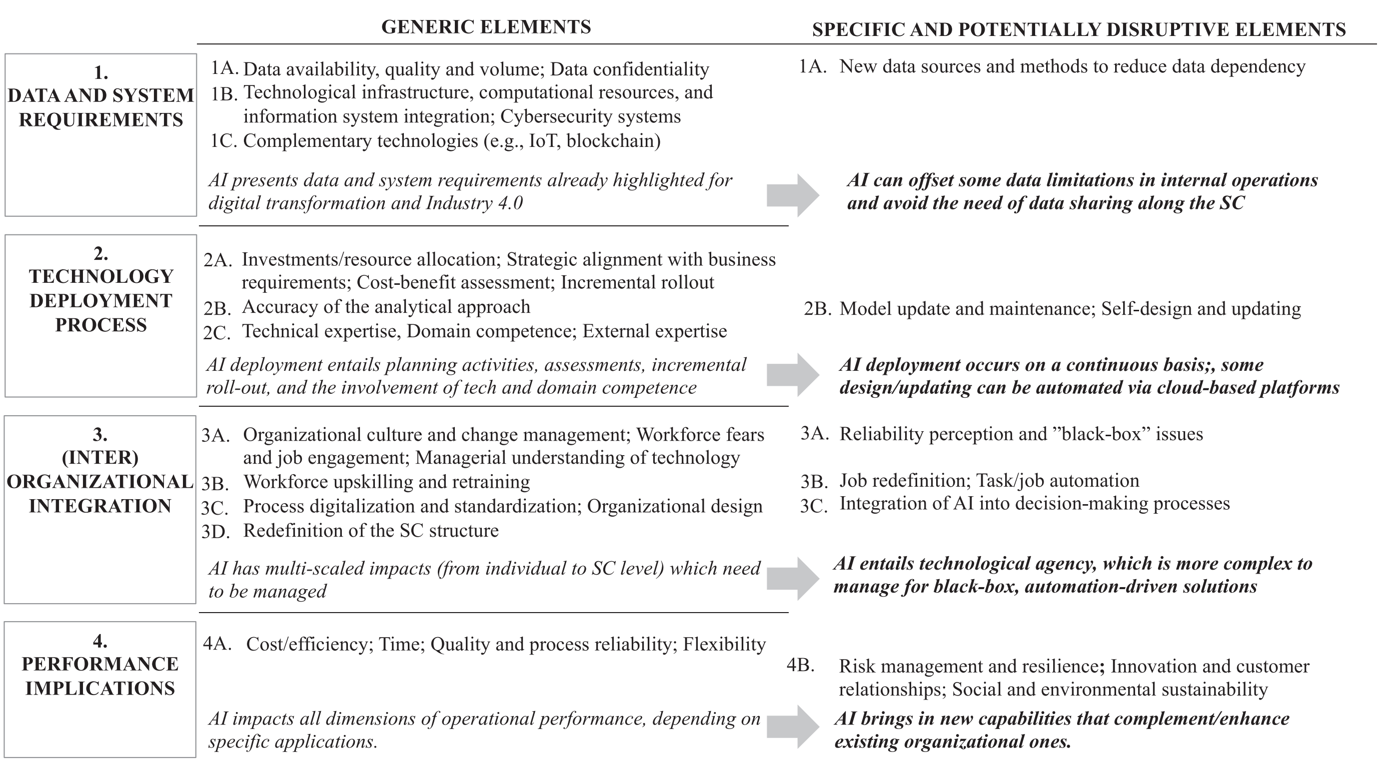

Fig. 4. Key messages of extant empirical studies on AI in SCM.

Table 1
Emerging AI trajectories and Research agenda.

Cross-cutting theme	Established SCM perspectives compared with emerging AI trajectories	Possible Research Directions
1. DATA AND SYSTEM REQUIREMENTS	**1A. Accessing data** **Perspective –** (Inter)organizational data-sharing entails several complexities despite the potential benefits (Kembro and Näslund, 2014) • Fears of opportunistic behaviors and confidentiality concerns. • Costs of sharing technologies, issues in multi-tier sharing initiatives. **SLR results –** Data availability and (inter)organizational data-sharing emerge as a precondition for applying AI; however, AI allows access to new sources of data and new forms of data pooling: • Processing of unstructured data (e.g., social media, the Internet, public sources) • Forms of federated learning approaches (e.g., raw data are not shared but jointly analyzed)	- What kind of (inter)organizational data-sharing is required for AI in SCM? What challenges emerge? What approaches? - When and how unstructured data can substitute/complement (inter)organizational data-sharing? - What drivers, barriers, and setups characterize new forms of data pooling for AI-enabled analytics in SCM (e.g., federated learning)? When and how competitors join forces in such initiatives?
	1B. Developing the technological backbone **Perspective** – The adoption of information systems requires companies to invest in hardware technologies and technological compatibility in terms of data formats and interfaces. These actions are normally driven by few dominant firms within an industry (Sodero et al., 2013). This might engender power dynamics and lock-in effects (Webster, 1995). **SLR results –** Most firms embracing AI need substantial investments to develop the necessary technological backbone. Cross-functional and (inter)organizational system integration/interoperability appear as a precondition, as well as the implementation of cybersecurity solutions. The literature shows approaches requiring lower investment levels, for example by accessing AI as a service and improving AI solutions that compensate for existing system gaps.	- How do firms assess and prioritize technological investments in hardware/software technologies that are required to adopt AI in SCM? What are the advantages/drawbacks of using legacy systems? - What role can lead firms assume to develop the technological backbone across their SCs, including small firms? What role is played by large digital players? What are the implications? - What solutions can AI support to overcome current challenges in interoperability and cybersecurity? What is their effectiveness?
	1C. Adopting complementary technologies **Perspective** – Technologies are part of bundles that include legacy and new technologies, rather than as standalone solutions (Cagliano and Spina, 2000). These are classified in typologies and taxonomies based on different criteria (e.g., technological complementarity, application area, performance objectives, technology-related capabilities) (e.g., Culot et al., 2020; Battaglia et al., 2023). **SLR results –** AI is often adopted with technologies that characterize the Industry 4.0/digital transformation phenomenon (e.g., the Internet of Things, cloud computing, blockchain technologies).	- What possible typologies of emerging technologies include AI in SCM? What is the rationale? - What possible taxonomies emerge of adopters of AI in SCM? What are the characteristics of the different possible clusters of firms?
2. TECHNOLOGY DEPLOYMENT PROCESS	**2A. Defining the AI strategy and approach** **Perspective –** Strategic choices can be analyzed through configurational lenses (Mikalef et al. 2015). In SCM, the debate has focused on the link between corporate and manufacturing strategy (Swink and Way, 1995). Similar efforts have characterized research in the information technology field for the alignment between firms' strategic objectives and technological solutions (e.g., Raymond and Bergeron, 2008). **SLR results –** Successful adoption of AI in SCM is characterized by strong strategic alignment with the business and leadership involvement. Moreover, adopting AI implies decisions on investments and resource allocation despite the lack of proven cost-benefits assessment tools. This, coupled with the novelty of the technology, prompts companies to pursue an incremental roll-out, rather than defining upfront a long-term strategy.	- How companies formulate decisions in the business, technology, and manufacturing strategy domains when adopting AI in SCM? What possible alignment pathways emerge at the intersection among the three areas? - What are the motivations and consequences of a poor/high alignment between the business, technology, and manufacturing strategy domains when adopting/developing AI in SCM? - What functions are involved in decisions concerning the adoption of AI in SCM? What is the role of organizational leaders? What are the characteristics of the decision process? What planning horizons emerge? - What cost-benefit assessment tools can firms deploy for AI in SCM?
	2B. Designing the technological solution **Perspective –** When considering the introduction of technologies in a manufacturing environment, there is a range of systematic methodologies that prescribe a sequence of interrelated process phases (Buede and Miller, 2016). **SLR results –** A series of phases characterize the design of AI solutions. A key activity is the evaluation of the accuracy of proposed approaches, also considering tradeoffs. Some studies address technology	- What engineering methodologies and process guidelines can support the design of AI solutions in SCM? - What decision process models can be used to decide on tradeoffs when designing AI solutions in SCM? How functional managers and technology specialists interact in such decisions?

