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Artificial intelligence in supply chain management: enablers and constraints in pre-development, deployment, and post-development stages

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ABSTRACT

This study presents a comprehensive investigation into the AI supply chain journey, combining a systematic literature review (SLR) and empirical interviews with supply chain experts. The objective is to identify and analyze key enablers and constraints influencing AI in the pre-development, deployment, and post-development stages. The research integrates empirical data with a Technology-Organization-Environment (TOE) framework, revealing the interactions between technological, organizational, and environmental factors. The thematic analysis uncovers six axial themes for the pre-development stage and one theme for the deployment and post-development stages respectively, providing valuable insights into factors influencing successful AI integration. Moreover, industry-specific insights are unveiled for the Airline, Agri-food, Retail, and Logistics sectors, emphasizing the importance of contextual factors and tailored AI strategies. The study contributes to the existing knowledge by offering practical implications for AI integration in supply chains, highlighting the significance of managing constraints and industry heterogeneity. By identifying and understanding the key constraints, this research provides a deeper understanding of the constraints faced during different stages of AI in supply chains. This study makes a substantial contribution to the current socio-technical discourse on the successful journey of AI in supply chains by deriving eight propositions that offer valuable insights. These propositions delve into the practical implications of addressing constraints and transforming them into enablers for achieving enhanced supply chain performance. The propositions offer guidance to both academic researchers and industry professionals, equipping them with actionable strategies to navigate the complexities and intricacies of integrating AI technologies into the supply chain. By embracing these propositions, stakeholders can effectively harness the power of AI to optimize various aspects of the supply chain, leading to improved efficiency, agility, and competitiveness. Ultimately, this research contributes to advancing the understanding of the AI journey in supply chains and offers practical solutions to drive the successful embracing of AI technologies in real-world supply chain environments.

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1. Introduction

COVID-19 has revealed the sensitivity and vulnerability of global supply chains in terms of supply chain risk management (Baryannis et al. 2019), supply chain resilience (Ivanov and Dolgui 2021) and agile and lean supply chain management (Upadhyay et al. 2022) especially in the industry of agri-food (Nayal et al. 2022), retail (Modgil, Kumar Singh, and Hannibal 2021), humanitarian (Rahman et al. 2022), and healthcare (Jæger, Moges Menebo, and Upadhyay 2021). Fortuitously, the age of Information 4.0 is upon us (Hofmann et al. 2019), enabled by advanced technologies Internet of Things (Ben-Daya, Hassini, and Bahroun 2019), Blockchain (Jraisat et al. 2022) and Artificial Intelligence (AI). The technical term 'AI' was first introduced at a Dartmouth workshop in 1956 to indicate the capability and skills of machines to exchange information with - and mimic the capabilities and features of – people (Russell 2010). The least AI breakthrough includes deep neural networks, long-short term memory networks, and convolutional neural networks drive AI boom in automating tasks that have previously been possible for humans only (Helo and Hao 2022). Accelerated by increasing computing, processing, and storing power, AI is now mature enough to be adapted to fulfilling the sustainable supply chain goals (Jraisat et al. 2021), as well as encouraging green practices (Sharma et al. 2022; Upadhyay 2021) with optimized supplier selection (Kunkel et al. 2022), demand forecasting (Feizabadi 2022), inventory management (Preil and Krapp 2022), logistics and transportation (Demir, Syntetos, and van Woensel 2022) to collaborative closed-loop supply chains (Jraisat et al. 2021).

The successful integration of AI within aforementioned supply chain tasks is a complex procedure, comprising three key stages: pre-development, deployment, and post-development (Wang, Skeete, and Owusu 2022), each of which is associated with distinct enablers and constraints. The pre-

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development stage motivates the recognition of operational gaps and the conception of an AI system to tackle them, however it may be constrained by limitations such as poor data quality and organizational readiness (Dubey et al. 2022; Hao and Demir 2023). The deployment phase, driven by technological sophistication and the compatibility with existing processes, can be constrained by complexities in system integration and user accessibility (Helo and Hao 2022). The post-development phase is marked by the aspiration for continuous performance monitoring and system optimization but is challenged by the need to maintain the adaptability and longevity of AI in the evolving technological landscape (Riahi et al. 2021). To harness the full potential of AI in the supply chain, a thorough understanding of these stages and their respective enablers and constraints is critical. The identification of these enablers and constraints should transcend the narrow lens of merely technology-based factors, encompassing a broader spectrum of considerations, which will capture within the Technological, Organizational and Environmental (TOE) framework. The AI journey is influenced by a series of combination enablers and constraints under the lens of TOE, with technological factors encompassing characteristics and capabilities of the technology such as functionality, compatibility, and complexity (Khosrowabadi, Hoberg, and Imdahl 2022), interact with organizational factors, including internal structures, processes, and resources such as management practices, organizational culture, and human resources (Gupta et al. 2022; Sodhi et al. 2022). These factors are further influenced by external environmental factors, including industry dynamics, regulatory frameworks, and societal norms, which shape the context in which the organization operates (Bag and Pretorius 2022; Lu et al. 2019).

Recognizing the interconnectedness and context-dependent nature of enablers and constraints in AI integration presents a significant research gap. The connection between technology and the organization is fundamental, as AI advancements present opportunities to optimize supply chain practices. Conversely, the technical capabilities, infrastructure, resources, readiness for change, management support and data governance are prerequisites for embracing AI. The environmental dimension further shapes these connections, with market conditions, industry dynamics, and regulatory frameworks impacting the opportunities and constraints for AI integration. Such an intertwined landscape calls for a well-structured framework in addressing the enablers and constraints of AI integration from both academic and industry perspectives.

In light of these literature gaps, this review intends to answer three research questions.

RQ1: What are the most prevalent techniques of AI that are applied in supply chain industries and tasks?

RQ2: What are the enablers of and constraints to the pre-development, deployment, and post-development of AI in the supply chain?

RQ3: How do these enablers and constraints impact the success of AI in the supply chain journey, and what are the relationships between these factors?

In an effort to bridge the existing knowledge gap, this research employs a systematic literature review (SLR), fortified by closed-ended quantitative bibliometric analysis, open-ended qualitative thematic analysis, and an amalgamation of open-ended and close-ended interviews to ensure a rich and comprehensive perspective. The resultant insights—pertinent to scholars and practitioners involved in AI journey within supply chain—shed light on the enablers and constraints present throughout the critical phases of AI integration, including pre-development, deployment, and post-development stages. Consequently, our study differs from previous studies for the following reasons, addressing AI history and identifying the application of AI in supply chain is not the aim, because published theoretical and technical papers cover this subject broadly. Instead of simply listing enablers and constraints across the various stages of the AI lifecycle, this study aims to surpass the limitations of current research by applying and extending the TOE framework with aims of delving deeper into the academic-industry interface of AI in supply chain and fostering comprehensive understanding of the real-world enablers and constraints encountered throughout the AI supply chain journey.

To fulfil the research goals and answer the RQs, the research progresses as follows. Section 2 offers a theoretical underpinning of TOE framework. Section 3 details the methodological procedures employed in conducting a systematic review. Section 4 discusses the research context and research findings, and Section 5 derives the conceptual model with discussion. Section 6 concludes with a summary of the key findings and responses to the research questions, limitations of the study, and suggestions for future research directions.

2. Background knowledge

The complex and dynamic external environment, coupled with evolving customer demands, has prompted a renewed focus on advanced technologies, particularly in the realm of AI innovation, to enhance flexibility and responsiveness in supply chain management (Cadden et al. 2021; Preil and Krapp 2022). Supply chain organizations have emphasized AI as a competitive advantage, a secret weapon, and a key successful factor in improving operational performance (Dubey et al. 2020), promoting process integration (Pournader et al. 2021), and achieving sustainable supply chain (Demir, Syntetos, and van Woensel 2022). In the literature, there are studies that consider the integration of robust technological innovation conceptual framework, namely Unified Theory of Acceptance and Use of Technology (Venkatesh et al. 2003), Technology Acceptance Model (Davis, Bagozzi, and Warshaw 1989), and TOE framework. The combination of both human and nonhuman actors (Awa, Ukoha, and Emecheta 2016) and internal and external factors (Marija, Bach, and Vukšíc 2021) provides TOE a more holistic view of the technology integration enablers and constraints which is the reason for its dominance over other acceptance models (Wen and Chen 2010). Therefore, the aim of the TOE framework is to study the use of technological innovations, envisaging a three-fold focus on technological innovation: the technological, organizational, and environmental contexts (Baker 2012). The technological context refers to the pool of diverse internal and external technologies of the firm and their relative advantage, complexity, compatibility, trialability, and observability (Wang, Wang, and Yang 2010). The organization perspective refers to the characteristics and resources within the organization, including the firm size, leadership style, management structure, human resource quality, and the amount of slack resources (Low, Chen, and Wu 2011). The environmental context, which encompasses a broader industry perspective and involves multiple stakeholders, including competitors, government, and partners, should also be taken into consideration. More specifically, it describes the structure of industry, the level of competition, the regulatory environment, the support infrastructure, the development of local economics and the presence or absence of technology providers (Tornatzky, Fleischer, and Chakrabarti 1990). The TOE framework, comprising technology, organization, and environment (with sub-factors shown in Table 1) (inspired by Nayal et al. 2022; Paul, Riaz, and Das 2020; Mahroof 2019; Dora et al. 2021), represents a tripartite lens through which the enablers and constraints of AI integration will be examined across the pre-development, deployment, and post-development stages.

3. Methodology

To enrich the robustness and comprehensiveness of the research questions posed, a triangulation approach has been employed, merging three-step research methodologies including a bibliometric analysis and thematic analysis, both underpinned by an SLR, as well as empirical research driven by industry interviews. While SLRs offer comprehensive insights into a research area by surveying and synthesizing existing academic studies, they often lack empirical insights derived from real-world industry scenarios. To compensate for this limitation, this research proposes integrating industry interviews into the methodology, entailing conducting interviews with industry professionals who have first-hand experience in the AI supply chain domain. The combination of findings from the SLR and industry interviews is anticipated to provide a more holistic understanding of the application of AI in supply chains.

