Artificial intelligence in supply chain decision-making: An environmental, social, and governance triggering and technological inhibiting protocol

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Abstract

Purpose

Decision-making, reinforced by Artificial Intelligence (AI), is predicted to become potent tool within the domain of Supply Chain Management (SCM). Considering the importance of this subject, the purpose of this research is to explore the triggers and technological inhibitors affecting the adoption of AI. This study also aims to identify three-dimensional triggers, notably those linked to Environmental, Social, and Governance (ESG), as well as technological inhibitors.

Design/methodology/approach

Drawing upon a six-step systematic review following the PRISMA guidelines, a broad range of journal publications was recognized, with a thematic analysis under the lens of the ESG framework, offering a unique perspective on factors triggering and inhibiting AI adoption in the supply chain.

Findings

In the *environmental dimension*, triggers include product waste reduction and greenhouse gas emissions reduction, highlighting the potential of AI in promoting sustainability and environmental responsibility. In the *social dimension*, triggers encompass product security and quality, as well as social well-being, indicating how AI can contribute to ensuring safe and high-quality products and enhancing societal welfare. In the *governance dimension*, triggers involve agile and lean practices, cost reduction, sustainable supplier selection, circular economy initiatives, supply chain risk management, knowledge sharing, and the synergy between supply and demand. The inhibitors in the *technological category* present challenges, encompassing the lack of regulations and rules, data security and privacy concerns, responsible and ethical AI considerations, performance and ethical assessment difficulties, poor data quality, group bias, and the need to achieve synergy between AI and human decision-makers.

Research limitations/implications

Despite the use of PRISMA guidelines to ensure a comprehensive search and screening process, it is possible that some relevant studies in other databases and industry reports may have been missed. In light of this, the selected studies may not have fully captured the diversity of triggers and technological inhibitors. The extraction of themes from the selected papers is subjective in nature and relies on the interpretation of researchers, which may introduce bias.

Originality/value

The research contributes to the field by conducting a comprehensive analysis of the diverse factors that trigger or inhibit AI adoption, providing valuable insights into their impact. By incorporating the ESG protocol, the study offers a holistic evaluation of the dimensions associated with AI

adoption in the supply chain, presenting valuable implications for both industry professionals and researchers. The originality lies in its in-depth examination of the multifaceted aspects of AI adoption, making it a valuable resource for advancing knowledge in this area.

Keywords

Artificial Intelligence (AI); Supply chain decision-making; Environmental, social and governance (ESG); Triggers and inhibitors

1. **Introduction**

Supply chain landscapes are currently undergoing a transformative change, as they are urged to integrate sustainable practises into their operational, tactical, and strategic decision-making. Pressure from environmentally-conscious consumers and net-zero deadlines set by regulators press the necessity for supply chains to embrace sustainable practices throughout all stages, spanning from production (Sarkar et al., 2021) to last-mile delivery (Demir et al., 2022). Consistently, supply chains are confronted with escalating demands to prioritize social responsibility, particularly within the agri-food supply chain (Di Vaio et al., 2020), healthcare supply chain (Damoah et al., 2021) and humanitarian aid supply chain (Van Wassenhove, 2006). In response, a multitude of governance responsibilities address the environmental-social aspects by monitoring and managing supplier performance (Allal-Chérif et al., 2021), ensuring that suppliers comply with ethical and sustainability standards (Ciliberti et al., 2008) and optimizing operational costs while maximizing customer satisfaction (Gupta et al., 2021).

Artificial intelligence (AI) as a game-changer creates new opportunities for the aforementioned challenges. By definition, the term of “AI” was originally introduced in 1956 at Dartmouth workshop to indicate the capability and skills of machines to exchange information with-and mimic the capabilities and features of-people (Russell, 2010). The emergence of advanced computing technologies, coupled with the growing availability of data and storage capabilities, has led to a renewed interest in data-driven decision-making in the field of supply chain, In particular, the use of AI has gained significant momentum in recent years, enabling supply chain industries including but not limited to agri-food (Mishra et al., 2022), manufacturing (Bag et al., 2021a), service (Belhadi et al., 2021), retail (Sarma et al., 2021) and healthcare supply chain (Spieske et al., 2022) to leverage advanced analytics techniques to optimize their decision-making processes.

Given the increasing adoption of AI, comprehending the triggers that fuel this adoption becomes a critical necessity. Triggers, in the context of this study, are factors or conditions that stimulate the adoption of AI in the supply chain. These triggers originate in multifaceted dimensions: environmental sustainability triggers enhance the streamlining of production and inventory management (Abideen and Mohamad, 2021) and the optimisation of vehicle routing (Masmoudi et al., 2022); social responsibility triggers advance the refinement of demand forecasting methodologies (Aksoy et al., 2014) and the evolution of supply chain risk management practices (Paul et al., 2020); and ethical governance triggers augment the processes of supplier selection and evaluation (Nodeh et al., 2020), as well as fostering the formation and fortification of supply chain networks (Baryannis et al., 2019).

On the other hand, inhibitors refer to circumstances or factors that impede or decelerate the incorporation of AI within the supply chain. These inhibitors span an extensive spectrum, ranging from technological and organizational barriers (Nayal et al., 2022) to regulatory constraints (Riahi et al., 2021). Technological inhibitors crystallize as a dominant category and encapsulate a variety of issues such as deficits in digital infrastructure, inadequate data management capabilities, along with cybersecurity and ethical considerations (Helo and Hao, 2022). In particular, the ethical implications accompanying AI emerge as formidable inhibitors, primarily concerning transparency, traceability, explainability, interpretability, and accountability (Manning et al., 2022).

Despite the existing body of scholarly work on the impact of AI on supply chain, there is a notable research gap in comprehensively examining the multifaceted triggers and inhibitors that affect AI adoption. This research seeks to contribute to the ongoing debate on triggers and inhibitors by addressing the overarching research question: "What are the triggers and technological inhibitors influencing the adoption of AI in the supply chain?" To achieve this, the study adopts the Environment, Social, and Governance (ESG) protocol, which offers a holistic assessment of the triggers for AI adoption and technological inhibitors. Through this enquiry, this research expects to gain insights into the following sub-questions:

- RQ1: What are the environmental, social and governance triggers and technological inhibitors influencing the adoption of AI in supply chain?
- RQ2: How do the identified triggers and inhibitors impact the adoption of AI in the supply chain, and what are the implications for supply chains?