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Table 1 (*continued*)

Cross-cutting theme	Established SCM perspectives compared with emerging AI trajectories	Possible Research Directions
	maintenance and update. One article (Bokrantz et al., 2023) specifically focuses on adapting engineering methodologies.	
	2C. Accessing competencies and expertise **Perspective –** Innovation develops both within and outside organizational boundaries and is subject to: • The exposure of firms to external knowledge within their environment (e.g., exposure to suppliers of state-of-the-art technologies and research institutions) (Kostopoulos et al., 2011). • Learning processes that take place for identifying SC partners' knowledge and converting it into value for the firm (Saenz et al., 2014). • The level of dependence between the business partners, which affects innovation outcomes and appropriation of results (Jajja et al., 2017) **SLR results –** Implementing AI in SCM requires the integration of technical and domain competence. Access to technical competence might be a challenge for manufacturing firms; collaborations with technology providers and universities are sought after.	- What (inter)organizational relationships are taking shape when adopting AI in SCM? What criteria manufacturing companies adopt when selecting external partners? - How are the core competencies of manufacturing firms changing when adopting AI in SCM? How can the collaboration with technology providers/universities facilitate the acquisition of such competencies? - How do the collaboration with different partners (e.g., technology giants, start-ups, academic institutions) affects innovation at manufacturing firms? How can this facilitate the acquisition/ development of competencies that are relevant for AI in SCM?
3. (INTER) ORGANIZATIONAL INTEGRATION	**3A. Managing acceptance and sensemaking** **Perspective –** The adoption of SC technologies is determined by: • Individual-level acceptance in terms of cognitive approval and sensemaking (Venkatesh and Bala, 2008) • Organizational-level acceptance including considerations on cost, availability, and vendor reputation (Autry et al., 2010) • Network-level diffusion dynamics (Patterson et al., 2003). **SLR results –** AI acceptance and productive use depends on cultural elements of the organization/SC, which can be addressed through change management programs and leadership engagement. There can be differences depending on the technological characteristics of AI: • Black-box models are more difficult to accept than white-box models. • AI-enabled automation generates more fears and skepticism in the workforce than solutions aimed at employees' assistance.	- What are the differences in individual-/organizational-level technology acceptance based on AI technological features (e.g., white-box vs. black-box models, AI-enabled automation)? - What cultural characteristics enable the adoption/use of AI in SCM? How does this affect performance improvements? What actions are firms undertaking on organizational culture prior, during, and after AI adoption? - What are the diffusion patterns of AI across SC networks?
	3B. Redefining job content **Perspective –** SCs encompass people who use technologies within dynamic work systems (Gattorna and Pasmore, 2022). When implementing a new technology, it is thus important to consider also organizational design issues (Sony and Naik, 2020). Key topics include job and work design (Trist, 1981). This is also important to sustain employee motivation (Walton, 1985). **SLR results –** AI automates several tasks (e.g., documental management, analytics) and jobs (e.g., chatbots and virtual assistants). Together with a redefinition of jobs, training and upskilling are necessary.	- How are work systems designed when integrating AI-enabled autonomous agents? How can responsibility be assigned on AI-generated outcomes? - How is employee motivation affected based on the level of assistance provided by AI? - What is the impact on employment when adopting AI in SCM? What roles are displaced? What roles are created? - How are employees' competencies changing due to AI in SCM? What differences emerge among different roles?
	3C. Aligning (inter)organizational processes and design **Perspective – S**everal process standardization initiatives characterize SCM (e.g., Supply-Chain Operations Reference Model – SCOR) as well as specific areas (e.g., quality, environmental, risk management) (Neiger et al., 2009; Uzumeri, 1997). These are characterized by a common focus on information and evidence-based decision-making. This is also in line with lean management, six sigma, and similar managerial approaches (Näslund, 2008). Some research already connects the implementation of Industry 4.0/digital transformation with process standardization initiatives (Bittencourt et al., 2021) **SLR results –** When adopting the technology, firms are mostly revising their processes and organizational design. Companies already adopting standardized processes are in a better position to reap the benefits of AI in SCM.	- How is AI integrated into standardized management systems and lean organizations? What changes are necessary? - What approaches to process flexibility emerge when introducing AI in SCM? How is the locus of decision-making changing within implementing organizations? - How is the governance of AI implementation in SCM? What are the coordination mechanisms?

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Table 1 (*continued*)

Cross-cutting theme	Established SCM perspectives compared with emerging AI trajectories	Possible Research Directions
	3D. Adapting the SC structure/relationships **Perspective –** Technologies affect the governance of transactions along SCs by determining the convenience/inconvenience of external sourcing (Ketokivi and Mahoney, 2020) and facilitating coordination between the involved parties (Cao and Lumineau, 2015). Technologies can also enable remote coordination driving SC geographic dispersion (Ancarani and Di Mauro, 2018). These dynamics are complex and several factors are at play (Culot et al., 2020). **SLR results –** AI can support a reconfiguration of SC structures and reshoring choices. New coordination mechanisms are enacted among business partners.	- What governance mechanisms characterize the relationships among the parties involved in (inter) organizational implementation of AI in SCM? How can AI automate governance-related activities? What are the implications? - What are the effects of adopting AI in SCM in terms of in-/outsourcing and the location of production? - To what extent SC configuration decisions can be automated and implemented?
4. PERFORMANCE IMPLICATIONS	**4A. Improving operational performance** **Perspective –** Operational performance is affected by the technologies that are adopted in internal and SC operations: • Firms can reach a maximum level of performance based on their setup (i.e., technologies, managerial practices, and the nature of inputs) (Frohlich and Westbrook, 2001; Schmenner and Swink, 1998). • There is a relationship between the different operational performance dimensions (i.e., performance improvements can be cumulative/sequential or generate tradeoffs – Gupta and Boyd, 2008; Schroeder et al., 2011). • In SC relationships, there might be an asymmetric value appropriation (Cox, 2001; Ellegaard et al., 2014). **SLR results –** There is still limited empirical evidence of the impact of AI on operational performance. Cost, quality, and time appear with a similar frequency in the analyzed literature. As far as value appropriation is concerned, there has been a limited debate so far.	- What are the effects of adopting AI in SCM on the operational performance of implementing firms? Does it determine a new performance frontier? What are the differences depending on the kind of application? - What is the relationship between the different dimensions of operational performance (i.e., cost, time, quality, and flexibility) in AI adopters? Are there any dark sides or tradeoffs? - What are the operational performance implications of AI-enabled SCs? What value appropriation dynamics emerge among SC partners?
	4B. Enhancing organizational capabilities **Perspective –** Different theories commonly used in SCM can help explaining why a specific lever (i.e., technology adoption) can generate performance improvements (Denyer et al., 2008; Pilbeam et al., 2012). For example, performance improvements can be motivated by lower transaction costs, accumulation of distinctive resources, higher responsiveness to stakeholder demands, development of distinctive capabilities (Chicksand et al., 2012). **SLR results –** The literature indicates that adopting AI affects (inter)organizational capabilities in risk management and resilience, customer insights and relationships, and environmental and social sustainability management. However, the reasons of these improvements are not clarified.	- Which conceptual categories can explain the performance improvements of adopting companies? Do current theories offer an adequate explanatory framework or is theoretical advancement required? - What specific capabilities are related to AI in risk management and resilience, customer insights and relationships, and environmental and social sustainability management?

models (Post et al., 2020). As clarified in the Introduction, this should start from a deep understanding of extant empirical research to mitigate the risk of confusing expectations and unrealistic scenarios. For each cross-cutting theme, we thus reflected on the consistency between SLR results and established assumptions in SCM and formulated a series of future research avenues (Table 1). Established assumptions are derived from reviews and seminal papers that are central to the academic debate on the specific issues. Given the relative novelty of the phenomenon, the list of possible research directions is long and varied to encompass different possible aspects relevant for the debate intercepting the interest of various groups within the broader SCM community.