In addressing RQ1, a closed-ended quantitative bibliometric analysis is used, effectively mapping out the landscape of current research and identifying prevalent supply chain tasks and subfields within the role of AI. The RQ2 benefits from the insights provided by an open-ended thematic analysis, offering detailed three-stage perspectives on the enablers and constraints of the AI supply chain journey. Finally, to validate the model developed for the RQ3, a mixed open-ended and closed-ended empirical interview is implemented. The inclusion of open-ended questions provides an avenue for comprehensive insights from the respondents with different backgrounds, potentially uncovering new facets or perspectives not initially anticipated. On the other hand, closed-ended questions are integrated to generate quantifiable data that can be systematically analyzed and compared, leading to precise measurements and rankings views on themes related to the model.

3.1. Systematic literature review

This paper examines the literature on AI in the supply chain domain by systematically reviewing published peer-reviewed journal articles, extracting from Web of Science, Scopus, and Science Direct. SLR is essentially appropriate for developing an understanding of theoretical concepts and building an evidence-based management body of knowledge (Tranfield, Denyer, and Smart 2003). To address the challenges arising from the varying theoretical perspectives that shape the interpretation of research findings in supply chain domain, this paper adheres to the six-step process proposed by Durach, Kembro, and Wieland (2017) with a focus on ensuring the reproducibility of the research methodology. The process begins with defining the research questions, followed by establishing inclusion and exclusion criteria using pilot research, retrieving a baseline sample of potentially relevant articles, applying pre-defined criteria to refine the database, synthesizing the articles, and ultimately reporting the findings of the SLR (Table 2).

In order to conduct an inclusive yet practical literature review, current research draws upon the work of Stock and Boyer (2009) who cover the fundamental keywords in the definition of supply chain management, categorized as marketing, logistics, production and supply chain management (procurement, inventory management and distribution are included in the latter). AI as a broad field covers an array of techniques and approaches designed to make machines mimic human intelligence, which can be further classified into a number of sub-fields namely 'thinking humanly', 'acting humanly', 'thinking rationally' and 'act rationally' (Min

Table 1. TOE perspective.

Perspectives	Sub-factor	Definition
T	Relative advantage	The degree to AI offers improvements or benefits in terms of efficiency, and effectiveness.
	Trust	The degree to which stakeholders trust the capabilities and effectiveness of AI.
	Security	The degree to which AI used in supply chain are secure and protected against cyber-attacks.
	Compatibility	The degree to which AI is compatible within the existing systems and technologies.
	Availability	The degree to which AI is accessible to the organization.
O	Infrastructure	The hardware and software components support the use of AI.
	Monetary resources	The financial resources required to acquire, install, and maintain AI.
	Authority support	The degree to which senior executive and top-level decision-making are supportive of the integration of AI.
	Expertise and knowledge	The technical knowledge and skills required to develop, implement, and maintain AI.
E	Partners pressure	The pressure exerted by partners to adopt and implement AI.
	Rivalry pressure	The degree of competition in the industry, which creates pressure for organizations to adopt and implement AI.
	Regulatory support	Government policies and regulations that support the integration of AI.
	Customer pressure	The pressure exerted by customers to adopt and implement AI.

Table 2. Completion of the six-step SLR methodology.

Step 1: Formulate research questions
Since the paper aims at exploring enablers and constraints of AI in supply chain decision-making, the following research questions are formulated: 'RQ1: What are the most prevalent techniques of AI that are applied in supply chain industries and tasks? RQ2: What are the enablers of and constraints to the pre-development, deployment, and post-development of AI in the supply chain? RQ3: How do these enablers and constraints impact the success of AI in the supply chain journey, and what are the relationships between these factors?'
Step 2: Determine inclusion and exclusion criteria
To identify articles that could potentially offer significant contributions and merit further review, this study followed a pilot search process as outlined by Denyer and Tranfield (2009).
- Articles should be peer-reviewed journal articles.
- Articles should be written in English.
- Articles must contain at least one predefined keyword from each subset in their title, abstract, or keywords to ensure substantive relevance.
- Articles that were deemed substantively irrelevant were excluded.
- The abstracts of the remaining articles were read to ensure substantive and empirical relevance.
- The remaining articles were thoroughly reviewed in their entirety to further ensure substantive and empirical relevance.
Step 3: Retrieve a baseline sample of articles
A systematic search was conducted within the Web of Science, Scopus, and Science Direct databases, specifically focusing on peer-reviewed journal articles. The search was limited to a single set of keywords to ensure comprehensive coverage of the relevant literature.
('artificial intelligence' or 'AI' or 'machine learning' or 'deep learning' and 'supply chain' or 'marketing' or 'logistics' or 'production') and ('enablers' or 'barriers' or 'opportunities' or 'challenges' or 'facilitators' or 'constraints')
- To ensure comprehensive coverage of relevant literature and minimize the likelihood of missing important studies, specific keywords related to distinct subfields of supply chain management such as marketing, logistics, and production were included to achieve data saturation (Toorajipour et al. 2021).
- The search process was conducted without restrictions on journals, disciplines, or date of publication, with the set of keywords applied to the title, abstract, and keyword fields. The outcome of this comprehensive search yielded 4,195 articles that were potentially relevant to the research question under investigation (1919 in Web of Science, 1,414 in Science Direct, and 862 in Scopus).
Following a rigorous screening process, which included removing duplicates ($n = 892$) and removing non-journal articles ($n = 56$), a total of 3,247 distinct articles were identified in April 2023.
Step 4: Apply the inclusion/exclusion criteria from step two
To obtain a subset of pertinent studies, the inclusion/exclusion criteria (Step 2) were meticulously applied to the baseline sample. To mitigate any potential bias, the criteria were individually and collaboratively assessed by two scholars during the article review process. This rigorous approach ensures a high degree of rigour in the selection of studies, minimizing the risk of introducing extraneous or irrelevant information into the analysis.
Following a comprehensive screening process, a total of 326 pertinent articles were initially identified. Additionally, the snowball sampling method was used, which involved reviewing the reference lists of the selected articles, resulting in the addition of 35 additional relevant articles.
The relevance of each article to the intersection of AI and supply chain was assessed, leading to the identification of a synthesis sample comprising 361 articles.
Step 5: Synthesize the articles
The methodology employed in this study adopted an aggregative synthesis approach that encompasses both quantitative and qualitative components (Denyer and Tranfield 2009).
The quantitative synthesis entailed a meticulous process of extracting data from the selected articles, adhering to a predefined coding structure that encompassed various key variables: publication date, including the publication date, research method employed, industry type, distribution of supply chain tasks, and the use of AI techniques.
The qualitative synthesis is to conduct a thematic analysis to answer the research questions formulated at the outset of the review, based on themes that emerge during the qualitative synthesis part of the review. Thematic analysis, a qualitative research methodology, is deemed as a less intricate form of analysis compared to other qualitative approaches which makes it an advantageous option for researchers who are still in the nascent stages of their research career (Braun and Clarke 2006). As thematic analysis has been posited as a valuable research method for exploring diverse perspectives, highlighting similarities and differences, and generating unexpected insights from research participants which has been widely adapted in supply chain research (Modgil et al. 2022; Riahi et al. 2021).
Step 6: Report the results
The synthesis sample ($n = 361$) underwent a descriptive analysis that involved applying a set of predefined coding structures, as outlined in Step 5 of the study. The findings from this analysis are presented first, followed by a thematic analysis.
The thematic analysis was conducted to address the research questions that were formulated in Step 1, leveraging the themes that emerged during the qualitative synthesis process of Step 5.

2010). Within this spectrum, Machine Learning (ML) and Deep Learning (DL) emerge as critical subsets. ML algorithms, which could be seen as a manifestation of 'acting humanly and rationally', make machines learn from data and progressively refine their actions based on patterns they discern, closely mirroring how humans learn from experiences and adapt their behaviours accordingly. DL, on the other hand, imitates 'thinking humanly and rationally' by using artificial neural networks to replicate the structure and functioning of human brain. Therefore, the classification of AI into subsets of ML and DL offers a more comprehension of the diverse expressions of AI (Helo and Hao 2022; Woschank, Rauch, and Zsifkovits 2020).

3.2. Empirical interview

Controlling for industry, firm size and structure, geographic location and industry setting is crucial to establish robust sample controls and clear research boundaries, thereby avoiding bias, enhancing comparability, improving generalizability, and facilitating industry-specific empirical insights. Upon considering the industries ripe for the application of AI, the wealth of data volumes becomes the prerequisite for selecting an empirical industry. From the vast trove of data that the airline industry accumulates from areas such as flight planning, passenger management, and aircraft maintenance, to the abundant data harvested in retail through customer engagement, sales operations, and inventory control, the comprehensive data landscape in agri-food from farm to fork, and the wealth of data in logistics and manufacturing from production lines, storage facilities, transport coordination, and quality assurance, each organization form a fertile ground for AI to facilitate automation, augmentation and provision of valuable insights.

The empirical data collection took place between September 2022 and April 2023. Semi-structured interviews were chosen as the primary data source due to their effectiveness and adaptability in gathering rich empirical data (Eisenhardt and Graebner 2007). The potential interview candidates were identified and selected from the extensive research network established by the authors over the past decade. The longstanding relationships between the practitioners and authors ensured the credibility of the input contribution from experts. Following established guidelines on purposive sampling and data saturation (Glaser and Strauss 2017), and considering the constraints of resources and time, an initial target range of 10–20 interviewees within seven industries were set. The sampling process stopped when data saturation was achieved, indicating that further interviews yielded limited additional insights. Ultimately, a total of 12 experts were interviewed in the industry of airline, retail, agri-food, transport, and logistics (Table 3).

To ensure accuracy, each interview was first recorded and subsequently transcribed. Field notes were independently taken by two researchers to reduce subjective bias. Field notes were independently taken by two researchers to reduce subjective bias. A semi-structured interview protocol was developed in which the questions focused on the enablers and constraints in the stages of pre-development, deployment, and post-development stages. Semi-structured interviews facilitated a flexible and exploratory conversation, promoting mutual reflection and knowledge sharing while collecting targeted evidence specifically tailored for research purposes. While all respondents were asked the same set of questions outlined in the protocol, the level of detail and focus of the discussion varied depending on the role of the respondents (Pandey and Patnaik 2014).