To answer research questions, this study aims to conduct a thematic analysis to identify industry-specific themes and patterns related to triggers and technological inhibitors of AI adoption in the supply chain domain. Furthermore, the study undertakes a comprehensive analysis to evaluate the impact of these identified triggers and inhibitors on the adoption of AI in the supply chain. Through the identification of prominent themes and patterns, the study also explores the propositions that arise from the findings, offering insights and recommendations for supply chains to navigate and address the challenges and opportunities associated with AI adoption.

By addressing the research questions and sub-questions, the study aims to comprehensively examine the multifaceted triggers and technological inhibitors, shedding light on their influence on AI adoption. Furthermore, the research explores the implications of these triggers and inhibitors for supply chains, including their impact on sustainable practices, operational efficiency, decision-making processes, and overall supply chain performance. The findings of this research contribute to a deeper understanding of the complexities surrounding AI adoption and its implications for supply chains, thereby informing strategies and practices that promote sustainability and effectiveness in the evolving supply chain landscape.

The present study is structured as follows: Section 2 presents the research methodology, providing comprehensive details on the literature selection and evaluation process. Section 3 shows the bibliometric and thematic analysis, which systematically deconstructs the selected literature into its constituent parts. Sections 4 and 5 offer an analysis and discussion with theoretical and practical propositions. Concluding remarks, research limitations, and future research suggestions are presented in the subsequent sections.

2. Methodology

This study applies a systematic literature review for AI in supply chain decision-making, adopting a replicable process performed according to the guidelines established by the Preferred Reporting Items for Systematic Reviews and Meta Analysis (PRISMA) (Moher et al., 2009), being a robust method for conducting literature review analysis in supply chain (Nimmy et al., 2022, Kar et al., 2022). PRISMA emphasizes exhaustive literature search strategies, detailed data extraction, risk of bias assessment, and clear, structured reporting. This allows for a high degree of reproducibility and robustness in the evidence synthesis process, ensuring that systematic reviews and meta-analyses following the PRISMA guidelines are of high quality, reliable, and credible (Kumar et al., 2023b). Furthermore, PRISMA is an evolving guideline. It is regularly updated to incorporate advancements in research synthesis methods and changes in evidence reporting standards, making it a dynamic, up-to-date protocol that continues to improve and align with the best research practices (Hussein et al., 2021). The widespread recognition and adoption of PRISMA by supply chain researchers (Agac et al., 2023, D'Eusanio et al., 2019) has led to a uniform standard of conducting and reporting systematic reviews and meta-analyses, facilitating ease of interpretation and comparison across different studies, and enhancing the overall quality of research synthesis in the scientific community.

To address the challenges arising from the varying theoretical perspectives that shape the interpretation of research findings in supply chain domain, this paper adopts the six-step process outlined by Durach et al. (2017) to ensure the reproducibility of the research methodology. The process commences with the formulation of research questions, followed by the establishment of inclusion and exclusion criteria through pilot research. Subsequently, a baseline sample of potentially relevant articles is retrieved, and pre-defined criteria are applied to refine the database. The articles are then synthesized, and the findings of the systematic literature review are reported, as presented in Table 1. Anchored in a systematic literature review, thematic analysis involves identifying and analyzing patterns within textual data to identify recurring themes, to investigate the implicit themes and provides answers to 'what' questions (Braun and Clarke, 2006). The amalgamation of bibliometric and thematic analysis provides valuable insights into the scope and extent of the literature in AI and the supply chain decision-making field. The subsequent discussion and conclusion allow a comprehensive assessment of the state of current research and emerging propositions that are shaping its direction.

Table 1. Completion of the six-step PRISMA checklist (Source: Authors own creation).

Step 1: Formulate research questions

Since the paper aims at exploring triggers and technological inhibitors of AI in supply chain, the following research questions are formulated: "RQ1: What are the environmental, social and governance triggers and technological inhibitors influencing the adoption of AI in supply chain? RQ2: How do the identified triggers and inhibitors impact the adoption of AI in the supply chain, and what are the implications for supply chains?"

Step 2: Determine inclusion and exclusion criteria

To identify articles with potential significant contributions warranting further review, this study followed a pilot search process based on the guidelines outlined by Denyer and Tranfield (2009).

- The articles should be peer-reviewed journal articles.
- The articles should be written in English.
- The articles must include at least one predefined keyword from each subset in their title, abstract, or keywords to ensure substantive relevance.
- The articles that were found to be substantively irrelevant were excluded from the review.
- The abstracts of the remaining articles were carefully examined to ensure both substantive and empirical relevance.
- The remaining articles were reviewed in their entirety to ensure their continued substantive and empirical relevance.

Step 3: Retrieve a baseline sample of articles

A systematic search was conducted within three prominent databases: Emerald Insight, Scopus, and Science Direct, specifically focusing on peer-reviewed journal articles. These databases were chosen due to their extensive coverage of peer-reviewed journal articles across a wide range of disciplines. 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’) and (‘decision making or decision) and (‘enablers’ or ‘barriers’ or ‘triggers’ or ‘inhibitors’ or ‘opportunities’ or ‘challenges’ or ‘facilitators’ or ‘constraints’)

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 1394 articles that were potentially relevant to the research question under investigation (526 in Emerald Insight, 292 in Scopus, and 576 in Science Direct).

Following a screening process, which included removing duplicates (n=65) and removing non-journal articles (n=56), a total of 1273 distinct articles were identified in April 2023 (500 in Emerald Insight, 275 in Scopus, 498 in Science Direct)

Step 4: Apply the inclusion/exclusion criteria from step two

To acquire a subset of relevant studies, the inclusion/exclusion criteria (Step 2) were applied to the initial sample. In order to mitigate any potential bias, the criteria were independently and collectively evaluated by two scholars during the article review process. This methodology guarantees a high level of precision in the selection of studies, reducing the possibility of introducing extraneous or irrelevant information into the analysis. Following a comprehensive screening process, a total of 73 pertinent articles were initially identified.