Given the lack of strong theoretical anchoring in extant research (see Section 3.1), we believe it is important for future studies to draw on established frameworks. These are the ones normally and most broadly uses in the discipline (Halldórsson et al., 2015; Storey et al., 2006). Several RQs can be approached indeed from perspectives like Transaction Cost Economics, Resource-based View, Contingency Theory, Dynamic Capabilities, Absorptive Capacity. Future research should adhere to these lenses to better understand what is truly new about AI in SCM and determine whether theoretical constructs require refinement or new kinds of relationships posited (Busse et al., 2017). Moreover, researchers can leverage configurational theorizing to understand the complex mix of factors influencing emerging setups of AI in SCM, thereby accounting for the interrelationships between technological, functional, and (inter)organizational aspects (Furnari et al., 2021). In this respect, in addition to what is illustrated in Table 1, there is the opportunity to consider contextual factors that affect technology adoption, implementation and performance. Although contingencies represent an important dimension of technology in SC context (Søgaard et al., 2019), the results of the SLR highlight a still limited understanding in this respect.

Although there is value for SCM researchers to approach AI through proven paths, there are also opportunities to leverage pertinent theoretical advances in neighboring fields like General Management and Information Systems, particularly the debate on Data Network Effects in AI-based digital platforms (Clough and Wu, 2022; Gregory et al., 2021): the idea is that the more AI can learn from the data it collects, the more valuable it becomes to each user. The validity and implications of these concepts beyond the consumer sector have not been explored yet and the dynamics might be very different in SC business relationships characterized by data confidentiality and power dynamics. Similarly, the Information Ecology Theory formulated for digital innovation ecosystems could be interesting (Wang, 2021). This suggests that digital technologies enable multi-scaled and coherent integration among independent parties operating within an innovation ecosystem. In particular, these perspectives might prove interesting to investigate the peculiarities of AI in terms of learning patterns and third-party services and data usage (see Fig. 4).

To conclude, two important methodological suggestions emerge from a critical review of extant research. First, as AI encompasses various technologies, an excessive level of detail can be confusing for managerial scholarship and hinder the formulation of a general understanding; a pragmatic approach is recommended based on broad classifications (e.g., black-box vs. white-box models). Second, in terms of methodologies, explorative research is still needed to clearly understand the unique facets of this phenomenon and is consistent with the fact that many firms are still experimenting with AI.

5. Conclusions

This study presents a SLR (123 papers) of empirical studies regarding AI in SCM, deriving cross-cutting themes and topics that inform the formulation of a comprehensive research agenda. Our focus was motivated by the need to discriminate between the promise and reality of AI in order to enable a solid theorizing on the topic.

Naturally, there are some limitations that should be clarified. We reviewed a body of knowledge that is rapidly developing following real-life applications that are still in a state of flux. In this respect, while we advance studies that have completed just a few years back (e.g., Toorajipour et al., 2021; Pournader et al., 2021) and hope that our effort can illuminate current issues and research opportunities, we also urge for frequent updates as time goes by.

Moreover, besides the usual drawbacks of manual selection and coding—which we believe are compensated by the depth of the findings that are reported—we acknowledge that relevant information for the purpose of our study could have been found in conference papers, books, and in the gray literature. This body of knowledge has not been included in the SLR due to its vastity—which would have required bibliometric data processing rather than a formal content analysis—and the need to ensure rigor by including only articles published in peer-reviewed journals. Specifically, regarding books, there are several titles for class use (e.g., Vermeulen, 2019) and others describing architectural frameworks and AI technical solutions without real-world applications (e.g., Chatterjee et al., 2022a; Vermesan and Marples, 2024; Karim et al., 2023). Further, some books present insights into specific themes (e.g., legislation, sustainability, security – Munoz and Maurya, 2022; Kumar et al., 2023; Motahhir and Maleh, 2022), industries (e.g., apparel/textile – Wong et al., 2013), and SCM challenges (e.g., production scheduling – Bär, 2022). Finally, there are several books that provide a brief overview of AI for SCM that can still be used to gain a high-level understanding of the issues at hand (e.g., Vermesan et al., 2022; Chand et al., 2023; Sharma and Jain, 2022; Perumal et al., 2022).

In terms of contributions to the literature, this article has three major implications. First, we provide a systematic overview of the state-of-the-art of AI research in SCM. This allows a consolidation of current understanding while supporting early alignment on themes emerging across application areas and research foci, which have been expounded in earlier works (e.g., Carvalho et al., 2019; Dalzochio et al., 2020). Against a new technological trajectory, this effort enables a better understanding of the depth and breadth of new dynamics. In this respect, the exclusion of purely conceptual papers ensures that findings are grounded in substantive verification. Moreover, differently than previous reviews (e.g., Culot et al., 2020; Dalenogare et al., 2018), our work specifically focuses the novel elements that are specific of AI and those that are common with current technological trajectories towards greater digitalization and automation of SCs.

Second, we formulate a detailed research agenda that compares SLR findings with established perspectives in SCM. Again, this approach is instrumental to derive a solid understanding of the phenomenon. We provide a comprehensive list of possible research directions. Some of them reflect specific interests within SCM, other are more general and provide a springboard for broader conversations within the community. Moreover, we introduce some recent theoretical developments in neighboring fields that might reasonably applied and adapted. This approach is in line with influential reviews in other disciplines (e.g., Hanelt et al., 2021)

Third, we advance some methodological recommendations. Specifically, we urge for a sharper operationalization of AI in empirical studies, which should balance out the need of differentiating among approaches and techniques with pragmatic considerations.

This study also provides valuable insights to managers. While AI has become a top priority for SCM executives, several implementation challenges hinder its successful adoption (e.g., WEF, 2023; McKinsey, 2023). By providing a comprehensive synthesis of common factors and contextual conditions, we trust to have drawn attention to the most salient issues. Similarly, the results of our review should caution managers against over-optimistic expectations as to the performance implications of AI, which still require empirical verification. Moreover, the study shows that technology itself is rarely sufficient, as organizational and (inter)organizational factors play a major role.

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CRediT authorship contribution statement

Giovanna Culot: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Guido Nassimbeni:** Supervision. **Matteo Podrecca:** Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization.

Declaration of Competing Interest

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

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.compind.2024.104132.