Each interview lasted on average from 40 to 60 min. To validate the information and address any misunderstandings, a structured summary of verbatim transcripts was provided to the interviewees, including all the relevant information requiring feedback. The aim of providing a structured summary, instead of the entire transcript, was to maximize feedback response rates and minimize the potential bias. Table 3 provides an overview of a set of professionals spanning across four different countries-the United States, China, the United Kingdom, and Demark-and four distinct industries-airline, retail, agri-food and global transport and logistics. The listed professionals play various roles in the supply chain domain, utilizing AI for scheduling, demand forecasting, warehousing, risk management, logistics and route optimization, as well as continuous improvement and optimization.

4. Findings from the descriptive and thematic analysis

This section offers an extensive overview of the temporal distribution, research methods, industry sectors, supply chain tasks, and AI techniques employed in the study. The subsequent thematic analysis endeavours to identify enablers and constraints with the integration of AI into supply chain management across the pre-development, deployment, and post-development phases.

4.1. Descriptive analysis

The descriptive analysis synthesizes our study findings and offers an overview of the current status of publications on AI supply chain enablers and constraints. Based on saturated data found in the systematic literature, including time distribution, methodology, industry sectors, supply chain tasks, and AI techniques. This section contains important information for future discussion in accordance with RQ1.

To gain information about the AI supply chain research across time, we analyzed the trend in publication dates. Figure 1 illustrates the distribution of journal papers across the review period, revealing that all papers were published between 1989 and 2023. In particular, there has been a growing interest in AI in the supply chain, as evidenced by the fact that 78% of the articles were published after 2019.

Figure 2 depicts the study methodologies used to investigate the enablers and constraints of AI integration in the supply chain. The methods found were case study, review, survey, modelling, experiment, and simulation.

When categorizing research methods, the purpose of this section was to present a list of standard and comparable methodologies. To cluster similar methods and distinguish them from others, we conducted a detailed analysis of the research methodology part. For example, some authors refer their method as an unstructured and a semi-structured interview. In this instance, a standardized category 'interview' has been assigned. A comparable issue is provided in the 'survey' category, which includes research methodologies such as

Table 3. Overview of the interviews.

Background	Industry	Code	Interviewees	Nature of work	Year of experience
US-1924	Airline supply chain	R1	Operations Research Scientist	Operational optimization-scheduling	1-5
		R2	Operations Research Scientist		1-5
		R3	Decision Science and Analytics Leader		1-5
China-1998	Retail supply chain	R4	Algorithm Engineer	Logistics and supply chain-demand forecasting	1-5
		R5	Algorithm Engineer		1-5
		R6	Algorithm Engineer		1-5
UK-2000	Agri-food supply chain	R7	Director of Planning and Analytics	Operational optimization-warehousing	6-10
		R8	Senior Data Scientist	Logistics and supply chain-warehousing	1-5
		R9	Data Scientist Team Lead	Operational optimization-risk management	6-10
Denmark-1976	Global transport and logistics	R10	Operations Research Scientist	Logistics manufacturing services-logistic and route optimization	1-5
		R11	Operations Research Scientist	Warehousing optimization- logistic and route optimization	1-5
		R12	Solution Design Engineer	Transport and logistics-continuous improvement and optimization	1-5

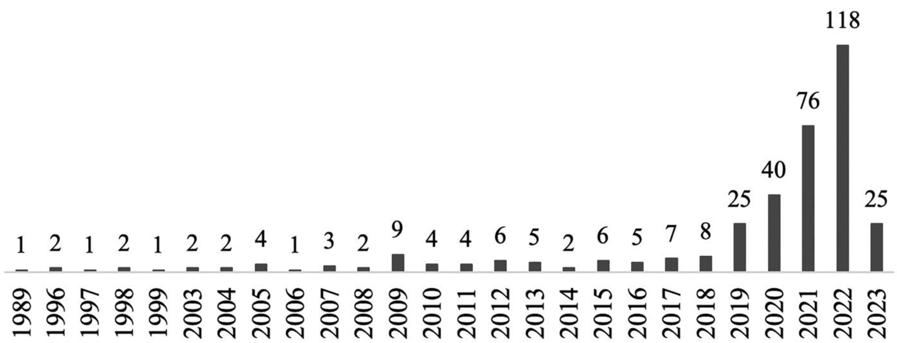

Figure 1. Distribution of articles over time (until April 2023).

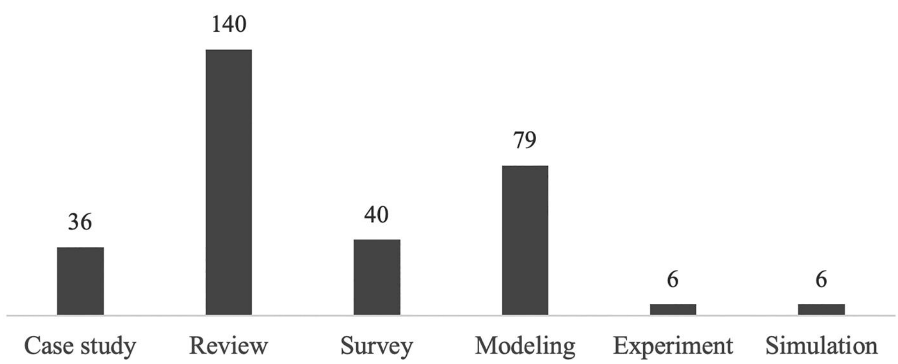

Figure 2. Distribution of research methods.

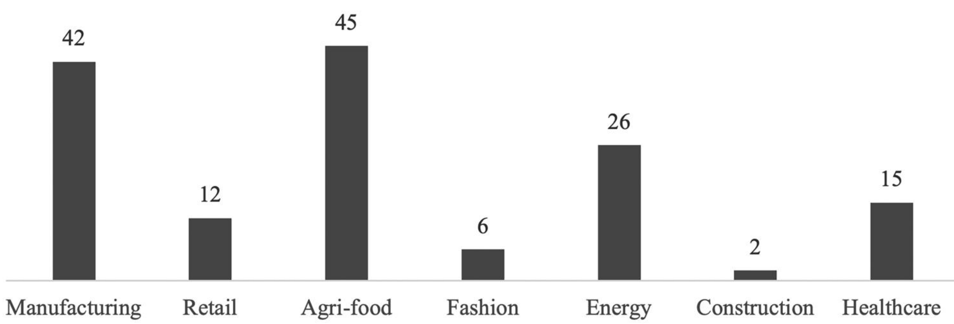

Figure 3. The distribution of supply chain industries.

open-ended and closed-ended questionnaires. Furthermore, the 'modelling' category gathers papers that use the mathematical framework to understand the dynamics of a system to predict future outcomes, such as linear programming, discrete mathematics, game models and statistical models. The 'literature review' category collects papers taking advantage of published literature to carry out their research, systematic literature review and bibliometric analysis are two representatives.

The findings indicate that the primary research methodologies carried out, when investing the AI in supply chain are review, modelling, survey, and case study account for 96% of the frequency. As an illustration, Wu and Barnes (2014) applied a fuzzy intelligent mathematical modelling approach in their investigation of partner selection within an agile supply chain context. The dynamic capability of AI in supply chain has been subject to scrutiny through the implementation of a systematic literature review (Dhamija and Bag 2020; Riahi et al. 2021; Toorajipour et al. 2021), which can be delved into multiple industries, such as fashion (Mohiuddin Babu et al. 2022), retail (Cai and Lo 2020), and agri-food (Kumar et al. 2021). A survey has been utilized to gather in-depth AI insights from a predefined group of supply chain experts (Cadden et al. 2021), while a case study has been widely implemented to explore the application of AI in real-word scenarios (Ajwani-Ramchandani et al. 2021). It is worth noting that scholars adopt hybrid research approaches rather than relying solely on individual research methods, for instance, the case study and simulation have been collaboratively implemented to evaluate the effectiveness of a proposed system (Jin and Ma 2018).

The integration of AI in various supply chain industries has gained significant interest, with the outcomes of seven main sectors presented in Figure 3, namely agri-food, manufacturing, energy, healthcare, retail, fashion, and construction. Agri-food (30%) and manufacturing (28%) are two mostly represented industries, due to the intricate processes, ranging from production to quality control, which can be

Figure 4. The distribution of supply chain subtasks.

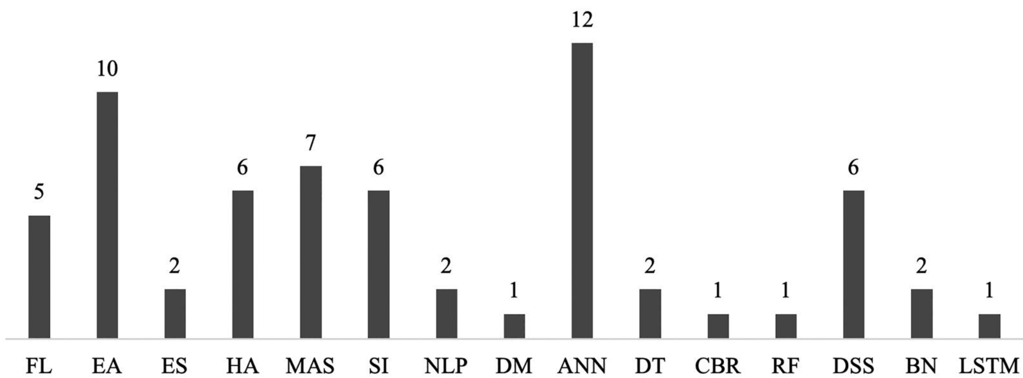

Figure 5. The distribution of AI techniques.

optimized through the integration of AI solutions. Energy (18%) and healthcare (10%) stand out as the second and third most common areas where AI has been implemented, driven by the sustainability focus on optimizing resource utilization, reducing carbon emissions, and improving supply chain resilience. Remaining emerging industries including retail, fashion, and construction share 8, 4, and 1%.