Step 5: Synthesize the articles

The methodology employed in this study embraced an aggregative synthesis approach that integrates both quantitative and qualitative components (Denyer and Tranfield, 2009).

- The quantitative synthesis involved a data extraction process from the chosen articles, following a predefined coding structure that encompassed essential variables such as publication date, research methodology and innovation, industry sector, and utilization of AI techniques.
- The qualitative synthesis involves conducting a thematic analysis to address the research questions formulated at the beginning of the review, based on the themes that emerge during the qualitative synthesis phase of the review. Thematic analysis, a qualitative research methodology, is considered a less complex form of analysis compared to other qualitative approaches, making it a favourable choice for researchers who are still in the early stages of their research career (Braun and Clarke, 2006). Thematic analysis has been recognized as a valuable research method for exploring diverse perspectives, highlighting similarities and differences, and generating unexpected insights from research participants. It has also been widely adopted in supply chain research (Riahi et al., 2021, Younis et al., 2022).

Step 6: Report the results

The sample of synthesis (n=73) was subjected to a descriptive analysis, which involved the application of pre-defined coding structures outlined in Step 5 of the study. The initial presentation includes the findings derived from this analysis, while the subsequent thematic analysis focuses on addressing the research questions formulated in Step 1, using the themes that emerged during the qualitative synthesis process in Step 5.

3. Findings from descriptive and thematic analysis

This section offers an extensive examination of the industry sectors, temporal distribution, research methodologies, AI techniques, and research innovations. Subsequently, employing a thematic analysis approach to identify the recurring themes and patterns of triggers and technological inhibitors linked to the adoption of AI in industry-specific supply chains. The ultimate phase of this research entails integrating the identified triggers and inhibitors with the foundational ESG conceptual framework, thereby generating insightful propositions.

3.1 Descriptive analysis

When categorizing the supply chain by industry, the aim of this section was to provide a standardized directory of industries. Through a detailed analysis conducted throughout the selected papers, clustering similar industries, and differentiating them from others. The use of standardized terminology to categorize supply chain industries is essential for ensuring comparability across different studies. In some instances, authors may refer to their research industry as either agricultural or food supply chain. To address this issue, we have adopted the standardized category of 'agri-food'. Similarly, the healthcare supply chain encompasses various sub-industries, including pharmaceuticals, medical devices and equipment, clinical supplies, and other healthcare-related products and services. On the other hand, fashion, chemical, timber and petroleum supply chains are distinct and not combined with other industries. By using standardized categories, this research distinguishes between different supply chain industries and ensure consistency in their terminology. The findings presented in Figure 1 indicate that the agri-food industry is a widely discussed topics among scholars, constituting 30% of the total frequency, followed by manufacturing and healthcare supply chain, accounting for 27% and 15% of selected papers respectively. The obtained result is consistent with the current research and industry development, as the increasing use of AI in the agricultural and food industry is driven by the need for food security (Bhatia and Albarrak, 2023), traceability (Hassoun et al., 2023) and sustainability (Sharma et al., 2022); the use of AI in manufacturing supply chain motivated by circular economy (Bag et al., 2021b); while the necessity for sustainable healthcare services is promoting significant attention towards the implementation of AI (Sood et al., 2022).

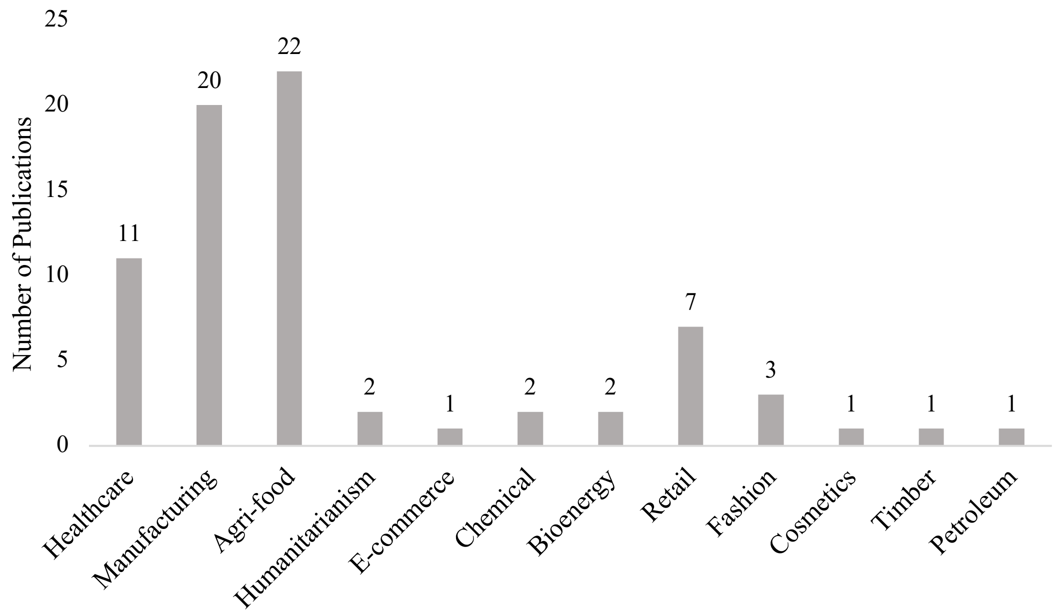

Figure 1. The distribution of supply chain industries (Source: Authors own creation).

In order to gain insights into the evolution of AI research in supply chain industry-specific decision-making, a time series analysis of relevant literature has presented in Figure 2. As depicted, all the journal publications identified were published between 2001 and 2023 Notably, a significant increase in scholarly attention towards AI in supply chain decision-making is evident, with 75% of papers published after the year of 2017.