References

Abidi, H., De Leeuw, S., Klumpp, M., 2014. Humanitarian supply chain performance management: a systematic literature review. Supply Chain Manag. Int. J. 19 (5/6), 592–608.
Abualsauod, E.H., 2023. Machine learning based fault detection approach to enhance quality control in smart manufacturing. Prod. Plan Control.
Agrawal, P., Narain, R., 2023. Analysis of enablers for the digitalization of supply chain using an interpretive structural modelling approach. Int. J. Prod. Perform. Manag 72 (2), 410–439.
Al-Hajj, L.H., Mahmassani, H.S., Chen, Y., 2020. Reinforcement learning framework for freight demand forecasting to support operational planning decision. Transp. Res. Part E 137, 101926.
Allal-Chérif, O., Simón-Moya, V., Ballester, A.C.C., 2021. Intelligent purchasing: How artificial intelligence can redefine the purchasing function. J. Bus. Res. 124, 69–76.
Al-Surmi, A., Bashiri, M., Koliousis, I., 2022. AI based decision making: combining strategies to improve operational performance. Int. J. Prod. Res. 60 (14), 4464–4486.
Ancarani, A., Di Mauro, C., 2018. Reshoring and Industry 4.0: how often do they go together? IEEE Eng. Manag. Rev. 46 (2), 87–916.
Ardito, L., Messeni Petruzzelli, A., Panniello, U., Garavelli, A.C., 2019. Towards Industry 4.0: Mapping digital technologies for supply chain management-marketing integrationTowards Industry 4.0: mapping digital technologies for supply chain. Bus. Process Manag. J. 25 (2), 323–346.
Aria, M., Cuccurullo, C., 2017. bibliometrix: An R-tool for comprehensive science mapping analysis. J. Inf. 11 (4), 959–975.
Autry, C.W., Grawe, S.J., Daugherty, P.J., Richey, R.G., 2010. The effects of technological turbulence and breadth on supply chain technology acceptance and adoption. J. Oper. Manag. 28 (6), 522–536.
Babina, T., Fedyk, A., He, A., Hodson, J., 2024. Artificial intelligence, firm growth, and product innovation. J. Financ. Econ. 151, 103745.
Bag, S., Pretorius, J.H.C., Gupta, S., Dwivedi, Y.K., 2021. Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. Technol. Forecast. Soc. Change 163, 120420.
Bär, S., 2022. Generic Multi-Agent Reinforcement Learning Approach for Flexible Job-Shop Scheduling. Springer.
Battaglia, D., Galati, F., Molinaro, M., Pessot, E., 2023. Full, hybrid and platform complementarity: exploring the industry 4.0 technology-performance link. Int. J. Prod. Econ. 263, 108949.
Belhadi, A., Kamble, S., Fosso Wamba, S., Queiroz, M.M., 2022. Building supply-chain resilience: an artificial intelligence-based technique and decision-making framework. Int. J. Prod. Res. 60 (14), 4487–4507.
Bittencourt, V.L., Alves, A.C., Leão, C.P., 2021. Industry 4.0 triggered by Lean Thinking: insights from a systematic literature review. Int. J. Prod. Res. 59 (5), 1496–1510.
Bodendorf, F., Dentler, S., Franke, J., 2023. Digitally enabled supply chain integration through business and process analytics. Ind. Mark. Manag. 114, 14–31.
Bodendorf, F., Lutz, M., Michelberger, S., Franke, J., 2022a. An empirical investigation into intelligent cost analysis in purchasing. Suppl. Chain Manag. Int. J. 27 (6), 785–808.
Bodendorf, F., Merkl, P., Franke, J., 2022b. Artificial neural networks for intelligent cost estimation–a contribution to strategic cost management in the manufacturing supply chain. Int. J. Prod. Res. 60 (21), 6637–6658.
Bodendorf, F., Xie, Q., Merkl, P., Franke, J., 2022c. A multi-perspective approach to support collaborative cost management in supplier-buyer dyads. Int. J. Prod. Econ. 245, 108380.
Bokrantz, J., Subramaniyan, M., Skoogh, A., 2023. Realising the promises of artificial intelligence in manufacturing by enhancing CRISP-DM. Prod. Plan. Control.
Braganza, A., Chen, W., Canhoto, A., Sap, S., 2022. Gigification, job engagement and satisfaction: the moderating role of AI enabled system automation in operations management. Prod. Plan. Control 33 (16), 1534–1547.
Bretas, V.P., Alon, I., 2021. Franchising research on emerging markets: Bibliometric and content analyses. J. Bus. Res. 133, 51–65.
Brintrup, A., Kosasih, E., Schaffer, P., Zheng, G., Demirel, G., MacCarthy, B.L., 2023. Digital supply chain surveillance using artificial intelligence: definitions, opportunities and risksQ1ADigital supply chain surveillance using artificial intelligence. Int. J. Prod. Res. 62 (13), 4674–4695.
Brintrup, A., Pak, J., Ratiney, D., Pearce, T., Wichmann, P., Woodall, P., McFarlane, D., 2020. Supply chain data analytics for predicting supplier disruptions: a case study in complex asset manufacturing. Int. J. Prod. Res. 58 (11), 3330–3341.
Brock, J.K.U., Von Wangenheim, F., 2019. Demystifying AI: What digital transformation leaders can teach you about realistic artificial intelligence. California Manage. Rev 61 (4), 110–134.
Brynjolfsson, E., Jin, W., McElheran, K., 2021. The power of prediction: predictive analytics, workplace complements, and business performance. Bus. Econ. 56, 217–239.
Budak, A., Sarvari, P.A., 2021. Profit margin prediction in sustainable road freight transportation using machine learning. J. Clean. Prod. 314, 127990.
Buede, D.M., Miller, W.D., 2016. The engineering design of systems: models and methods. John Wiley & Sons.
Burger, M., Nitsche, A.M., Arlinghaus, J., 2023. Hybrid intelligence in procurement: Disillusionment with AI's superiority? Comput. Ind. 150, 103946.
Busse, C., Kach, A.P., Wagner, S.M., 2017. Boundary conditions: What they are, how to explore them, why we need them, and when to consider them. Organ. Res. Methods 20 (4), 574–609.
Cadden, T., Dennehy, D., Mantymaki, M., Treacy, R., 2022. Understanding the influential and mediating role of cultural enablers of AI integration to supply chain. Int. J. Prod. Res. 60 (14), 4592–4620.
Cagliano, R., Spina, G., 2000. Advanced manufacturing technologies and strategically flexible production. J. Oper. Manag. 18 (2), 169–190.
Calatayud, A., Mangan, J., Christopher, M., 2019. The self-thinking supply chain. Supply Chain Manag. Int. J. 24 (1), 22–38.
Cannas, V.G., Ciano, M.P., Saltalamacchia, M., Secchi, R., 2023. Artificial intelligence in supply chain and operations management: a multiple case study research. Int. J. Prod. Res.
Cao, Z., Lumineau, F., 2015. Revisiting the interplay between contractual and relational governance: A qualitative and meta-analytic investigation. J. Oper. Manag. 33, 15–42.
Carvalho, T.P., Soares, F.A., Vita, R., Francisco, R.D.P., Basto, J.P., Alcalá, S.G., 2019. A systematic literature review of machine learning methods applied to predictive maintenance. Comput. Ind. Eng. 137, 106024.
Chand, M., Jain, V., Ajmera, P. (Eds.), 2023. Data-Driven technologies and artificial intelligence in supply chain. CRC.
Chatterjee, J.M., Garg, H., Thakur, R.N. (Eds.), 2022a. A Roadmap for Enabling Industry 4.0 by Artificial Intelligence. Wiley.
Chatterjee, S., Chaudhuri, R., Vrontis, D., 2022b. AI and digitalization in relationship management: Impact of adopting AI-embedded CRM system. J. Bus. Res. 150, 437–450.
Chatterjee, S., Chaudhuri, R., Vrontis, D., Kadić-Maglajlić, S., 2023. Adoption of AI integrated partner relationship management (AI-PRM) in B2B sales channels: Exploratory study. Ind. Mark. Manag. 109, 164–173.
Chatterjee, S., Rana, N.P., Dwivedi, Y.K., Baabdullah, A.M., 2021. Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. Technol. Forecast. Soc. Change 170, 120880.
Chen, Y., Biswas, M.I., Talukder, Md.S., 2022. The role of artificial intelligence during COVID-19. Int. J. Emerging Mark.
Chen, Y.T., Sun, E.W., Chang, M.F., Lin, Y.B., 2021. Pragmatic real-time logistics management with traffic IoT infrastructure: Big data predictive analytics of freight travel time for Logistics 4.0. Int. J. Prod. Econ. 238, 108157.
Chicksand, D., Watson, G., Walker, H., Radnor, Z., Johnston, R., 2012. Theoretical perspectives in purchasing and supply chain management: an analysis of the literature. Supply Chain Manag. Int. J. 17 (4), 454–472.
Chuang, H.H., Chou, Y., Oliva, R., 2021. Cross-item learning for volatile demand forecasting: An intervention with predictive analytics. J. Oper. Manag. 67 (7), 828–852.
Clough, D.R., Wu, A., 2022. Artificial intelligence, data-driven learning, and the decentralized structure of platform ecosystems. Acad. Manag. Rev. 47 (1), 184–189.
Cox, A., 2001. Managing with power: strategies for improving value appropriation from supply relationships. J.Supply Chain Manag. 37 (2), 42.
Crespo, A., Crespo Del Castillo, A., Gómez Fernández, J.F., 2020. Integrating artificial intelligent techniques and continuous time simulation modelling. Practical predictive analytics for energy efficiency and failure detection. Comput. Ind. 115, 103164.
Culot, G., Nassimbeni, G., Orzes, G., Sartor, M., 2020. Behind the definition of Industry 4.0: Analysis and open questions. Int. J. Prod. Econ. 226, 107617.

Culot, G., Orzes, G., Sartor, M., Nassimbeni, G.., 2024. The data sharing conundrum: revisiting established theory. Supply Chain Manag. Int. J.

Dalenogare, L.S., Benitez, G.B., Ayala, N.F., Frank, A.G., 2018. The expected contribution of Industry 4.0 technologies for industrial performance. Int. J. Prod. Econ. 204, 383–394.