Supply chain comprises a diverse array of tasks that entail various operational and strategic activities, as shown in Figure 4. In this regard, the present study recognizes several publications that leverage AI to improve subtasks including supplier selection (Wu and Barnes 2014), procurement (Guida et al. 2023), warehousing (Mahroof 2019), production planning (Dohale et al. 2022), demand planning (Khosrowabadi, Hoberg, and Imdahl 2022) and logistics (Govindan et al. 2022).

Upon classification of the AI techniques employed in the literature under study, noteworthy algorithms that have garnered considerable attention include artificial neural networks (ANN), evolutionary algorithms (EA), multi-agent systems (MAS), heuristics algorithms (HA), swarm intelligence (SI), decision support systems (DDS), and fuzzy logic (FL). Notably, various publications have implemented a collaborative approach by utilizing multiple algorithms simultaneously; for instance, ANN has been applied to manage supplier relationships (Choy et al. 2004); SI and FL have been integrated to plan the process and schedule the production (Zhao et al. 2010); FL and MAS have been applied to build supply chain resilience (Belhadi et al. 2021). The predominant portion of the published literature, a total of 82%, did not prioritize the scrutiny of particular AI techniques. This pattern can be attributed to the inherent characteristics of methodologies, particularly in the context of literature review. Instead, the concentration of such literature inclined towards the exploration of general AI. Figure 5 illustrates the significant AI algorithms utilized in the literature, as well as a small proportion of expert system (ES), natural language processing (NLP), data mining (DM), decision tree (DT), case-based reasoning (CBR), random forest (RF), Bayesian networks (BN) and long short-term memory (LSTM).

4.2. Thematic analysis

To answer the RQ2, this section focused on integrating common codes related to enablers and constraints to the pre-development, development, and post-development of AI in the supply chain. With the aim of grouping meaningful themes from group pf codes, thematic analysis is one of the most accessible, flexible, and popular methods in conducting qualitative research. In line with the established practice of qualitative research, this study employed a three-stage coding process to facilitate the identification of themes, namely open, axial and selective coding (Williams and Moser 2019). For instance, customer demand-driven and competition-driven were identified as two external enablers playing in the pre-development stage. Both factors were individually labelled and stored in the open coding list, then merged to the axial coding stage as external enablers. Finally, considering the concept and repetition, these factors were further merged into a broader level, named Environment. This method was performed consecutively over the whole database of journal publications chosen, yielding a large list of open and axial coding associated with enablers and constraints, finally grouped into the TOE for selective coding purpose. It is worth noticing that the number of authors mentioned both enablers and constraints in one publication, which have been separated based on the respective stages in current research. Tables 4–6 show the coding process for enablers, whereas Tables 7–9 display the constraints, in terms of pre-development, deployment and post-development respectively.

For pre-development enablers, six axial coding have been identified under the umbrella of TOE framework, namely technical benefit for T, organizational strategy and alignment support, leadership support, behaviour and cultural support, and resource support for O, and external enabler for E.

In tandem with the identification of enablers, this study has also identified six similar axial coding for constraints during the pre-development phase. The divergence between these constraints and enablers lies in the open coding stage. The identified technical constraints include data quality and availability, explainable and responsible AI, AI ethics and trust, fairness and bias, and privacy and security concerns. The theme of behavioural and cultural constraints is an umbrella for human acceptance and domain knowledge. The unclear business goal and top management support have been classified into organizational strategy and alignment constraints and leadership constraints, respectively. Resource constraints, such as funding limitations, poor infrastructure, and lack of expertise, are covered under the theme of resource constraints. The theme of external constraints includes technical standards and rules and the lack of benchmark cases as factors that can hinder the integration of AI in the supply chain.

In the context of constraints to deployment, the single axial coding method has identified process constraints, which encompass various factors such as robustness, adaptiveness, change management, communication, training, collaboration, and stakeholder consensus. These factors play a crucial role in the successful deployment of AI in supply chain, and their absence or insufficiency can result in significant obstacles to the deployment process.

The constraints to post-development are centred around issues of accountability, governance frameworks, and copyright concerns, which fall under the overarching theme of performance evaluation.

4.3. Empirical analysis

4.3.1. Pre-development-technology for AI in supply chain

Perceived benefits, especially those associated with time-saving, are crucial in promoting the use of AI in supply chain. As respondent R2 has noted, even partially complete AI solutions can result in substantial time savings. Moreover, the utility of AI extends to wider areas of logistics, supply chain, and in-store operations, as suggested by R7. In these domains, AI can optimize various processes, leading to significant efficiency gains. In specific areas like engine health and maintenance, the benefits of AI become even more apparent which can tackle complex issues such as predicting

Table 4. Pre-development enablers for AI in supply chain.

Selective coding	Axial coding	Open coding	Reference (see Supplemental Appendix for bibliographic details)
T	Technical benefit	Perceived benefits	[1,3,4,7,8,13,14,16,17,21-27,31,33-39,41,44,45,47,49-51,58-60,62-69, 71-73,75,78,80,81,83,90,92,94,100, 102,104,106-109,111,114,117,122, 123,124,126-130,131,132,133,137-143,146-152,155,157,159,161,162, 164-169,171,172,173,177-180,183, 184,187,190-195,198,207,209,211, 212,214,215,217-220,222-228,231-234,237-239,242,244-249,253,254, 256-259,261,265-267,271-273,276, 279-281,282-289,291,294,296,297, 300-304,306-311,313-320,324-326, 329,331-337,339-341,347-350,352, 353,355-358]
O	Organizational strategy and alignment support	Strategy formulation	[197,328]
	Leadership support	Top management support	[292]
	Behavioural and cultural support	AI understanding	[252]
	Resource support	In-house expertise	[46]
		IT infrastructure	[257]
E	External enabler	Environment protection driven	[1,2,11,66,70,81,83, 91,96,104,110,144,158,182,206,208,213]
		Stakeholders buy-in	[4,7,17,37,41,76,85,93,101,118,133,178,217,221,270,290,291,343,344]
		Competition driven	[6,82,98,233,256,271,284,290,299,304,305,327,328,348]
		Government incentives	[11,48,241,257,272,332]
		Customer demand-driven	[3,19,35,71,92,97,105,106,107,117,153,170,178,210,233,237,238,290,299,304,312,313,324,328]
		External expertise	[252]

Table 5. Deployment enablers for AI in the supply chain.

Selective coding	Axial coding	Open coding	Reference (see Supplemental Appendix for bibliographic details)
O	Process support	AI governance	[293]
		Cross-sectors collaboration	[57,185]
		Effective communication	[277]
		Adequate training	[175]
		Stakeholder engagement	[306]

Table 6. Post-development enablers for AI in the supply chain.

Selective coding	Axial coding	Open coding	Reference (see Supplemental Appendix for bibliographic details)
O	Performance evaluation	AI review	[235,241]
		KPIs achievement	[56,236]
		Feedback	[121]

Table 7. Pre-development constraints for AI in supply chain.

Selective coding	Axial coding	Open coding	Reference (see Supplemental Appendix for bibliographic details)
T	Technical constraint	Data quality and availability	[3,27,35,40,42,46,95,135,142,163,176,181,186,241,292,315,338]
		Explainable and responsible AI	[2,118,182,191,263,292,293,307,315,342,346,351,360,361]
		Ethic and trust	[229,6,20,37,38,53,84,118,119,125,196,216,251,252,255,268,269,275,277,280,282,321]
		Fairness and bias	[54,84,235]
		Privacy and security	[6,10,15,18,19,28,29,54,120,142,188,233,239,241,262,270,273,282,321]
O	Behavioural and cultural constraint	Human acceptance	[37,269,280,252,43,74,295]
		Domain knowledge	[9,54,78,188,273,302,305]
	Organizational strategy and alignment constraint	Unclear business goal	[270,271]
	Leadership constraint	Top management support	[53,115,186,241,282,292]
	Resource constraint	Funding constraint	[8,188]
		Poor infrastructure	[6,15,23,30,46,135,233,319]
		Lack of expertise	[23,35,46,54,74,181,233,252,273,279,319]
E	External constraint	Technical standards and rules	[54,134,142,186,302,334]
		Benchmark cases	[61,233,319]

Table 8. Deployment constraints for AI in supply chain.

Selective coding	Axial coding	Open coding	Reference (see supplemental appendix for bibliographic details)
O	Process constraints	Robustness and adaptiveness	[136,270,12,48,260,327,359]
		Change management	[6,54,59,74,136,186]
		Insufficient communication	[53,241,274,48,250]
		Insufficient training	[136,241,292,48]
		Insufficient collaboration	[277,186,3,5,160,174,230,298]
		Stakeholder consensus	[20,84,264,101,248]

Table 9. Post-development constraints for AI in the supply chain.

Selective coding	Axial coding	Open coding	Reference (see Supplemental Appendix for bibliographic details)
O	Performance evaluation	Accountability in AI	[235]
		Governance framework	[121,240,268,276,282, 307,241,32,103]
		Copyright	[54,239]

and identifying engine deterioration, bird strikes, and abnormal temperature fluctuations. The utilization of advanced AI techniques, such as Reinforcement Learning and Supervised Learning, enables accurate problem detection and resolution. These AI-driven solutions surpass the capabilities of traditional human-led or simple regression-based methods (R1), highlighting the remarkable benefits of AI integration within the supply chain sector.

The quality and accessibility of data are crucial considerations in the pre-development phase of AI in supply chain management, underpinning the efficacy and accuracy of the resultant AI solutions. Respondent R1 draws attention to constraints such as the absence of required data or the need for modification in rule sets to accommodate dynamic variables. Additionally, the integrity of outputs is heavily contingent upon the quality of input data, leading to a situation where flawed or insufficient data inevitably yields subpar results. Consequently, the importance of ensuring high-quality, readily available data cannot be overstated, as it forms the backbone of any successful AI deployment.

The understandability or explainability of AI mechanisms represents a critical challenge in the supply chain context.

According to R1 and R3, efforts are made to explain AI logic to stakeholders, often translating it into more accessible language. However, as R5 highlights, certain AI outcomes, such as unexpected increases in orders, remain difficult to explain due to 'black box' nature of AI. Therefore, while explainability is pursued, it can pose a constraint due to the inherent complexity and opacity of some AI mechanisms. This highlights the importance of responsibility in AI application, as the unexplained outcomes could potentially lead to accountability issues.