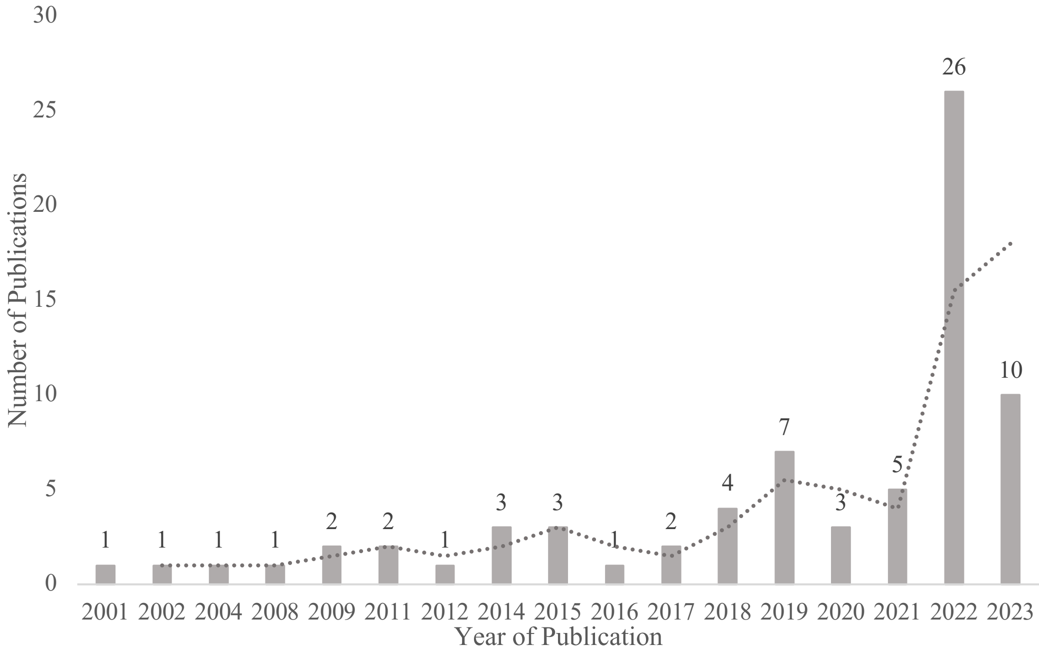

Figure 2. Temporal distribution (Source: Authors own creation).

When outlining research methodologies, the purpose of this section was to present a comprehensive and comparable list of methods. To achieve this goal, a detailed analysis of the research methodology was conducted to cluster similar methods and distinguish them from others, as shown in Table 2. For instance, authors may refer to their methods as either interviews or questionnaires, but both methods have been categorized as ‘survey’ to ensure a standardized category. Moreover the ‘literature review’ category encompasses papers that rely on published literature to conduct their research, such as bibliometric analysis and systematic literature review. The ‘modeling’ category encompasses papers that utilize mathematical frameworks to understand system dynamics and predict future outcomes. Ultimately, other scholarly works have emphasized the utilization of simulation, experimental research, and case studies. Authors also demonstrate particular significance in their attempt to integrate hybrid research methods, particularly the combination of Modeling approaches and case studies (Leung et al., 2018, Momenitabar et al., 2022, Ortiz-Barrios et al., 2023), as a means of evaluating results and generating innovative research.

Table 2. Research methods (Source: Authors own creation).

Industry	Method	Articles
Agri-food (22)	Modeling	8
	Literature review	11
	Experiments	1
	Case study	1
	Survey	1
Manufacturing (20)	Modeling	14
	Simulation	1
	Survey	2
	Literature review	1

	Case study	1
	Experiments	1
Healthcare (11)	Modeling	5
	Literature review	2
	Survey	2
	Case study	1
	Experiments	1
Humanitarianism (2)	Survey	2
E-commerce (1)	Modeling	1
Chemical (2)	Modeling	2
Bioenergy (2)	Modeling	1
	Literature review	1
Retail (7)	Case study	1
	Literature review	1
	Simulation	1
	Modeling	3
	Experiments	1
Fashion (3)	Survey	1
	Literature review	2
Cosmetics (1)	Modeling	1
Timber (1)	Modeling	1
Petroleum (1)	Modeling	1

The application of AI technique has been described as methods used to enable computers to perform intelligent activities resembling human decision-making. Prior to conducting research on AI techniques, a list of such techniques is evaluated from existing literature (Table 3). For the chosen journal papers, 48% of authors do not concentrate on individual algorithms or models, owing to the research methods employed, particularly in the case of literature review. Instead, a broad perspective of general AI has been provided, including machine learning, deep learning, and reinforcement learning. Regarding the remaining 52%, it has been found that artificial neural networks and genetic algorithms are frequently employed techniques within industry-specific supply chain domain.

Table 3. The implementation of AI techniques (Source: Authors own creation).

Techniques	Features	Articles
Genetic algorithm	Determining an optimal set	6
Case based modeling	Modeling the reasoning process	1
Artificial neural networks	Learning nonlinear function	8
Expert system	Providing recommendations or solutions	1
Random forest	Assisting classification and regression	2
Intelligent decision support system	Providing information and analysis	5
Multi-agent systems	Solving monolithic system problems	4
Robotics	Executing task autonomously	2
Heuristics	Solving no extract solution problems	2
Ant colony optimization	Simulating behaviour with optimal solution	1

Swarm intelligence	Solving non-deterministic polynomial time	1
Bayesian networks	Predicting the likelihood	2
Natural language processing	Breaking down and interpret human language	1
Fuzzy logic	Modeling logical reasoning	2

A range of research outcomes pertaining to different industries have been explored and identified in Table 4. These outcomes include model (21%), review (19%), framework (19%), application (15%), approach (14%), methods (4%), system (3%), comparison (3%), application scenario (1%) and tool (1%). For the agri-food, manufacturing, and healthcare supply chains, the most notable research advancements are in the areas of literature review, framework development, and model creation, in that order of importance.

Table 4. Research outcome distribution (Source: Authors own creation).