Dalzochio, J., Kunst, R., Pignaton, E., Binotto, A., Sanyal, S., Favilla, J., Barbosa, J., 2020. Machine learning and reasoning for predictive maintenance in Industry 4.0: Current status and challenges. Comput. Ind. 123, 103298.

Deiva, A.G., Kalpana, P., 2022a. Future of artificial intelligence and its influence on supply chain risk management–A systematic review. Comput. Ind. Eng. 169, 108206.

Deiva, A.G., Kalpana, P., 2022b. Supply chain risk identification: a real-time data-mining approach. Ind. Manag. Data Syst. 122 (5), 1333–1354.

Demlehner, Q., Schoemer, D., Laumer, S., 2021. How can artificial intelligence enhance car manufacturing? A Delphi study-based identification and assessment of general use cases. Int. J. Inf. Manag. 58, 102317.

Dengler, S., Lahriri, S., Trunzer, E., Vogel-Heuser, B., 2021. Applied machine learning for a zero defect tolerance system in the automated assembly of pharmaceutical devices. Decis. Support Syst. 146, 113540.

Dey, P.K., Chowdhury, S., Abadie, A., Vann Yaroson, E., Sarkar, S., 2023. Artificial intelligence-driven supply chain resilience in Vietnamese manufacturing small-and medium-sized enterprises. Int. J. Prod. Res.

Dhamija, P., Bag, S., 2020. Role of artificial intelligence in operations environment: a review and bibliometric analysisRole of artificial intelligence in operations. TQM J. 32 (4), 869–896.

Dolgui, A., Ivanov, D., 2022. 5G in digital supply chain and operations management: fostering flexibility, end-to-end connectivity and real-time visibility through internet-of-everything. Int. J. Prod. Res. 60 (2), 442–451.

Dora, M., Kumar, A., Kumar Mangla, S., Pant, A., Muhammad, M.K., 2022. Critical success factors influencing artificial intelligence adoption in food supply chains. Int. J. Prod. Res. 60 (14), 4621–46410.

Durach, C.F., Kembro, J., Wieland, A., 2017. A new paradigm for systematic literature reviews in supply chain management. J. Supply Chain Manag 53 (4), 67–85.

Duriau, V.J., Reger, R.K., Pfarrer, M.D., 2007. A content analysis of the content analysis literature in organization studies: Research themes, data sources, and methodological refinementsA content analysis of the content analysis literature. Organ. Res. Methods 10 (1), 5–34.

Dwivedi, Y.K., Sharma, A., Rana, N.P., Giannakis, M., Goel, P., Dutot, V., 2023. Evolution of artificial intelligence research in Technological Forecasting and Social Change: Research topics, trends, and future directions. Technol. Forecast. Soc. Change 192, 122579.

El Garrab, H., Lemoine, D., Lazrak, A., Heidsieck, R., Castanier, B., 2023. Predicting the reverse flow of spare parts in a complex supply chain: contribution of hybrid machine learning methods in an industrial context. Int. J. Logist. Syst. 45 (2), 131–158.

Ellegaard, C., Medlin, C.J., Geersbro, J., 2014. Value appropriation in business exchange–literature review and future research opportunitiesValue appropriation in business exchange. J. Bus. Ind. Mark. 29 (3), 185–198.

Enrique, D.V., Lerman, L.V., Sousa, P.R.D., Benitez, G.B., Bigares Charrua Santos, F.M., Frank, A.G., 2022. Being digital and flexible to navigate the storm: How digital transformation enhances supply chain flexibility in turbulent environments. Int. J. Prod. Econ. 250, 108668.

Fatorachian, H., Kazemi, H., 2021. Impact of Industry 4.0 on supply chain performance. Prod. Plan. Control 32 (1), 63–81.

Feizabadi, J., 2022. Machine learning demand forecasting and supply chain performance. Int. J. Logist. Res. Appl. 25 (2), 119–142.

Flath, C.M., Stein, N., 2018. Towards a data science toolbox for industrial analytics applications. Comput. Ind. 94, 16–25.

Frank, A.G., Dalenogare, L.S., Ayala, N.F., 2019. Industry 4.0 technologies: Implementation patterns in manufacturing companies. Int. J. Prod. Econ. 210, 15–26.

Frohlich, M.T., Westbrook, R., 2001. Arcs of integration: an international study of supply chain strategiesArcs of integration. J. Oper. Manag. 19 (2), 185–200.

Furnari, S., Crilly, D., Misangyi, V.F., Greckhamer, T., Fiss, P.C., Aguilera, R.V., 2021. Capturing causal complexity: Heuristics for configurational theorizing. Acad. Manag. Rev. 46 (4), 778–799.

Gama, F., Magistretti, S., 2023. Artificial intelligence in innovation management: A review of innovation capabilities and a taxonomy of AI applications. J. Prod. Innov. Manage.

Gattorna, J., Pasmore, W., 2022. Supply Chains as Dynamic Socio-technical Systems. In Handbook of Theories for Purchasing. Supply Chain and Management Research. Edward Elgar.

Gauder, D., Gölz, J., Jung, N., Lanza, G., 2023. Development of an adaptive quality control loop in micro-production using machine learning, analytical gear simulation, and inline focus variation metrology for zero defect manufacturing. Comput. Ind. 144, 103799.

Gonçalves, J.N.C., Cortez, P., Carvalho, M.S., Frazão, N.M., 2021. A multivariate approach for multi-step demand forecasting in assembly industries: Empirical evidence from an automotive supply chain. Decis. Support Syst. 142, 113452.

Gregory, R.W., Henfridsson, O., Kaganer, E., Kyriakou, H., 2021. The role of artificial intelligence and data network effects for creating user value. Acad. Manag. Rev. 46 (3), 534–551.

Guida, M., Caniato, F., Moretto, A., Ronchi, S., 2023a. The role of artificial intelligence in the procurement process: State of the art and research agenda. J. Purch. Supply Manag. 29 (2), 100823.

Guida, M., Caniato, F., Moretto, A., Ronchi, S., 2023b. Artificial intelligence for supplier scouting: an information processing theory approach. Int. J. Phys. Distrib. Logist. Manag. 53 (4), 387–423.

Gupta, M.C., Boyd, L.H., 2008. Theory of constraints: a theory for operations management. Int. J. Oper. Prod. Manag. 28 (10), 991–1012.

Gupta, S., Modgil, S., Choi, T.M., Kumar, A., Antony, J., 2023. Influences of artificial intelligence and blockchain technology on financial resilience of supply chains. Int. J. Prod. Econ. 261, 108868.

Gupta, S., Modgil, S., Meissonier, R., Dwivedi, Y.K., 2022. Artificial intelligence and information system resilience to cope with supply chain disruption. IEEE Trans. Eng. Manage.

Halldórsson, Á., Hsuan, J., Kotzab, H., 2015. Complementary theories to supply chain management revisited–from borrowing theories to theorizing. Supply Chain Manag. Int. J. 20 (6), 574–586.

Hanelt, A., Bohnsack, R., Marz, D., Antunes Marante, C., 2021. A systematic review of the literature on digital transformation: Insights and implications for strategy and organizational change. J. Manag. Stud. 58 (5), 1159–1197.

Hasija, A., Esper, T.L., 2022. In artificial intelligence (AI) we trust: A qualitative investigation of AI technology acceptance. J. Bus. Logist. 43 (3), 388–412.

Helo, P., Hao, Y., 2022. Artificial intelligence in operations management and supply chain management: An exploratory case study. Prod Plan. Control 33 (16), 1573–1590.

Hendriksen, C., 2023. AI for Supply Chain Management. J. Supply Chain Manag.

Hoffmann, M.L., Da Costa, C.A., De Oliveira Ramos, G., Da Rosa Righi, R., 2021. A feature identification method to explain anomalies in condition monitoring. Comput. Ind. 133, 103528.

Hopkins, J.L., 2021. An investigation into emerging industry 4.0 technologies as drivers of supply chain innovation in Australia. Comput. Ind. 125, 103323.