The issues of fairness, bias, ethics, and trust can pose significant challenges during the pre-development phase of AI in supply chain, as indicated by respondent R4. Balancing the accuracy of model with the generated business value necessitates careful consideration. Employing both percentage features and absolute quantity features may help balance the representation of large and small customers, reflecting a sense of fairness. However, inherent biases in data or the model can affect this balance, leading to skewed or unfair results that favour certain segments over others. These issues not only compromise the ethical standing of AI applications but also affect trust in these systems, as consistent biases may lead to stakeholders questioning the reliability and fairness of the system.

The incorporation of AI into supply chain necessitates careful consideration of privacy and security constraints during the pre-development stage. The extensive data requirements inherent in AI systems inevitably evoke concerns regarding data privacy and the security of its storage and processing. Whether through unintentional leaks or deliberate misuse, the potential exploitation of such data underscores the importance of robust security measures. The imperative to uphold data privacy standards and regulations not only enhances stakeholder trust but is also an ethical prerequisite for AI deployment (R4&R7).

4.3.2. Pre-development-organization for AI in supply chain

Strategy formulation is a crucial step in the pre-development stage of AI in supply chain management. According to respondent R7, the employment of a 'Machine Learning Canvas' framework facilitates a comprehensive examination of all pertinent factors prior to progressing significantly with the project. This methodical, strategy-oriented approach underscores the importance of formulating a comprehensive strategy before proceeding with the AI project. As per respondent R4, the process begins with defining the overall goal, which is followed by data collection, processing, and analysis, which lays the foundation for the subsequent development of algorithms and models. Once developed, these algorithms undergo debugging before the final review of the entire project. This structured, step-wise approach ensures a well-directed and effective AI solution, tailored to meet the overall goal of the company, thereby underlining the importance of a well-articulated strategy formulation.

As respondent R10 points out, embracing AI requires a commitment from the top leadership to embrace and drive this change. It is necessary to have executives who can envision and spearhead these transformative initiatives. While a bottom-up approach might be challenging, a top-down approach ensures that AI considerations are incorporated into the main strategy. This clearly demonstrates the importance of having strong top management backing when considering AI in the pre-development stages.

Grasping the intricacies of AI is a fundamental prerequisite to its successful incorporation within supply chain. As elucidated by Respondent R1, the prevalent anxieties related to job displacement due to the introduction of AI pose a notable constraint. Additionally, Respondent R8 emphasized the ongoing necessity for human intervention in AI-operated tasks, such as those involving supply chain forecasts and stock orders. Respondent R9 further contended that the understanding of AI, coupled with effective communication and meticulous documentation, are instrumental to properly defining the problem at hand and apprehending the constraints of AI deployment. Collectively, these perspectives underscore the pivotal role that comprehensive understanding of AI plays in effectively harnessing its capabilities within the realm of supply chain.

As articulated by respondent R9, certain tasks, due to their inherent complexity or broad scope, may not be adequately addressed solely through comprehensive AI solutions. These scenarios necessitate the application of decision support techniques. Consequently, the presence of in-house expertise proves invaluable, as it facilitates a nuanced understanding and deployment of AI solutions, while also enabling the usage of supplementary techniques when AI falls short.

A robust IT infrastructure is a fundamental requirement for the successful incorporation of AI within supply chain. Respondent R9 and R10 paint a vivid picture of the diverse spectrum of AI techniques in use, spanning from linear regression to deep neural networks. These methods find utility across a wide range of applications, including standard e-commerce functionalities like recommendations and demand forecasting, as well as more specialized areas like computer vision and natural language processing. This diverse utilization of AI technologies underlines the necessity for a well-equipped IT infrastructure, capable of supporting the smooth operation of these varied AI tools and methodologies. Not only does such an infrastructure facilitate seamless integration of AI technologies into existing systems, but it also strengthens decision-making capacities and enhances overall operational efficiency. Hence, a solid IT infrastructure emerges as a critical enabling factor in unlocking the full potential of AI within supply chain.

AI projects in this domain require substantial financial resources, particularly in the early stages, which encompass data acquisition and processing, algorithm development and customization, computational infrastructure procurement and maintenance, and hiring skilled personnel with expertise in AI and machine learning. Additionally, the iterative nature of AI projects necessitates continuous investment to accommodate updates and improvements, further contributing to the financial burden. The long-term return on investment may be uncertain, and the tangible benefits might not be immediately evident, leading to hesitancy in allocating adequate funding. Furthermore, unanticipated obstacles such as technical difficulties, regulatory challenges, or project timeline delays can escalate costs beyond initial estimates, underscoring the need for consistent and sufficient funding to successfully initiate and sustain AI projects in supply chain (R7 & R9).

4.3.3. Pre-development-environment for AI in supply chain

In the context of AI in supply chain, there are various external incentives recognized in the pre-development stages. Customers increasingly expect efficient and personalized experiences in their interactions with businesses where AI-powered algorithms can analyze customer data to provide personalized recommendations, forecast demand patterns, and optimize inventory management, leading to better customer satisfaction and retention. By leveraging AI to align with customer demands, businesses can gain a competitive edge in the market and enhance their overall customer experience (R6 & R10). Environment protection is another crucial enabler for embracing AI in the last mile delivery of goods, particularly in addressing CO2 emissions. The last mile delivery stage is known for its significant environmental impact due to factors such as inefficient routing, multiple stops, and high vehicle emissions. AI-powered algorithms can consider various factors like traffic patterns, weather conditions, and real-time data to determine the most efficient routes for delivery vehicles, resulting in reduced carbon footprint. Additionally, AI facilitate the adoption of alternative delivery methods such as electric vehicles or drones, further lowering CO2 emissions and promoting sustainability in the last mile delivery process (R10). Governments worldwide are increasingly recognizing the importance of sustainable practices and are implementing policies and incentives to encourage businesses to reduce their carbon footprint and embrace environmentally friendly solutions. In the case of last mile delivery, governments offer incentives such as tax credits, subsidies, or grants to organizations that implement AI technologies to optimize their logistics and reduce CO2 emissions. These incentives can help offset the initial costs associated with embracing AI systems and encourage businesses to adopt sustainable practices (R11). By obtaining the support and agreement of various stakeholders, organizations can maximize the positive effects of embracing AI while minimizing any potential negative impacts. Achieving stakeholder buy-in requires a thorough understanding of the metrics within the system, enabling rational trade-offs and configurability options that allow clients to make informed decisions (R10). Another external incentive is competition-driven, particularly evident in high-competitive industries like airlines. Airlines regularly compare their KPIs to benchmark their performance against each other on a monthly basis. This competitive benchmarking pushes organizations to continuously improve their operational efficiency and effectiveness through AI integration (R2). Furthermore, collaborating with external experts and leveraging their knowledge and experience can significantly contribute to the successful AI initiatives (R11 & R12).

Technical standards and rules can pose constraints in the pre-development stages of AI for several reasons. Firstly, the absence or ambiguity of established standards can lead to uncertainty and inefficiency in AI development. Without clear technical standards, different AI systems may have incompatible designs, making it challenging to integrate or exchange data and algorithms effectively (R1). Moreover, compliance with rules and regulations is essential to ensure ethical and responsible AI development. However, the rapidly evolving nature of AI technology often surpasses existing legal frameworks, creating uncertainties around issues like privacy, data protection, and bias mitigation (R5). Adhering to these rules requires careful consideration and compliance measures, which can add complexity and constraints during the pre-development stages. Furthermore, technical standards and rules can limit the availability and accessibility of certain data sources. Data, particularly in sensitive domains, may be subject to regulations or restricted access due to privacy concerns. These limitations can hinder data acquisition efforts, impacting the quality and diversity of datasets available for AI deployment (R6).

4.3.4. Deployment-organization for AI in the supply chain

Robustness and adaptiveness can pose challenges as AI systems need to handle real-world complexities and stochasticity. Building models that can effectively account for these complexities and produce reliable results can be a complex task (R2). Additionally, the need for continuous adaptation and improvement of AI models to evolving business requirements and environmental factors can require ongoing adjustments and refinements (R1). Change management is another constraint that arises when implementing AI systems. Organizations need to navigate the process of transitioning from traditional methods to AI-driven solutions. This involves managing resistance to change, addressing concerns, and ensuring smooth integration of AI into existing workflows and processes (R11). Insufficient communication can hinder AI development as effective communication channels and collaboration are essential for successful deployment. Inadequate communication between stakeholders, such as technical teams, management, and end-users, can lead to misunderstandings, delays, and difficulties in aligning expectations and requirements (R12). Insufficient training poses a constraint as AI systems require a skilled workforce to develop, deploy, and maintain them. Insufficient training in AI and related technologies can limit the organization's ability to effectively leverage AI and achieve desired outcomes (R9). Insufficient collaboration among different teams or departments can impede AI development. Collaboration is necessary to bring together domain expertise, data science capabilities, and operational knowledge for developing effective AI solutions (R2). Stakeholder consensus and engagement are vital for AI development. Lack of consensus and engagement can lead to resistance, limited adoption, and challenges in achieving desired outcomes (R5 & R6).

4.3.5. Post-development-organization for AI in the supply chain

AI review and feedback mechanisms enable continuous improvement and refinement of AI models and systems. By analyzing bad cases and understanding why a model does not perform well, organizations can identify areas for enhancement and make necessary adjustments (R6 & R8). This process of attribution allows for targeted improvements to be made, addressing specific weaknesses or limitations in the AI system. The feedback loop created through AI review and feedback mechanisms enables organizations to iterate on their models and simulations, making iterative improvements over time. This iterative process leads to enhanced performance, increased accuracy, and better alignment with the intended goals and objectives of the AI system. During the post-development stage, organizations evaluate the performance of model against the identified KPIs to determine its effectiveness (R10, R5, R6). These KPIs serve as benchmarks for measuring the success of model in achieving the desired outcomes, whether it is improved operational efficiency, enhanced customer satisfaction, or cost savings. By quantifying the impact of AI using KPIs, organizations can assess the tangible value and benefits that the AI tool brings to their business (R1). Both online and offline, key metrics are monitored to gauge the model's performance and drive improvements (R8 & R9). By analyzing the KPIs and key metrics, organizations can identify potential bottlenecks, inefficiencies, or opportunities for further enhancement, enabling continuous iteration and improvement of the AI models and systems. Establishing governance frameworks to verify feasibility, ethics, and legality, as well as addressing issues of bias and transparency, requires additional resources and efforts (R9 & R11). Copyright considerations also arise, necessitating careful evaluation and adherence to legal and contractual obligations (R11). However, these processes require dedicated resources, expertise, and a commitment to transparency and accountability. Managing these constraints effectively is essential for responsible and ethical AI deployment in the post-development stage.