Industry	Result	Articles
Agri-food (22)	Methods	1
	Approach	4
	Review	9
	Application	1
	Framework	3
	Model	4
Manufacturing (20)	Approach	3
	Framework	7
	Model	3
	Tool	1
	Application	2
	Comparison	1
	Review	1
	Methods	2
Healthcare (11)	Model	4
	Application	3
	Framework	2
	Review	1
	Approach	1
Humanitarianism (2)	Framework	1
	Approach	1
E-commerce (1)	System	1
Chemical (2)	Model	1
	Application	1
Bioenergy (2)	System	1
	Review	1
Retail (7)	Framework	1
	Review	1
	Model	1
	Approach	1
	Comparison	1
	Application	2
Fashion (3)	Application scenario	1

	Review	1
	Model	1
Cosmetics (1)	Model	1
Timber (1)	Application	1
Petroleum (1)	Application	1

3.2 *Thematic Analysis*

To answer the RQ1, this purpose of this section was to integrate common codes related to AI in supply chain industry-specific decision-making triggers and technological inhibitors. To achieve the aim, this research innovatively combine the ESG framework with thematic analysis. Thematic analysis is one of the most accessible qualitative research methods that aims to group meaningful themes from a group of codes (Braun and Clarke, 2012). For instance, in argi-food industry, when the food waste and agricultural environment impact emerged, they were collaboratively labelled as codes and stored under the themes of environmental sustainability. While, in manufacturing industry, when the waste reduction and supply chain risk management emerged, they were separately labelled as codes and then stored under the overarching theme of environmental sustainability. This method was performed consecutively over the whole database of selected journal publications, resulting in a large list of open coding associated with triggers and technological inhibitors for AI adoption. It is noteworthy that some authors mentioned environmental, social and governance perspectives in one paper, which were separated into different codes in the current thematic analysis. The next stage of the thematic analysis aimed to group the relevant open coding into notable themes based on the features of ESG. Table 5 displays the open coding for triggers and how they were combining to a significant axial theme, while Table 6 displays the technological inhibitors of AI implementation.

Table 5. The triggers of AI in supply chain industry-specific decision-making (Source: Authors own creation).

Industries	Axial Themes	Open Coding	Articles
Agri-food	Environmental Sustainability	Monitoring crop and reduce negative environment impact	(Javaid et al., 2023, Serazetdinova et al., 2019)
		Reduce food waste	(Ramirez-Asis et al., 2022, Sharma et al., 2022)
	Social Responsibility	Food security and quality	(Hassoun et al., 2023, Craigon et al., 2023, Ramirez-Asis et al., 2022, Serazetdinova et al., 2019, Talari et al., 2021, Yu et al., 2022, Bhatia and Albarrak, 2023, Makridis et al., 2022)
	Governance	Operation cost	(Chiadamrong

		reduction; improve production efficiency	and Kawtummachai, 2008, Smith, 2019, Cai et al., 2018, Nakandala et al., 2016, Lambert et al., 2014)
		Sustainable agriculture supply chain performance	(Sharma et al., 2020, Kliangkhlao et al., 2022)
		Satisfy need of stakeholders	(Lezoche et al., 2020)
		Supply chain integration	(Nayal et al., 2022)
Manufacturing	Environmental Sustainability	Reduce waste generation in production	(Sinha and Anand, 2017)
	Governance	Sustainable supplier selection	(Orji and Wei, 2015)
		Circular economy and sustainable capabilities	(Bag et al., 2021b, Jamwal et al., 2022)
		Supply risk management	(Liu, 2022, Cavalcante et al., 2019)
		Supply chain collaboration	(Li et al., 2001)
		Supply network performance and optimization	(Chan and Chan, 2004, Narwane et al., 2021, Choy et al., 2002, Dubey et al., 2020, Bourke, 2019, Che et al., 2022, Dong, 2022, Kasie et al., 2017, Chen et al., 2022)
		Tactical knowledge sharing	(Al-Mutawah et al., 2009)
		Production monitoring and scheduling	(Guo et al., 2015, Kehayov et al., 2022)
		Sustainable logistics	(Arunmozhi et al., 2022)
Healthcare	Environmental Sustainability	Hospital environmental performance	(Benzidia et al., 2021)
	Social Responsibility	Improve the treatment capability and public	(Benzidia et al., 2021, Kumar et

		health; sustainable healthcare services	al., 2023a, Sood et al., 2022, Piccialli et al., 2021, Bag et al., 2023, Ortiz-Barrios et al., 2023, Abukhousa et al., 2014, Alrajhi et al., 2022, Azadi et al., 2023)
	Governance	Green supply chain collaboration	(Benzidia et al., 2021)
		Resilience pharmaceutical supply chain	(Santos et al., 2022)
		Inter-organizational healthcare networks	(Cannavale et al., 2022)
Humanitarianism	Governance	Alliance management capability	(Dubey et al., 2021)
		Agility and resilience supply chain	
E-commerce	Environmental Sustainability	Circular economy	(Leung et al., 2018)
	Governance	Reduction in order processing time and traveling distance	
Chemical	Environmental Sustainability	Sustainable production	(Chiang et al., 2022)
	Social Responsibility	Safe and reliable production	
	Governance	Sustainable supply network	(Momenitabar et al., 2022)
Bioenergy	Environmental Sustainability	Net-Zero emissions	(Ayoub et al., 2009)
	Social Responsibility	Labour rights	
	Governance	Fuel production efficiency	
		Bioenergy supply optimization	(Castillo-Villar, 2014)
Retail	Governance	Price optimization	(Simchi-Levi and Wu, 2018)
		Cost reduction	(Borade and Sweeney, 2015, Li and Li, 2022)
		Supply-demand synchronization	(Pereira et al., 2018, Pereira and Frazzon, 2019, Pereira et al.,

			2022)
		Efficiency and productivity	(Mahroof, 2019)
Fashion	Environmental Sustainability	Assist customers to gauge environmental sustainability	(Pereira et al., 2022)
	Social Responsibility	Preservation of jobs	
	Governance	Agile supply chain	(Mohiuddin Babu et al., 2022, Guo et al., 2011)
Cosmetics	Governance	Supplier performance evaluation	(Vahdani et al., 2012)
Timber	Environmental Sustainability	Land use optimization	(Frayret, 2011)
	Governance	Production and transportation operations management	
Petroleum	Environmental Sustainability	Reduce carbon emission and oil spills	(Kumar and Barua, 2022)
	Social Responsibility	Mental, physical, and social well-being of works	
	Governance	Sustainable dimensions in the oil and natural gas	

This research identified three primary codes, namely environmental sustainability, social responsibility, and governance. The code of 'environmental sustainability' encompasses a range of environmentally beneficial practices, such as achieving net-zero emissions, adopting circular economy principles, reducing waste, and promoting environmentally sustainable production. These practices are particularly relevant in supply chain industries such as agri-food, manufacturing, petroleum, bioenergy, and timber. Similarly, the code of 'social responsibility' encompasses aspects related to mental, physical, and social well-being, food security and quality, and the resilience of healthcare systems, reflecting the public's demand for responsible and ethical practices. Under the code of operational governance, various codes such as supply chain agility and resilience, sustainable supply chain management, supply chain network optimization, and performance evaluation have been identified, emphasizing the importance of governance in ensuring effective and sustainable supply chain operations. Overall, the findings highlight the potential of AI to enhance transparency and accountability in supply chain operations, thereby facilitating the achievement of environmental and social sustainability objectives.