Hu, W., Wang, T., Chu, F., 2023. A Wasserstein generative digital twin model in health monitoring of rotating machines. Comput. Ind. 145, 103807.

Islam, S., Amin, S.H., Wardley, L.J., 2021. Machine learning and optimization models for supplier selection and order allocation planning. Int. J. Prod. Econ. 242, 108315.

Jajja, M.S.S., Kannan, V.R., Brah, S.A., Hassan, S.Z., 2017. Linkages between firm innovation strategy, suppliers, product innovation, and business performance: Insights from resource dependence theory. Int. J. Oper. Prod. Manag. 37 (8), 1054–1075.

Ji, B., Ameri, F., Cho, H., 2021. A non-conformance rate prediction method supported by machine learning and ontology in reducing underproduction cost and overproduction cost. Int. J. Prod. Res. 59 (16), 5011–5031.

Johnsen, T.E., 2009. Managing supplier involvement in new product development: a portfolio approach. J. Purch. Supply Manag. 15 (3), 187–197.

Kang, H., Kang, S., 2021. A stacking ensemble classifier with handcrafted and convolutional features for wafer map pattern classification. Comput. Ind. 129, 103450.

Kaparthi, S., Bumblauskas, D., 2020. Designing predictive maintenance systems using decision tree-based machine learning techniques. Int. J. Qual. Reliab. Manag. 37 (4), 659–686.

Karim, R., Galar, D., Kumar, U., 2023. AI factory: theories, applications and case studies. CRC.

Kembro, J., Näslund, D., 2014. Information sharing in supply chains, myth or reality? A critical analysis of empirical literature. Int. J. Phys. Distrib. Logist. Manag. 44 (3), 179–200.

Ketokivi, M., Mahoney, J.T., 2020. Transaction cost economics as a theory of supply chain efficiency. Prod. Oper. Manag. 29 (4), 1011–1031.

Kim, S., 2023. Innovating knowledge and information for a firm-level automobile demand forecast system: A machine learning perspective. J. Innov. Know. 8 (2), 100355.

Kinkel, S., Baumgartner, M., Cherubini, E., 2022. Prerequisites for the adoption of AI technologies in manufacturing–Evidence from a worldwide sample of manufacturing companies.Technovation 110, 102375.

Kinkel, S., Capestro, M., Di Maria, E., Bettiol, M., 2023. Artificial intelligence and relocation of production activities: An empirical cross-national study. Int. J. Prod. Econ. 261, 108890.

Ko, T., Lee, J.H., Cho, H., Cho, S., Lee, W., Lee, M., 2017. Machine learning-based anomaly detection via integration of manufacturing, inspection and after-sales service dataMachine learning-based anomaly detection. Ind. Manag. Data Syst. 117 (5), 927–945.

Kosasih, E.E., Brintrup, A., 2022. A machine learning approach for predicting hidden links in supply chain with graph neural networks. Int. J. Prod. Res. 60 (17), 5380–5393.

Kosasih, E.E., Margaroli, F., Gelli, S., Aziz, A., Wildgoose, N., Brintrup, A., 2022. Towards knowledge graph reasoning for supply chain management. Int. J. Prod. Res.

Kostopoulos, K., Papalexandris, A., Papachroni, M., Ioannou, G., 2011. Absorptive capacity, innovation, and financial performance. J. Bus. Res. 64 (12), 1335–1343.

Kumar, S., Pandey, N., Lim, W.M., Chatterjee, A.N., Pandey, N., 2021. What do we know about transfer pricing? Insights from bibliometric analysis. J. Bus. Res. 134, 275–287.

Kumar, R., Rani, S., Khangura, S.S. (Eds.), 2023. Machine Learning for Sustainable Manufacturing in Industry 4.0. CRC.

Detwal, P.K., Soni, G., Jakhar, S.K., Srivastava, D.K., Madaan, J., Kayikci, Y., 2023. Machine learning-based technique for predicting vendor incoterm (contract) in global omnichannel pharmaceutical supply chain. J. Bus. Res. 158, 113688.

Kuo, R.J., Wang, Y.C., Tien, F.C., 2010. Integration of artificial neural network and MADA methods for green supplier selection. J. Clean. Prod. 18 (12), 1161–1170.