5. Discussion

Table 10 displays the themes in the order in which they appeared throughout the axial thematic analysis. The quantification of the relative importance or prevalence of each theme, as illustrated in the analysis, is computed based on the frequency of their appearance throughout the collected research data. To exemplify this, consider the theme 'technical benefits' with a weightage of 68.6%. The derivation of this weightage is a two-tier process: initially, a frequency count is executed where every instance of the theme 'technical benefits' found in the data is noted. Subsequently, this count is normalized to convert it into a proportion of the total instances of all themes. The 'technical benefits' was identified 248 times amidst a total theme instance count of 361 papers, therefore the overall frequency is 68.6%. The same process is administered to all themes, transforming raw frequency counts into normalized weights indicative of each relative prevalence. Based on the findings of the pre-development stage, the themes of technical benefits and technical constraints represent 68.6 and 44.8% respectively, followed by external enablers and resource constraints accounting for 26 and 12.6% respectively. While leadership, behavioural and cultural support, organisational strategy and alignment are considered the least important factors. The significance of process constraints outweighs that of process support during the stage of AI deployment, with the same pattern found in the post-development stage for performance evaluation.

An empirical analysis of AI enablers and constraints across different industries is illustrated in Table 11. Understanding AI, strategy formulation, privacy, and security are prevalent enablers during the pre-development phase across the Airline, Retail, and Agri-food Supply Chains, reflecting a universal emphasis on foundational knowledge, strategic planning, and stakeholder safeguards. The emphasis in the Airline Supply Chain on cross-sector collaboration and robust AI systems reflects the necessity for inter-industry knowledge sharing and adaptable technology in response to dynamic market conditions. In Retail and Agri-food sectors, the focus on stakeholder engagement emphasizes their consumer-oriented approach and the crucial role of comprehensive feedback for effective AI deployment. The Agri-food sector further highlights the constraint of insufficient training, indicating a potential skill gap that necessitates capacity development. Lastly, the Global Transport and Logistics sector underscores effective change management and clear communication, demonstrating the complex dynamics within this sector and the importance of structured strategies and clear communication channels when navigating AI-induced changes. Post-development, the frequent focus on KPIs underscores a collective, results-oriented perspective. Despite these shared elements, unique enablers, and constraints surface. For example, competition and data quality are critical in the Airline Supply Chain, reflecting its competitive, data-intensive nature, whereas the Retail Supply Chain uniquely prioritizes bias and ethical considerations, aligning with its customer-centric model. The Agri-food Supply Chain displays distinct constraints such as funding and in-house expertise,

Table 10. Frequency analysis.

	Enablers	Frequency	Constraints	Frequency
Pre-development	Technical benefit	68.60%	Technical constraint	44.80%
	Organizational strategy and alignment support	0.64%	Organizational strategy and alignment constraint	1.20%
	Leadership support	0.32%	Leadership constraint	3.60%
	Behavioural and cultural support	0.32%	Behavioural and cultural constraint	4.20%
	Resource support	0.64%	Resource constraint	12.60%
	External enablers	26%	External constraint	5.40%
Deployment	Process support	1.90%	Process constraint	21%
Post-development	Performance evaluation	1.60%	Performance evaluation	7.20%

Table 11. Empirical analysis.

Industry	Code	Pre-development	Deployment	Post-development
Airline supply chain	R1	Perceived benefits AI understanding Competition driven Data quality and availability Explainable and responsible AI Technical standards and rules		KPIs
	R2	Perceived benefits Benchmark cases	Cross-sectors collaboration Robustness and adaptiveness	
	R3	Explainable and responsible AI		
Retail supply chain	R4	Strategy formulation Ethic and trust Fairness and bias Privacy and security	Stakeholder engagement	
	R5	Explainable and responsible AI Technical standards and rules	Stakeholder engagement	KPIs
	R6	Customer demand-driven		KPIs AI review
Agri-food supply chain	R7	Perceived benefits Strategy formulation Privacy and security Funding constraint	Stakeholder enagagement	
	R8	AI understanding		KPIs AI review
	R9	AI understanding In-house expertise IT infrastructure Funding constraint	Insufficient training	KPIs Governance framework
Global transport and logistics	R10	Top management support Environment protection driven IT infrastructure Stakeholders buy-in Government incentives		KPIs
	R11	Government incentives External expertise	Change management	Copyright Governance framework
	R12	External expertise	Insufficient communication	Accountability in AI

denoting potential resource challenges in the sector. The Global Transport and Logistics sector, on the other hand, illustrates a comprehensive approach to AI pre-development, emphasizing management support, environmental considerations, and government incentives during pre-development, and focusing on change management and governance post-deployment.

5.1. Pre-development

5.1.1. Technical benefit and constraint

The decisive factor that shapes the decision of supply chain towards integrating AI is primarily the technical benefit, which has been characterized by the capabilities of AI, including the ability to manage large volumes of data with exceptional speed and the capacity to withstand external uncertainties. The need for sustainability in a closed-loop supply chain has catalyzed the pre-development of AI, which provides robust optimization capabilities across various supply chain functions, including supplier selection (Ebinger and Omondi 2020), procurement (Barrad, Gagnon, and Valverde 2020; Guida et al. 2023), warehousing (Drakaki and Tzionas 2016; Lorson, Fügener, and Hübner 2022), production (Busato et al. 2019; Ghahramani et al. 2020), demand planning (Nikolopoulos, Babai, and Bozos 2016), and logistics (Bathla et al. 2022; Kovalishin et al. 2023). The supplier selection process is a pivotal aspect, as it directly impacts the quality of inputs and, consequently, the final products or services (Shore and Venkatachalam 2003). Traditionally, subjective evaluations such as supplier reputation and personal relationships have been relied upon to make supplier selection decisions. However, the emergence of AI has ushered in a more data-driven and objective approach. Various AI techniques are now utilized to analyze diverse data sources, encompassing performance data and external sources like news and social media feeds. Ultimately, AI-enabled early identification of potential suppliers exhibiting signs of supply chain disruptions or ethical concerns and continuous monitoring throughout the collaboration process is essential. In a parallel manner, the procurement process is undergoing substantial transformation, focusing on enhancing supply chain transparency and enabling the automation and streamlining of procurement activities, thereby facilitating more efficient, and sustainable procurement practices (Nissen and Sengupta 2006). Furthermore, significant benefits in warehousing and production lie in the ability to automate and optimize inventory management (Dev et al. 2016), accurately forecast production schedules (Flores and Villalobos 2020) delivery times (Menchaca-Méndez et al. 2022), prevent overstocking (Sinha, Zhang, and Tiwari 2012), and reduce waste (Yang, Feng, and Whinston 2022), which reduces errors and outperforms traditional human labour methods. To respond promptly to changes in consumer demand or supply chain disruptions, the need for AI in demand planning and forecasting has drawn great attention (Simchi-Levi and Wu 2018), with the analysis of consumer behaviour, market trends and sales history, thus reducing the risk of stockouts and increasing customer satisfaction. One of the central tenets of I4.0 is to foster sustainability across logistics, by harnessing the power of AI for real-time analysis (Alsudani et al. 2023). In particular, the AI-enabled analysis facilitates the identification of optimal transportation routes that are both efficient and economical, regardless of the mode of transportation, be it land, air, or sea, with the overarching objective of curbing fuel consumption and mitigating carbon emissions, thereby amplifying sustainability and profitability (Giuffrida et al. 2022).

Nevertheless, technical constraints have impeded AI in the pre-development stage. The availability of data forms the bedrock of AI integration (Govindan 2022; Mohiuddin Babu et al. 2022), as the lack of access or restricted availability of data may constraint the optimal functioning of AI systems, thereby hindering their widespread integration. Ethical principles that promote fairness and prevent discrimination should be implemented to address the potential for bias, which may arise when AI systems are trained on biased or incomplete data, leading to prejudicial decision-making (Manning et al. 2023; Sanders et al. 2019; Seo, Lee, and Jeon 2022). Organizations are obligated to take steps to design an unbiased model with a maximized group effort, taking into account diversity and inclusivity. Additionally, the use of AI to process data raises privacy concerns, since it may involve the processing of sensitive information without explicit consent (Aliahmadi and Nozari 2022; Dora et al. 2021; Nayal et al. 2021). Additionally, the increased usage of AI systems also heightens the risks of cyber-attacks and data breaches, which may cause significant financial losses and reputational damage. Thus, organizations should ensure that their AI systems incorporate robust privacy and security measures to protect sensitive data. Explainable and responsible AI systems are crucial nowadays as they allow transparent and understandable decision-making processes, which play an important role in business-to-business operation mode (Lehmann et al. 2022; Senoner, Netland, and Feuerriegel 2022).

5.1.2. Organizational strategy and alignment support and constraint

In supply chain organizations, strategy formulation is a crucial process that aims to maximize the benefits of AI systems in operational, tactical, and strategic decision-making (Sodhi et al. 2022). A well-defined strategy not only helps identify the key areas where AI can have the most significant impact, but also ensures that AI is aligned with broader goals and objectives (Abdulkader, Gajpal, and ElMekkawy 2018). However, focusing on short-term profits rather than sustainable long-term development goals can constraint AI in the supply chain (Hopkins 2021; Zhou, Awasthi, and Stal-Le Cardinal 2021). Moreover, a lack of alignment between different departments and stakeholders can lead to a lack of consensus on the importance of AI and the best approach to deploying it (Bodendorf et al. 2021).