Table 6. The technological inhibitors of AI in supply chain industry-specific decision-making (Source: Authors own creation).

Axial coding	Opening coding	Sources
Technological inhibitors	Lack of regulations and rules	(Nayal et al., 2021)
	Lack of data security and privacy	
	Responsible and ethical AI	(Craigon et al., 2023)
	Performance and ethical assessment	(Manning et al., 2023)

	Poor Data quality Group bias AI and human synergy	(Mahroof, 2019)

The theme of technological inhibitors is focused on addressing the various obstacles that impede the successful implementation of AI in supply chain industries, particularly within the agri-food and retail sectors (Table 6). These challenges include the absence of sufficient regulations and rules at both the state and central levels, as well as concerns regarding the quality, security, and privacy of data (Nayal et al., 2021). Another obstacle involves the lack of responsible and ethical AI practices (Craigon et al., 2023). Additionally, there is a lack of performance evaluation and measurement (Manning et al., 2023), which can lead to difficulties in assessing the effectiveness and benefits of AI in supply chain operations. Finally, there is a need to promote human-centric smart warehousing in the retail sector (Mahroof, 2019).

Table 7. Thematic analysis industry-specific frequency (Source: Authors own creation).

Industry	E	S	G
Agri-food	2 29%	1 14%	4 57%
Manufacturing	1 11%	0 0	8 89%
Healthcare	1 20%	1 20%	3 60%
Humanitarianism	0 0	0 0	2 100%
E-commerce	1 50%	0 0	1 50%
Chemical	1 33%	1 33%	1 33%
Bioenergy	1 25%	1 25%	2 50%
Retail	0 0	0 0	4 100%
Fashion	1 33%	1 33%	1 33%
Cosmetics	0 0	0 0	1 100%
Timber	1 50%	0 0	1 50%
Petroleum	1 33%	1 33%	1 33%

The examination of industry-specific supply chains within the context of the ESG framework enables current research to identify varying ESG focuses across different industries. The frequency has been conducted based on the axial codes for each respective industry, serving as a basis for the investigation of the respective industry's focus on ESG dimensions (Table 7). According to the findings, the agri-food supply chain exhibits the greatest emphasis on ESG factors, where 57% of the codes are associated with governance, 29% with environmental concerns, and 14% with social dimensions. This can be attributed to the substantial environmental impact of the industry, the heightened focus on responsible sourcing and sustainable supply chains, and the intricate and obscure nature of agri-food supply chains. The manufacturing industry demonstrates a notable emphasis on the governance dimension, as evidenced by the identification of 89% of codes related to this aspect, which can be attributed to the industry's need for efficient and optimized business practices, particularly given the complex and global nature of its supply chains. Conversely, chemical, fashion, and petroleum supply chains exhibit a relatively balanced focus across all three ESG dimensions. In terms of healthcare and bioenergy supply chains, the governance aspect is the focus. In contrast, E-commerce and timber supply chains demonstrate a focus on AI implementation in both the environmental and governance dimensions. Meanwhile, the humanitarianism, retail and cosmetics supply chains concentrate solely on the governance aspect. The chart provides insight into the different ESG priorities in different industries, and how these priorities are reflected in the use of AI in the supply chain. It underscores the importance of considering the unique characteristics of each industry when implementing sustainable and responsible practices.

In addressing RQ1, this section presents a synthesis of research findings pertaining to open coding, and ESG axial coding, utilizing the triggers of AI implementation in supply chain industry-specific decision-making. Through an examination of code similarities and overlaps in specific industry, following their identification, the codes were systematically grouped according to their respective environmental, social, and governance dimensions. Additionally, the selected journals were scrutinized to identify potential technological inhibitors, running in parallel with the triggers.

4. Discussion with practical implications

The adoption of AI in agri-food supply chain has directed its attention to the three dimensions of ESG for various reasons. Firstly, the agriculture and food industry has been associated with substantial environmental impacts, including soil degradation, water pollution (Javaid et al., 2023) and food waste (Ramirez-Asis et al., 2022). Consequently, prioritizing environmental sustainability has become critical in mitigating these adverse effects. Secondly, social issues such as food security and quality have gained attention (Hassoun et al., 2023), particularly in responsible sourcing and sustainable supply chain efforts. Lastly, given the intricate and often opaque nature of the supply chains, supply chain integration (Nayal et al., 2022), efficiency (Nakandala et al., 2016), and sustainability (Sharma et al., 2020) have become crucial factors to consider.

The Covid-19 pandemic has highlighted the need for resilient and agile healthcare supply chains that respond quickly to unexpected disruption. The pandemic exposed vulnerabilities in global healthcare supply chains, including the urgent need for improving stockpiling and inventory management (Alrajhi et al., 2022), collaboration and information sharing (Cannavale et al., 2022), and sustainable and green healthcare supply chain (Sood et al., 2022). To enhance public health and the capacity for medical treatment, AI has been utilized in various areas of medical supply chain management, including demand forecasting, enabling the prediction of future demand for medical supplies and equipment; inventory management, facilitating real-time monitoring of inventory to reduce waste and inefficiencies by identifying stockouts and overstocking; quality control, allowing for monitoring of the quality of medical supplies and equipment to identify defects and anomalies; and route optimization, enabling the optimization of delivery routes for medical supplies and equipment based on factors such as policies, traffic, weather, and road conditions.

The chemical and bioenergy supply chains exhibit some overlaps in axial codes with respect to the ESG dimensions. From an environmental perspective, the application of AI in these supply chains could aid in making more sustainable decisions and achieving the goal of net-zero emissions by analyzing environmental data and identifying opportunities for green chemistry and bioenergy throughout the production and logistics phases (Ayoub et al., 2009). From a social perspective, AI can facilitate the identification of potential health and safety risks associated with chemicals and promote ethical supply chain operations by identifying and selecting suppliers that prioritize fair labour practices, human rights, and healthy products (Chiang et al., 2022). For the governance perspective, AI play a crucial role in promoting transparency and accountability in both the chemical and bioenergy supply chains by providing real-time data on performance, ensuring a sustainable and efficient management of these supply chains (Castillo-Villar, 2014, Momenitabar et al., 2022).