Lagorio, A., Zenezini, G., Mangano, G., Pinto, R., 2022. A systematic literature review of innovative technologies adopted in logistics management. Int. J. Logist. Res. Appl. 25 (7), 1043–1066.
Leberruyer, N., Bruch, J., Ahlskog, M., Afshar, S., 2023. Toward Zero Defect Manufacturing with the support of Artificial Intelligence—Insights from an industrial application. Comput. Ind. 147, 103877.
Leoni, L., Ardolino, M., El Baz, J., Gueli, G., Bacchetti, A., 2022. The mediating role of knowledge management processes in the effective use of artificial intelligence in manufacturing firms. Int. J. Oper. Prod. Manag. 42 (13), 411–437.
Leukel, J., González, J., Riekert, M., 2023. Machine learning-based failure prediction in industrial maintenance: improving performance by sliding window selection. Int. J. Qual. Reliab. Manag. 40 (6), 1449–1462.
Loyer, J.L., Henriques, E., Fontul, M., Wiseall, S., 2016. Comparison of machine learning methods applied to the estimation of manufacturing cost of jet engine components. Int. J. Prod. Econ. 178, 109–119.
Manimuthu, A., Venkatesh, V.G., Raja Sreedharan, V., Mani, V., 2022a. Modelling and analysis of artificial intelligence for commercial vehicle assembly process in VUCA world: a case study. Int. J. Prod. Res. 60 (14), 4529–4547.
Manimuthu, A., Venkatesh, V.G., Shi, Y., Sreedharan, V.R., Koh, S.C.L., 2022b. Design and development of automobile assembly model using federated artificial intelligence with smart contract. Int. J. Prod. Res. 60 (1), 111–135.
Manyika, J., Bughin, J., 2018. The promise and challenge of the age of artificial intelligence. Available at: https://www.mckinsey.com/featured-insights/artificial-intelligence/the-promise-and-challenge-of-the-age-of-artificial-intelligence.
Mariani, M.M., Machado, I., Magrelli, V., Dwivedi, Y.K., 2023. Artificial intelligence in innovation research: A systematic review, conceptual framework, and future research directions. Technovation 122, 102623.
McElheran, K., Li, J.F., Brynjolfsson, E., Kroff, Z., Dinlersoz, E., Foster, L., Zolas, N.., 2021. AI adoption in America: Who, what, and where. J. Econ. Manage. Strat.33 (2),, 375–415.
McKinsey & Company, 2023. The state of AI in 2023: Generative AI's breakout year. Available at: https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2023-generative-ais-breakout-year#steady.
Merhi, M.I., Harfouche, A., 2023. Enablers of artificial intelligence adoption and implementation in production systems. Int. J. Prod. Res. 62 (15), 5457–5471.
Meyer, D., Henke, M., 2023. Developing design principles for the implementation of AI in PSM: An investigation with expert interviews. J. Purch. Supply Manag. 29 (3), 100846.
Mikalef, P., Pateli, A., Batenburg, R.S., Wetering, R.V.D., 2015. Purchasing alignment under multiple contingencies: a configuration theory approach. Ind. Manag. Data Syst. 115 (4), 625–645.
Mjimer, I., Aoula, E.S., Achouyab, E.L.H., 2023. Contribution of machine learning in continuous improvement processes. J. Qual. Maint. Eng. 29 (2), 553–567.
Modgil, S., Gupta, S., Stekelorum, R., Laguir, I., 2022. AI technologies and their impact on supply chain resilience during COVID-19. Int. J. Phys. Distrib. Logist. Manag 52 (2), 130–149.
Mohan, R., Roselyn, J.P., Uthra, R.A., 2023. LSTM based artificial intelligence predictive maintenance technique for availability rate and OEE improvement in a TPM implementing plant through Industry 4.0 transformation. J. Qual. Maint. Eng. 29 (4),, 763–798.
Mohiuddin, M., Akter, S., Rahman, M., Billah, M.M., Hack-Polay, D., 2022. The role of artificial intelligence in shaping the future of Agile fashion industry. Prod. Plan. Control.
Mokhtar, A.R.M., Genovese, A., Brint, A., Kumar, N., 2019. Supply chain leadership: A systematic literature review and a research agenda. Int. J. Prod. Econ. 216, 255–273.
Motahhir, S., Maleh, Y.(Eds.)., 2022. Security Engineering for Embedded and Cyber-Physical Systems. CRC.
Msakni, M.K., Risan, A., Schütz, P., 2023. Using machine learning prediction models for quality control: a case study from the automotive industry. Comput. Manag. Sci. 20 (1), 14.
Munoz, J.M., Maurya, A., 2022. International Perspectives on Artificial Intelligence. Anthem Press.
Näslund, D., 2008. Lean, six sigma and lean sigma: fads or real process improvement methods? Bus. Process. Manag. J. 14 (3), 269–287.
Nayal, K., Raut, R., Priyadarshinee, P., Narkhede, B.E., Kazancoglu, Y., Narwane, V., 2022. Exploring the role of artificial intelligence in managing agricultural supply chain risk to counter the impacts of the COVID-19 pandemic. Int. J. Logist. Manag. 33 (3), 744–772.
Naz, F., Agrawal, R., Kumar, A., Gunasekaran, A., Majumdar, A., Luthra, S., 2022. Reviewing the applications of artificial intelligence in sustainable supply chains: Exploring research propositions for future directions. Bus. Strat. Environ. 31 (5), 2400–2423.
Neiger, D., Rotaru, K., Churilov, L., 2009. Supply chain risk identification with value-focused process engineering. J. Oper. Manag. 27 (2), 154–168.
Nikolopoulos, K.I., Babai, M.Z., Bozos, K., 2016. Forecasting supply chain sporadic demand with nearest neighbor approaches. Int. J. Prod. Econ. 177, 139–148.
Oberdorf, F., Stein, N., Flath, C.M., 2021. Analytics-enabled escalation management: System development and business value assessment. Comput. Ind. 131, 103481.
OECD, 2017. The Next Production Revolution. OECD Publishing, Paris.
Olan, F., Arakpogun, E.O., Jayawickrama, U., Suklan, J., Liu, S., 2022. Sustainable Supply Chain Supply Networks. IEEE Trans. Eng. Manage.
Patterson, K.A., Grimm, C.M., Corsi, T.M., 2003. Adopting new technologies for supply chain management. Transp. Res. Part E 39 (2), 95–121.
Paul, S.K., Azeem, A., Ghosh, A.K., 2015. Application of adaptive neuro-fuzzy inference system and artificial neural network in inventory level forecasting. Int. J. Bus. Inf. Syst. 18 (3), 268.
Perano, M., Cammarano, A., Varriale, V., Del Regno, C., Michelino, F., Caputo, M., 2023. Embracing supply chain digitalization and unphysicalization to enhance supply chain performance: a conceptual framework. Int. J. Phys. Distrib. Logist. Manag. 53 (5/6), 628–659.
Perno, M., Hvam, L., Haug, A., 2023. A machine learning digital twin approach for critical process parameter prediction in a catalyst manufacturing line. Comput. Ind. 151, 103987.
Perumal, K., Chowdhary, C.L., Chella, L., 2022. I*nnovative Supply Chain Management Via Digitalization and Artificial Intelligence*. Springer.
Pessot, E., Zangiacomi, A., Fornasiero, R., 2022. Unboxing the hyper-connected supply chain. Prod. Plan. Control.
Pillai, R., Sivathanu, B., Mariani, M., Dwivedi, Y.K., 2022. Adoption of AI-empowered industrial robots in auto component manufacturing companies. Prod. Plan. Control 33 (16), 1517–1533.
Post, C., Sarala, R., Gatrell, C., Prescott, J.E., 2020. Advancing theory with review articles. J. Manage Stud 57 (2), 351–376.
Pournader, M., Ghaderi, H., Hassanzadegan, A., Fahimnia, B., 2021. Artificial intelligence applications in supply chain management. Int. J. Prod. Econ. 241, 108250.
Pozzi, R., Rossi, T., Secchi, R., 2023. Industry 4.0 technologies: critical success factors for implementation and improvements in manufacturing companies. Prod. Plann. Control 34 (2), 139–158.
Rad, F.F., Oghazi, P., Palmié, M., Chirumalla, K., Pashkevich, N., Patel, P.C., Sattari, S., 2022. Industry 4.0 and supply chain performance: a systematic literature review of the benefits, challenges, and critical success factors of 11 core technologies. Ind. Mark. Manag. 105, 268–293.
Raghuram, P., S., B., Manivannan, R., Anand, P.S.P., Sreedharan, V.R., 2023. Modeling and analyzing the inventory level for demand uncertainty in the VUCA world: evidence from biomedical manufacturer. IEEE Trans. Eng. Manag. 70 (8), 2944–2954.
Raut, R.D., Gotmare, A., Narkhede, B.E., Govindarajan, U.H., Bokade, S.U., 2020. Enabling technologies for Industry 4.0 manufacturing and supply chain: concepts, current status, and adoption challenges. IEEE Eng. Manag. Rev. 48 (2), 83–102.
Raymond, L., Bergeron, F., 2008. Enabling the business strategy of SMEs through e-business capabilities: a strategic alignment perspective. Ind. Manag. Data Syst. 108 (5), 577–595.
Riahi, Y., Saikouk, T., Gunasekaran, A., Badraoui, I., 2021. Artificial intelligence applications in supply chain: A descriptive bibliometric analysis and future research directions. Expert Syst. Appl. 173, 114702.
Richey, R.G., Chowdhury, S., Davis-Sramek, B., Giannakis, M., Dwivedi, Y.K., 2023. Artificial intelligence in logistics and supply chain management: A primer and roadmap for research. J. Bus. Logist. 44 (4), 532–549.
Rodríguez-Espíndola, O., Chowdhury, S., Dey, P.K., Albores, P., Emrouznejad, A., 2022. Analysis of the adoption of emergent technologies for risk management in the era of digital manufacturing. Technol. Forecast. Soc. Change 178, 121562.
Rolf, B., Jackson, I., Müller, M., Lang, S., Reggelin, T., Ivanov, D., 2023. A review on reinforcement learning algorithms and applications in supply chain management. Int. J. Prod. Res. 61 (20), 7151–7179.
Rousseau, D.M., Manning, J., Denyer, D., 2008. 11 Evidence in management and organizational science: assembling the field's full weight of scientific knowledge through syntheses. Acad. Manag. Ann. 2 (1), 475–515.
Rowley, J., Slack, F., 2004. Conducting a literature reivew. Manag. Res. N. 27 (6), 31–39.
Rußmann, M., Lorenz, M., Philipp, G., Waldner, M., Pascal, J.J., Harnisch, E. Harnisch, M.,2015. Industry 4.0: the future of productivity and growth in manufacturing industries. Boston Consulting Group Perspectives. Available at: https://www.bcg.com/publications/2015/engineered_products_project_business_industry_4_future_productivity_growth_manufacturing_industries.
Saenz, M.J., Revilla, E., Knoppen, D., 2014. Absorptive capacity in buyer–supplier relationships: empirical evidence of its mediating role. J. Supply Chain Manag. 50 (2), 18–40.
Sarkar, M., Seo, Y.W., 2021. Renewable energy supply chain management with flexibility and automation in a production system. J. Clean. Prod. 324, 129149.
Sauer, P.C., Seuring, S., 2023. How to conduct systematic literature reviews in management research: a guide in 6 steps and 14 decisions. Rev. Manag. Sci. 17 (5), 1899–1933.
Schmenner, R.W., Swink, M.L., 1998. On theory in operations management. J. Oper. Manag. 17 (1), 97–113.
Schroeder, R.G., Shah, R., Xiaosong Peng, D., 2011. The cumulative capability 'sand cone'model revisited: a new perspective for manufacturing strategy. Int. J. Prod. Res. 49 (16), 4879–4901.
Sen, S., Husom, E.J., Goknil, A., Politaki, D., Tverdal, S., Nguyen, P., Jourdan, N., 2023. Virtual sensors for erroneous data repair in manufacturing a machine learning pipeline. Comput. Ind. 149, 103917.
Senoner, J., Netland, T., Feuerriegel, S., 2022. Using explainable artificial intelligence to improve process quality: evidence from semiconductor manufacturing. Manag. Sci. 68 (8), 5704–5723.
Seuring, S., Gold, S., 2012. Conducting content-analysis based literature reviewsin supply chain management. Supply Chain Manag. Int. J. 17 (5), 544–555.
Sharma, D.K., Jain, M., 2022. Data Analytics and Artificial Intelligence for Inventory and Supply Chain Management. Springer.
Sharma, R., Shishodia, A., Gunasekaran, A., Min, H., Munim, Z.H., 2022. The role of artificial intelligence in supply chain management: mapping the territory. Int. J. Prod. Res. 60 (24), 7527–7550.
Sodero, A.C., Rabinovich, E., Sinha, R.K., 2013. Drivers and outcomes of open-standard interorganizational information systems assimilation in high-technology supply chains. J. Oper. Manag. 31 (6), 330–344.