5.1.3. Leadership support and constraint

The level of support provided by top management can significantly influence the integration of AI systems in the supply chain, serving either as an enabler or a constraint (Wang, Skeete, and Owusu 2022). Strong top management support can foster a culture of innovation and inspire employees to embrace novel technologies, facilitating AI integration. On the contrary, lack of top management support can constraint integration and lead the company to fall behind competitors that have already integrated AI systems. In the absence of top management support, employees may not perceive the value of AI systems, and efforts may not receive sufficient resources and attention (Dora et al. 2021; Mahroof 2019; Shrivastav 2022).

5.1.4. Behavioural and cultural support and constraint

The acceptance or resistance of employees towards AI in the supply chain is influenced by human behaviour and cultural factors, which are crucial determinants of the level of support or resistance towards AI (Klumpp and Ruiner 2022). The perception of AI systems as a threat to job security can create resistance to change among employees which arises from a lack of domain knowledge about AI systems or fear of being replaced by automation (Gupta et al. 2022;; Li and Epureanu 2020). Undoubtedly, AI systems require a deep understanding of the industry and specific supply chain processes to provide valuable insights, the absence of this knowledge adversely results in the ineffective performance of AI systems, constraint the overall success of AI.

5.1.5. Resource support and constraint

Organizations equipped with in-house expertise can develop bespoke AI systems, optimized for their specific supply chain processes, and glean valuable insights into customer behaviour and demand patterns (Deif and Vivek 2022; Pillai et al. 2022). The high costs associated with AI can pose a significant constraint for supply chain practitioners, which include not only hardware and software expenses but also expenses for the necessary expertise to develop and manage AI initiatives (Ahmed et al. 2022; Singh et al. 2023). The lack of internal expertise in AI can have significant implications for the early evaluation of AI projects, potentially resulting in suboptimal feasibility and potential impact assessments. Organizations that lack the necessary knowledge and skills may find it challenging to properly evaluate AI initiatives, leading to unrealistic expectations, improper deployment, or even project abandonment (Bag and Pretorius 2022; Budak and Sarvari 2021; Sharma et al. 2021). Similarly, the lack of a well-established infrastructure will adversely affect the integration of AI with other technologies under the umbrella of I4.0 (Ahmad et al. 2021; Belgaum et al. 2021).

5.1.6. External enablers and constraint

The integration of AI in the supply chain is influenced by a range of external factors, including environment protection (Giuffrida et al. 2022; Hemming et al. 2020; Hu and Bidanda

2009; Kar, Choudhary, and Singh 2022; Kovalishin et al. 2023), stakeholder buy-in (Alsudani et al. 2023; Cisneros-Cabrera et al. 2021; Vilas-Boas, Rodrigues, and Alberti 2023), customer demand (Arji et al. 2023; González Perea, Camacho Poyato, and Rodríguez Díaz 2021), competition (Kumar et al. 2023; Priore et al. 2019), government incentives (Chopra, Sodhi, and Lücker 2021), and external expertise (Dwivedi et al. 2021). In particular, the growing emphasis on environmental sustainability has highlighted the importance of adopting greener and more efficient supply chain processes, which can be achieved through the use of AI to optimize operations and minimize carbon footprint (Kar, Choudhary, and Singh 2022; Lenny Koh et al. 2013). The COVID-19 pandemic has further underscored the need for a sustainable and resilient supply chain, as demanded by stakeholders such as suppliers and customers (Ahmed et al. 2023; Arji et al. 2023; Modgil, Kumar Singh, and Hannibal 2021). In a competitive supply chain market, AI has been seen as a breakthrough to overcome the pressure to improve supply chain efficiency, reduce costs and provide better customer service to remain competitive in the market. Governments can also incentivize the AI in the supply chain by offering tax breaks and grants to organizations that embrace sustainable practices (Ferreira and Borenstein 2011; Govindan 2022; Pillai et al. 2022). Furthermore, external expertise from consulting firms and technology providers can complement the internal expertise of organizations.

Clear technical standards and benchmark cases are essential for the successful AI solutions in the supply chain, providing guidelines on how to effectively use and integrate these systems with existing technologies. A lack of such standards can result in vendor lock-in, limiting the availability of AI solutions and hindering opportunities for innovation and optimization (Lu et al. 2019). Without appropriate standards and benchmark cases, industries that have low trial and error costs, such as airlines and pharmaceuticals, may face significant risks associated with accidents and errors that could harm people and the environment (Ganesh and Xu 2022).

5.2. Deployment

5.2.1. Process support and constraint

Successful deployment of AI in the supply chain depends on a number of supportive factors, including AI governance (Wang, Skeete, and Owusu 2022), cross-sector collaboration (Shrivastav 2022), effective communication (Govindan 2022), adequate training (Wang, Skeete, and Owusu 2022), and stakeholder engagement (Dubey et al. 2021; Modgil, Kumar Singh, and Hannibal 2021). Proper AI governance is necessary to ensure ethical and safe deployment, while also identifying and mitigating potential risks. Effective communication and collaboration between different sectors of the supply chain facilitate knowledge sharing and address interoperability issues for successful deployment. Providing adequate training to the organization is essential to ensure that AI solutions are used to their full potential with appropriate model selection and continuous performance monitoring. Finally, stakeholder engagement throughout the deployment process plays a crucial role in increasing trust and supporting the successful deployment of AI solutions. Taking into account these factors will enable the responsible and effective deployment of AI in the supply chain. The deployment stage of AI in the supply chain presents constraints related to change management that is crucial to preparing employees (Ahmed et al. 2023), adapting AI changes (Guida et al. 2023); and robustness and adaptiveness (Li and Epureanu 2020), which can lead to errors, wasted resources, and missed opportunities if not well-addressed.

5.3. Post-development

5.3.1. Performance evaluation

In the realm of AI post-development in the supply chain, certain enablers and constraints must be considered. Enablers include regular AI reviews including KPIs achievement (Ponte et al. 2017), and feedback (Meena et al. 2021). Regular reviews of AI solutions are essential to update parameters based on market changes and ensure effective functioning. KPIs achievement, particularly through AI-driven solutions, helps ensure alignment with supply chain goals and ultimately contributes to success. Stakeholder feedback, including from end-users and vendors (Wamba et al. 2022), is crucial to identifying areas for improvement and ensuring engagement and trust. On the other hand, constraints to AI post-development in the supply chain involve issues of copyright (Wang, Skeete, and Owusu 2022), governance (Sharma et al. 2023), and accountability (Kuziemski and Misuraca 2020; Manning et al. 2022; Rodríguez-Espíndola et al. 2020). With the large amounts of data required to train AI models, copyrighted data poses a potential legal dispute if used without permission. This is particularly challenging in the supply chain, where data is often shared between multiple stakeholders. Additionally, a lack of clear governance framework for AI and responsible issues can lead to reluctance and mistrust among stakeholders.

5.4. Dimension relationship

This research aimed to analyze the weights assigned to enablers and constraints across the pre-development, deployment, and post-development stages to gain insights into the AI supply chain journey (refer to Table 10). The analysis revealed a distinct ranking of constraints in each stage. In the pre-development stage, the following constraints were identified in order of importance: technical constraints, resource constraints, external constraints, behavioural and cultural constraints, leadership constraints, and organizational strategy and alignment constraints. Technical constraints arise from limitations in the required technological infrastructure and capabilities for AI integration, while resource constraints result from limitations in budget, workforce, or necessary equipment. External constraints stem from factors beyond the internal control, such as regulatory or legal restrictions. Behavioural and cultural constraints relate to challenges in aligning employee behaviour and cultural

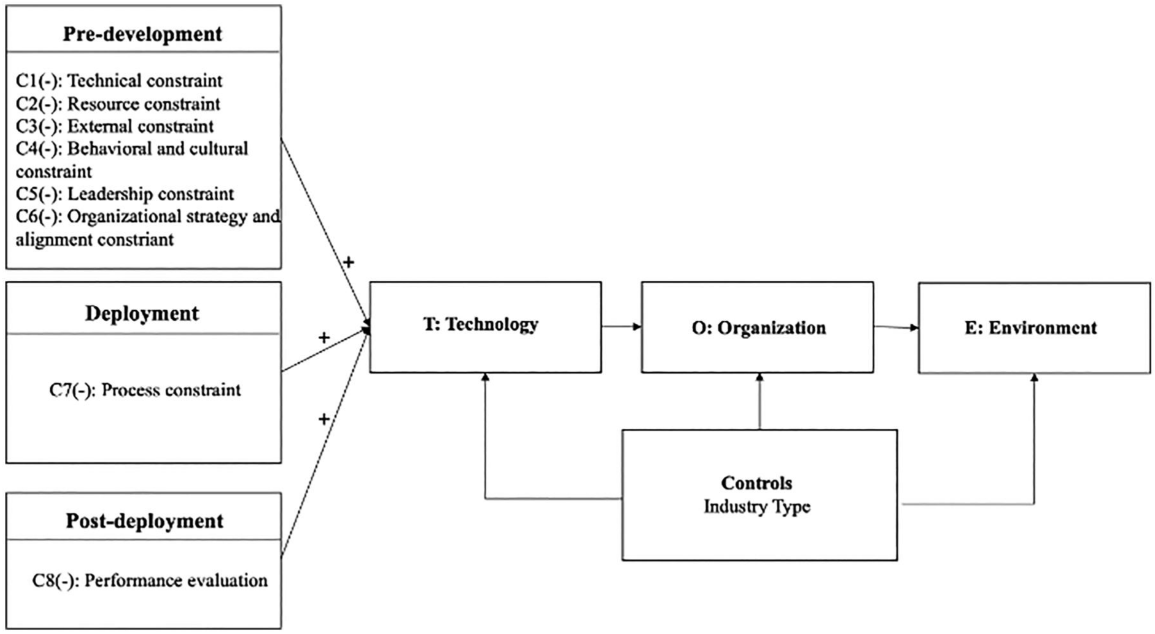

Figure 6. Renewed TOE conceptual model.

norms with AI adoption, whereas leadership constraints emerge when there are limitations in leadership vision, support, and commitment towards AI integration. Organizational strategy and alignment constraints occur due to difficulties in aligning AI initiatives with the overall organizational strategy and goals. Transitioning to the deployment and post-development stages, two primary constraints emerged. Process constraints involve challenges in redesigning or adapting existing processes to effectively accommodate AI technologies. Performance evaluation constraints encompass difficulties in accurately assessing and measuring the performance and impact of AI integration. The findings underscore the importance of prioritizing constraints and transforming them into enablers for successful AI journey (Figure 6). Prioritizing constraints requires recognizing their significance and allocating appropriate resources, attention, and efforts. By addressing and overcoming the identified constraints, organizations can unlock the potential of AI. Transforming constraints into enablers necessitates implementing necessary changes such as updating technical capabilities, allocating adequate resources, fostering a supportive organizational culture, providing strong leadership, and aligning AI initiatives with the overall organizational strategies. Within the context of AI in the supply chain, it is worth noting that one control factor falls under the organization dimension, specifically the industry type. Further empirical analysis specific to different industries is required to gain a deeper understanding of its implications. Our initial proposition is based on these observations.