Both the fashion and petroleum industries demonstrate a significant emphasis on the of environmental sustainability and social responsibility. Supply chains within the fashion industry seek to provide customers with comprehensive information about sustainable products and sustainable practices (Pereira et al., 2022). Moreover, the industry upholds its social responsibility by preserving jobs within the supply chain. Petroleum supply chain aims to minimize carbon emissions and oil spills to safeguard the environment, while prioritizing the physical, mental, and social well-being of their workforce (Kumar and Barua, 2022). It is crucial to recognize that the ESG aspects are interconnected and mutually impact one another. The implementation of agile and sustainable operational governance practices, which entail a complex decision-making process, will have a bearing on the response of industries to environmental and social responsibility. Based on these considerations, two propositions have been proposed.

Proposition 1: The agri-food, healthcare, chemical, bioenergy, fashion, and petroleum industries have demonstrated a collective commitment to addressing environmental, social, and governance concerns through the adoption of AI in their operations. These industries are leveraging AI to enhance their sustainable development efforts by improving ESG performance, minimizing environmental impact, and promoting social well-being, thereby fostering a more responsible and sustainable industrial ecosystem.

The supply chain industries include manufacturing, e-commerce, and timber focus heavily on environmental and governance dimensions. The manufacturing industry has always been a major contributor to environmental pollution. Specifically, in the manufacturing industry, the functions of AI in reducing waste generation and promoting environmental sustainability have been emphasized (Sinha and Anand, 2017). Furthermore, AI can be used to manage supply chain networks (Chen et al., 2022, Narwane et al., 2021), ensuring compliance with regulatory standards and promoting good governance practices. The e-commerce industry has seen a significant increase in demand due to the COVID-19 pandemic. However, this increase in demand has also led to an increase in the carbon footprint of the industry. To this extent, AI can facilitate the transition towards a circular economy, reducing order processing time and traveling distance, leading to better governance practices and increased efficiency, thereby reducing waste, and promoting environmental sustainability (Leung et al., 2018). The timber supply chain is a complex system that involves multiple stakeholders, including forest owners, suppliers, manufacturers, and retailers. However, this industry is also facing significant environmental challenges, including deforestation and habitat destruction. In the context of the timber industry, there is a pressing need to mitigate the detrimental effects of deforestation and promote ecological sustainability. To address these challenges, multi-agent system is being employed to oversee production and transportation activities, with the goal of ensuring adherence to regulatory frameworks and encouraging the adoption of best practices for governance (Frayret, 2011). From that point of view, the following proposition has been emphasized.

Proposition 2: Confronted with stricter governance regulations and dynamic competition, one way to achieve economically and environmentally sustainable is by leveraging AI to optimize the decisions of manufacturing, e-commerce, and timber supply chain, with the aim of reducing the negative environmental impact, and complying with regulatory requirements. However, social factors should be considered as a proactive approach to identify and address social issues to promote sustainable and ethical supply chain practices.

The supply chain industries, especially for the humanitarianism, retail and cosmetics, have a commonality of adopting AI as a means to enhance their supply chain performance, with a predominant focus on governance. The humanitarianism industry places emphasis on alliance management capability, an essential aspect for efficient coordination of relief efforts (Dubey et al., 2021). Governance is a key area of focus for the retail industry, with a focus on price optimization (Simchi-Levi and Wu, 2018), cost reduction (Borade and Sweeney, 2015, Li and Li, 2022), supply-demand synchronization (Pereira et al., 2022), and improving efficiency and productivity (Mahroof, 2019). In a similar vein, the cosmetics supply chains prioritize governance for the optimization of their operational processes (Guo et al., 2011), ranging from supplier selection to performance evaluation (Vahdani et al., 2012). When integrating AI technology, humanitarian organizations can enhance their supply chain visibility, risk mitigation, and decision-making processes. Retailers can optimize their pricing strategies, inventory management, and delivery efficiency by identifying customer demand trends. In addition, AI can assist cosmetics companies to monitor supplier performance, mitigate potential risks, and ensure compliance with ethical and sustainability standards. This brings to the third proposition in the context of humanitarianism, retail, and cosmetics.

Proposition 3: The integration of decision-making governance within the humanitarianism, retail and cosmetics supply chains presents a promising opportunity for AI to assist sustainability and ethical practices, with the aim of enhancing transparency, efficiency, and ethical standards, thus contributing to environmental sustainability.

Undoubtedly, the application of AI has potential to augment the resilience of the supply chain, reduce supply chain risk, and advance sustainable supply chain practices. Nevertheless, AI models possess intrinsic characteristics, particularly black-box decision-making, which encompasses the entire machine learning and deep learning model lifecycle, from data input with quality, security, and privacy features to performance and ethical AI assessment (Manning et al., 2023, Craigon et al., 2023). Hence, the pressing need for central and state regulations, AI traceability, and accountability heightens the demand for human-AI collaboration (Nayal et al., 2021). Therefore, the following proposition has been proposed to address the technological inhibitors of AI implementation.

Proposition 4: The successful implementation of AI in supply chain requires a holistic approach that ensures data quality, security, and privacy while also prioritizing AI performance and ethical considerations. Human-centred assessment must be incorporated into the implementation process to ensure that AI-driven decision-making is transparent, fair, and accountable, and that the potential biases and risks associated with AI are identified and mitigated.

5. Discussion with theoretical implications

For cross-industries, a comprehensive summary of the triggers and inhibitors in various dimensions has been provided in Table 8. In the environmental dimension, triggers include product waste reduction and emissions reduction, highlighting the potential of AI in promoting sustainability and environmental responsibility. In the social dimension, triggers encompass product security and quality, as well as social well-being, indicating how AI can contribute to ensuring safe and high-quality products and enhancing societal welfare. In the governance dimension, triggers involve agile and lean practices, cost reduction, sustainable supplier selection, circular economy initiatives, supply chain risk management, knowledge sharing, and the synergy of supply and demand. These triggers shed light on how AI can drive efficiency, effectiveness, and responsible governance practices in supply chains. The inhibitors in the technological category present challenges that hinder the adoption of AI in supply chain. These inhibitors encompass the lack of regulations and rules, data security and privacy concerns, responsible and ethical AI considerations, performance and ethical assessment difficulties, poor data quality, group bias, and the need to achieve synergy between AI and human decision-makers.