Sodhi, M.S., Seyedghorban, Z., Tahernejad, H., Samson, D., 2022. Why emerging supply chain technologies initially disappoint: Blockchain, IoT, and AI. Prod. Oper. Manag. 31 (6), 2517–2537.

Søgaard, B., Skipworth, H.D., Bourlakis, M., Mena, C., Wilding, R., 2019. Facing disruptive technologies: aligning purchasing maturity to contingencies. Supply Chain Manag. Int. J. 24 (1), 147–169.

Sohrabpour, V., Oghazi, P., Toorajipour, R., Nazarpour, A., 2021. Export sales forecasting using artificial intelligence. Technol. Forecast. Soc. Change 163, 120480.

Song, H., Li, C., Fu, Y., Li, R., Zhang, H., Wang, G., 2023. A two-stage unsupervised approach for surface anomaly detection in wire and arc additive manufacturing. Comput. Ind. 151, 103994.

Sony, M., Naik, S., 2020. Industry 4.0 integration with socio-technical systems theory: A systematic review and proposed theoretical model. Technol. Soc. 61, 101248.

Stock, J.R., Boyer, S.L., 2009. Developing a consensus definition of supply chain management: a qualitative study. J. Phys. Distrib. Logist. Manag. 39 (8), 690–711.

Storey, J., Emberson, C., Godsell, J., Harrison, A., 2006. Supply chain management: theory, practice and future challenges. Int. J. Oper. Prod. Manag. 26 (7), 754–774.

Swink, M., Way, M.H., 1995. Manufacturing strategy: propositions, current research, renewed directions. Int. J. Oper. Prod. Manag. 15 (7), 4–26.

Takeda-Berger, S.L., Frazzon, E.M., 2024. An inventory data-driven model for predictive-reactive production scheduling. Int. J. Prod. Res.62 (9),, 3059–3083.

Talwar, S., Kaur, P., Fosso Wamba, S., Dhir, A., 2021. Big Data in operations and supply chain management: a systematic literature review and future research agenda. Int. J. Prod. Res. 59 (11), 3509–3534.

Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., Fischl, M., 2021. Artificial intelligence in supply chain management: A systematic literature review. J. Bus. Res. 122, 502–517.

Tranfield, D., Denyer, D., Smart, P., 2003. Towards a methodology for developing evidence-informed management knowledge by means of systematic review. Br. J. Manag. 14 (3), 207–222.

Trist, E.L., 1981. The evolution of socio-technical systems. Ontario Quality of Working Life Centre.

Usuga-Cadavid, J.P., Lamouri, S., Grabot, B., Fortin, A., 2022. Using deep learning to value free-form text data for predictive maintenance. Int. J. Prod. Res. 60 (14), 4548–4575.

Uzumeri, M.V., 1997. ISO 9000 and other metastandards: principles for management practice? Acad. Manag. Perspect. 11 (1), 21–36.

van Donk, D.P., 2003. Redesigning the supply of gasses in a hospital. J. Purch. Supply Manag. 9 (5-6), 225–233.

Vanderschueren, T., Boute, R., Verdonck, T., Baesens, B., Verbeke, W., 2023. Optimizing the preventive maintenance frequency with causal machine learning. Int. J. Prod. Econ. 258, 108798.

Venkatesh, V., Bala, H., 2008. Technology Acceptance Model 3 and a Research Agenda on Interventions. Decis. Sci. 39 (2), 273–315.

Vermesan, O., John, R., De Luca, C., Coppola, M., 2022. Artificial Intelligence for Digitising Industry–Applications. CRC Press.

Vermesan, O., Marples, D., 2024. Advancing Edge Artificial Intelligence: System Contexts. Taylor & Francis.

Vermeulen, A.F., 2019. Industrial Machine Learning: using artificial intelligence as a transformational disruptor. Apress.

Vishwakarma, L.P., Singh, R.K., Mishra, R., Kumari, A., 2023. Application of artificial intelligence for resilient and sustainable healthcare system: Systematic literature review and future research directions. Int. J. Prod. Res. 1–23.

Walton, R.E., 1985. From Control to Commitment in the Workplace: In factory after factory, there is a revolution under way in the management of work. US Department of Labor, Bureau of Labor-Management Relations and Cooperative Programs.

Wang, P., 2021. Connecting the parts with the whole: Toward an information ecology theory of digital innovation ecosystems. MIS Q. 45 (1).

Webster, J., 1995. Networks of collaboration or conflict? Electronic data interchange and power in the supply chain. J. Strat. Inf. Syst. 4 (1), 31–42.

Webster, J., Watson, R.T., 2002. Analyzing the past to prepare for the future. MIS Q. xiii–xxiii.

Wieland, A., 2021. Dancing the supply chain: Toward transformative supply chain management. J. Supply Chain Manag. 57 (1), 58–73.

Wong, C., Guo, Z.X., Leung, S.Y.S., 2013. Optimizing decision making in the apparel supply chain using artificial intelligence (AI): from production to retail. Elsevier.

Wong, L.-W., Tan, G.W.-H., Ooi, K.-B., Lin, B., Dwivedi, Y.K., 2022. Artificial intelligence-driven risk management. Int. J. Prod. Res.

World Economic Forum (WEF), 2023. Harnessing the AI Revolution in Industrial Operations: A Guidebook. Available at: https://www3.weforum.org/docs/WEF_Harnessing_the_AI_Revolution_in_Industrial_Operations_2023.pdf.

Xia, H., An, W., Zhang, Z., Liu, G., 2022. Managing production systems with machine learning: a case analysis of Suzhou GCL photovoltaic technology. Prod. Plan. Control 33 (16), 1559–1572.

Yadav, G., Kumar, A., Luthra, S., Garza-Reyes, J.A., Kumar, V., Batista, L., 2020. A framework to achieve sustainability in manufacturing organisations of developing economies using industry 4.0 technologies' enablers. Comput. Ind. 122, 103280.

Yang, T., Lu, J.C., 2010. A hybrid dynamic pre-emptive and competitive neural-network approach in solving the multi-objective dispatching problem for TFT-LCD manufacturing. Int. J. Prod. Res. 48 (16), 4807–4828.

Yavuz, O., Uner, M.M., Okumus, F., Karatepe, O.M., 2023. Industry 4.0 technologies, sustainable operations practices and their impacts on sustainable performance. J. Clean. Prod. 387, 135951.

Zamani, E.D., Smyth, C., Gupta, S., Dennehy, D., 2023. Artificial intelligence for supply chain resilience: learning from Covid-19. Ann. Oper. Res. 327 (2), 605–632.

Zheng, G., Kong, L., Brintrup, A., 2023. Federated machine learning for privacy preserving, collective supply chain risk prediction. Int. J. Prod. Res.

Zhu, X., Ninh, A., Zhao, H., Liu, Z., 2021. Demand forecasting with supply-chain information and machine learning: Evidence in the pharmaceutical industry. Prod. Oper. Manag. 30 (9), 3231–3252.

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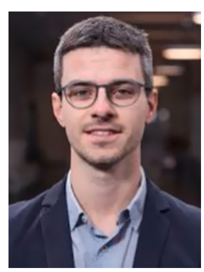

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