Proposition 1: Addressing technological, organizational, and environmental constraints is necessary to achieve a certain level of satisfaction and facilitate the transformation of constraints into enablers that promote the embracing of AI across the pre-development, deployment, and post-development stages.

In the pre-development stage of AI integration, it is crucial to prioritize addressing technical constraints, which serve as the foundation for the awareness of technical benefits. These constraints include ensuring data quality and availability, developing explainable and responsible AI, promoting ethics and trust, addressing issues of fairness and bias, and protecting privacy and security. Establishing adequate infrastructure and funding resources is considered the second priority constraint to be addressed, followed by the constraints posed by the absence of technical standards, rules, and benchmark cases. In addition, behavioural and cultural, leadership and organizational strategy and alignment constraints must be transformed into enablers through the incorporation of well-established human knowledge, well-aligned top management support, and well-structured business goals that facilitate the integration of AI. From that point of view, we derive the following proposition:

Proposition 2: During the pre-development stage, technical constraints have been identified as the most significant impediments that hinder the AI in the supply chain, followed by constraints related to resources, external factors, behaviour and culture, leadership, organizational strategy, and alignment. To facilitate the deployment of AI in the supply chain, organizations need to harness the power of both technology and organizational resources to transform these constraints into enablers.

During the deployment stage of AI, internal organizational constraints arise, particularly with regards to open coding in AI robustness and adaptiveness, change management, insufficient communication, training, collaboration, and stakeholder consensus. Although technical constraints hold a greater proportion of influence, these aforementioned process constraints significantly impact the effectiveness and efficiency of AI integration in the supply chain, thereby serving as determinants of added value. This leads to the following proposition.

Proposition 3: Organizations must prioritize addressing process constraints in the deployment stage to ensure the effectiveness and efficiency of the system and maximize added value.

Notably, the performance evaluation stage in the post-development phase was found to be a less relevant constraint and enabler in either constraint or promoting the AI journey. It should be noted that performance evaluation forms the foundation for sustainable AI innovation, with dynamic interaction with the external environment enabling the continuous updating of parameters and models for improved operational, tactical and strategic performance. Based on this consideration, we arrive to following proposition.

Proposition 4: While performance evaluation does not hold a significant role as either an enabler or constraint in AI supply chain journey, it still warrants attention from both academia and industry to achieve sustained competitive advantages.

While commonalities in embracing AI across supply chains do exist, as derived from a SLR, empirical data from various industries – including Airline, Retail, Agri-food, and Global Transport and Logistics sectors – underscore unique contextual factors that significantly shape AI strategies within these industries. For example, the highly regulated and safety-critical environment of the Airline industry necessitates a focus on data quality and robust AI solutions. In contrast, the customer-oriented Retail industry prioritizes ethics, trust, and privacy. The resource-sensitive and infrastructural complexity of the Agri-food industry places an emphasis on strategic planning and resource allocation, whereas the multi-stakeholder and environmentally impactful Global Transport and Logistics sector centres on management support and stakeholder buy-in. These empirical insights give rise to distinct four propositions for each industry, underlining the critical need for context-specific approaches in AI journey across different sectors.

Proposition 5: In data-intensive and highly competitive sectors such as the Airline Supply Chain, perceived advantages of AI and the quality of data assume significant roles during the pre-development phase. Industries of this kind tend to stress comprehensible AI and technical norms, promoting an environment conducive to robustness and adaptiveness during the deployment phase. This conforms with the ambition to enhance performance, as seen in the frequent references to KPIs following the development phase.

Proposition 6: In industries focusing on customers, such as the Retail Supply Chain, considerations around strategy formulation, ethical conduct, fairness, and privacy are pivotal in the pre-development stage. Such sectors attach substantial importance to stakeholder engagement during deployment and measure the impact of AI using KPIs and review mechanisms for AI after development.

Proposition 7: In industries that are sensitive to resources and possess intricate infrastructure such as the Agri-food Supply Chain, pre-development stage emphasizes understanding AI, formulating strategy, and securing funding. Stakeholder involvement is critical during the deployment phase, while governance frameworks, KPIs, and reviews of AI become crucial after the development phase.

Proposition 8: In sectors characterized by complex stakeholder relationships and high environmental impact such as the Global Transport and Logistics sector, pre-development is largely guided by support from senior management, stakeholder engagement, and governmental incentives. Management of change is crucial during the deployment phase, and following the development phase, the emphasis is placed on establishing a governance structure for ensuring accountability.

6. Conclusion

This study integrates findings from a SLR of 361 journal publications with empirical data gathered through interviews with 12 supply chain experts. The objective was to identify and analyze key enablers and constraints influencing the AI journey in supply chains. These elements were situated within a conceptual TOE framework to explain their interactions. These research aims have been achieved by answering the following for research questions.

In RQ1, starting from the descriptive analysis, the key research trends have been recognized, namely the time distribution of publications, the variety of the methodological approaches used, the type of industry sectors and supply chain subfields studied and the AI techniques that have been carried out. In terms of the time distribution of publications, we discovered that the number of publications increased progressively and 78% of the papers were published after 2019. As for the methodologies carried out to explore AI in the supply chain, the primary methodologies are listed in this order of appearance case study, review, survey, modelling, experiment, and simulation. The findings show that the prevalence of the aforementioned methods account for 85% of the frequency, which considered as preferable methods to study the AI in supply chain. Seven industry sectors have been found, with a concentration of investigations in agri-food, manufacturing, energy, healthcare, retail, fashion, and construction. With respect to supply chain subfields, the publications cover different perspectives including supplier selection, procurement, storage, production planning, demand planning and logistics with the aim of achieving an agile supply chain, improving supply chain resilience, generating a green supply chain, and finally building a sustainable supply chain network. The investigation revealed significant algorithms such as ANN, EA, MAS, HA, SI, DDS, and FL. Moreover, the study confirms the significance of other AI techniques, including ES, DM, DT, CBR, RF, BN, and LSTM, in the supply chain context. These results align with the existing trend observed in the literature, highlighting the maturity of AI research in the supply chain domain. Subsequently, to answer RQ2, a thematic analysis was carried out to investigate the meaningful enablers and constraints involved in the AI journey, with a focus on the pre-development, deployment, and post-deployment stages. The open coding process was performed consecutively across the entire database to achieve saturation, and then two long lists of codes have been merged into six axial themes in the pre-deployment stage: 'technical benefits and constraints', 'strategy and alignment support and constraints'; 'leadership support and constraints'; 'behavioural and cultural support and constraints'; 'resource support and constraints'; 'external enablers and constraints'; and one axial theme for deployment and post-development stage, namely 'process support and constraints' and 'performance evaluation'. The eight axial themes identified in this study were integrated into a more comprehensive TOE framework, serving as the basis for conducting the relationship analysis. To address RQ3, this involved a deep dive into four distinct industries - Airline, Agri-food, Retail, and Logistics – allowing for an exploration of industry heterogeneity. Recognizing that each industry carries unique characteristics and faces disparate challenges, the empirical analysis was designed to unearth distinctive enablers and constraints within each industry. By conducting a thorough academic study and analyzing empirical data from industries such as Airline, Retail, Agri-food, and Global Transport and Logistics, this research uncovers a crucial finding: prioritizing constraints such as technical limitations, resource availability, external factors, and organizational behaviour and culture serves as a significant enabler for the successful integration of AI. Further, unique contextual factors across industries were found to shape AI strategies significantly. For instance, data quality and robust AI solutions are prioritized in the highly regulated Airline industry, while the Retail industry, being customer-oriented, focuses on ethics, trust, and privacy. Meanwhile, the Agri-food industry, with its resource sensitivity and infrastructural complexity, emphasizes strategic planning and resource allocation, and the Global Transport and Logistics sector highlights management support and stakeholder buy-in due to its multi-stakeholder and environmentally impactful nature.

This study significantly contributes to our understanding of the AI journey in supply chains. By conducting a systematic literature review and interviews with supply chain experts, the study identifies the key factors that enable or constraint the AI in supply chains. The research integrates empirical data with a theoretical TOE framework, which helps us comprehend how technological, organizational, and environmental factors interact in this context. Through thematic analysis, the study uncovers six key themes related to the pre-development stage and two themes for the deployment and post-development stages, offering valuable insights into the specific factors that impact the successful integration of AI. Furthermore, the study delves into the nuances of different industries, such as Airline, Agri-food, Retail, and Logistics, revealing industry-specific insights and highlighting the importance of tailoring AI strategies to the unique contextual factors of each sector.

As this research aimed to find supply chain publications related to predefined keywords, therefore, one of the limitations of this paper is selection bias. Other papers not on the predefined list have not been selected and the keywords presented only in the main body of the paper may also be excluded in our selection. Regardless of the limitation, given the insights set out in this paper, it may be possible for future researchers to better apply the research findings to understand the journey of AI in supply chain. Future research should examine benchmarking cases in various supply chain industries to add further insights to this field. Further research could employ a Delphi study in conjunction with the Decision-Making Trial and Evaluation Laboratory (DEMATEL) approach to explore and validate the themes identified in this study, or even to uncover new themes. This combined approach can provide a structured, interactive means of expert elicitation and consensus building to refine our understanding of AI enablers and constraints across industries. Additionally, it would be beneficial to quantify the impact of these factors, potentially through mathematical modelling. This would add another dimension to the research, offering a more precise evaluation of the relative importance and influence of the different factors within and across industries.

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