Even with the triggers in enhancing environmental, social, and governance dimensions of supply chains, a theoretical gap lingers in understanding the exact mechanisms through which these triggers are activated. Moreover, while triggers for product waste reduction, gas emissions reduction, social well-being, and efficient governance practices is acknowledged in AI adoption, the means through which they act differently as triggers across diverse industrial contexts remains a subject of investigation. Future research can fill this theoretical void by delving into in diverse industrial contexts. The inhibitors signal a theoretical gap in our understanding of how these challenges can be successfully navigated to harness the potential triggers of AI. The technological inhibitors associated with AI, in particular, pose questions about privacy, fairness, and accountability that existing supply chain theories might not sufficiently address. Furthermore, the task of ensuring AI works in harmony with human decision-makers exposes a need for theories that can integrate both human and AI agents in the supply chain. As such, future research should endeavour to comprehend these inhibitors more thoroughly and establish frameworks that can guide the ethical, secure, and collaborative implementation of AI in supply chains.

Table 8. Summary of cross-industries triggers and inhibitors (Source: Authors own creation).

Triggers/Inhibitors	Dimensions	Themes
Triggers	Environmental	Product waste reduction
		Emissions reduction
	Social	Product security and quality
		Social well-being
	Governance	Agile and lean practices
		Cost reduction
		Sustainable supplier selection
		Circular economy
		Supply chain risk management
		Knowledge sharing
		Synergy of supply and demand
Inhibitors	Technological	Lack of regulations and rules
		Lack of data security and privacy
		Responsible and ethical AI
		Performance and ethical assessment
		Poor Data quality
		Group bias
		AI and human synergy

6. Conclusions

This study has presented a systematic literature review comprising 73 journal publications. The objective of the review was to identify the triggers under the ESG framework and the technological inhibitors that impede the adoption of AI in supply chain decision-making.

By conducting the systematic literature review, the current outline of AI decision-making practices in supply chain domain have been addressed. Starting from the descriptive analysis, the key research trends have been recognized, namely the variety of supply chain industries, the time distribution of publications, the diverse range of research methodologies employed AI techniques, and the observed various research innovations. A total number of 12 supply chain industries have been found, with a concentration of investigations in the agri-food, manufacturing, healthcare, humanitarian, e-commerce, chemical, bioenergy, retail, fashion, cosmetics, timber, and petroleum. In terms of time distribution, a significant increase in scholarly attention towards AI in supply chain decision-making is evident, with 75% of papers published after the year of 2017. As for methodologies carried out to explore AI in supply chain industry-specific decision-making, hybrid modeling is an outstanding method for manufacturing, healthcare, e-commerce, chemical, bioenergy, retail, cosmetics, timber, and petroleum; survey is a primary method for humanitarianism and fashion supply chain, while literature review is a predominant method for agri-food supply chain. Approximately 48% of selected papers do not concentrate on specific models, owing to the research methods employed, a broad perspective of general intelligent action has been provided. While the remaining 52% has showed that artificial neural networks and genetic algorithms are frequently employed techniques within industry-specific supply chain domain. Finally, a range of research outcomes pertaining to different industries have been explored, with a focus on model, review, framework, application, and approach. These findings support the study trend found in the literature. First, it represents the maturity of AI research in supply chain industry, especially in the neural network and genetic algorithms; second, it confirms the importance of research methods, especially for the hybrid modeling with case studies.

In RQ1 and RQ2, this research carried out a thematic analysis to investigate the meaningful triggers that promote AI in supply chain decision-making. The open coding process was performed consecutively across the entire database to achieve saturation, and then the codes have been merged into ESG dimensions with an industry-specific perspective. The agri-food, healthcare, chemical, bioenergy, fashion, and petroleum industries have demonstrated a collective commitment to addressing environmental, social, and governance concerns through the adoption of AI in their operations. In contrast, the manufacturing, e-commerce, and timber supply chain have predominantly concentrated their efforts on environmental and governance perspectives, utilizing the potential of AI to mitigate adverse environmental impacts and conform to regulatory mandates. In the case of supply chains pertaining to retail and cosmetics industries, the primary focus has been on governance considerations to bolster transparency, efficiency, and ethical standards, ultimately working towards the goal of environmental sustainability. Conversely, humanitarianism supply chains display a more nuanced approach, taking into account a broader set of factors beyond governance, such as social and economic considerations, in addition to environmental impact mitigation. The successful adoption of AI within supply chain management necessitates a comprehensive approach that emphasizes the importance of data quality, security, and privacy, while simultaneously prioritizing AI performance and ethical considerations. In this regard, it is crucial to incorporate human-centred assessments throughout the implementation process to ensure that AI-powered decision-making is transparent, fair, and accountable, while identifying and mitigating any potential biases and risks associated with AI. Additionally, supply chain industries seeking to leverage AI technologies must prioritize the optimization of operational, tactical, and strategic decision-making processes with the ultimate aim of promoting social well-being and realizing a sustainable, green, collaborative, and agile supply chain.

Due to the aim of this study, which was to identify industry-specific supply chain and management science publications related to predefined keywords, a selection bias is a limitation of this paper. The exclusion of other database and industry reports not on the predefined list and the possibility of keywords presented only in the main body of the paper being excluded from our selection also contribute to this limitation. However, despite this limitation, the insights presented in this paper may serve as a valuable resource for future researchers to better understand the implementation of AI in the sustainable supply chain. Future research should explore benchmarking cases across various supply chain industries to gain further insights into this field. Additionally, the use of Delphi studies with DEMATEL approach can help to clarify the themes we investigated or identify new themes for the ESG framework. It is also of interest to examine the weight of themes in different sectors through a large-scale survey, which would enhance our understanding of the implementation of AI in the supply chain and contribute to sustainable, social and governance domain.

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