Enhancing Supply Chain Efficiency: The Role of Artificial Intelligence in Modern Business Logistics

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Received: 15.07.2024 Revised: 13.08.2024 Accepted: 07.09.2024

ABSTRACT
Many papers suggest that AI can enhance supply chain efficiency. The causes of this effect have also been explored. At this juncture, it was considered appropriate to review some recent trends in research on AI enhancing supply chain efficiency. Hence, this systematic review aimed to synthesise evidence from the recent literature on the role of AI in enhancing supply chain efficiency. Google Scholar was searched using an appropriate search term to achieve the aim. The identified papers were screened to select 25 papers through the PRISMA flow process using some inclusion and exclusion criteria. The 25 papers were used for this review. The review showed that the enthusiasm for research on the impact of AI on supply chain efficiency declined since 2022. The most discussed topics in the 25 reviewed papers were performance and its efficiency, resilience and mention of COVID. Collaboration, including green collaboration and various types of factors related to AI and supply chains, received less attention. Very few papers use d mixed methods for their research. Organisational information processing theory and dynamic capabilities theory seem to be more relevant to research on AI's impact on supply chain efficiency. The qualities of the reviewed papers were moderate to high. Future research on this topic should focus on supply chain efficiency to a greater extent. Green and sustainable chains, collaborations and risks should receive increased attention. They should use mixed methods more. Country comparisons, especially among developed, emerging and developing countries, may be useful. The best practices of using AI for supply chain efficiency should be studied in such multi-country comparisons. Some limitations of this review were relying on a single database, targeting a fixed number of papers and setting the period as 2020 to 2024 reduces the scope for selecting many good papers. However, as was said above, the quality of the selected papers was good. The period was chosen deliberately to reflect the latest research trends. These trends were discussed above.

Keywords: Artificial Intelligence, supply chain efficiency, organisational information processing theory, dynamic capabilities, T-O-E framework, collaboration, green supply chain.

INTRODUCTION

Organisational success depends on the interactions between the flows of information, materials, money, human power, equipment and capital. How these five flow systems interlockto amplify one another, and cause changes and fluctuationsaffects decisions, policiesand investment choices.Mentzer, et al. (2001) defined supply chains (SC) as “a set of three or more entities (organizations or individuals) directly involved in the upstream and downstream flows of products, services, finances, and/or information from a source to a customer.” “Source to customer” can be substituted by “raw material to finished products to customer.” (p 4). Thus, the supply chain is the group of manufacturers, suppliers, distributors, retailers transportation, information and other logistics management service providers that are engaged in providing goods to consumers and consists of both internal and external agencies.

“Supply chain management (SCM) is the design, planning, execution, control, and monitoring of supply chain activities to create net value, build a competitive infrastructure, leverage worldwide logistics, synchronise supply with demand, and measure performance globally” (ASCM, 2024).

According to the Supply Chain Forum, "Supply Chain Management (SCM) is the integrated planning and execution of processes required to manage the movement of materials, information, and financial capital across the entire supply chain, from raw material sourcing to the delivery of finished goods to the end

customer, with a focus on optimizing efficiency, cost-effectiveness, and customer satisfaction through collaboration among all supply chain partners.".
Supply chain efficiency (SCE) can be defined as the best use of all resources (financial, human, technological and physical) with minimum cost, time and wastage. (Merimi & Taghipour, 2021).
SCE can be enhanced using AI to analyse the large volume of data, inventory management, automate routine tasks and data-driven decisions. These uses of AI facilitate precise demand forecasting, optimisation of inventory management, optimisation of route, warehouse management, quality control, procurement optimisation, predictive maintenance and real-time visibility. These applications lead to cost reduction, increased agility and improved customer service.
Thus, many advantages of using AI for SCM are identified by research. Hence, it is appropriate to systematically review the literature on the role of AI in enhancing SCE in modern management logistics. This is attempted here. The aim and objectives of this review are listed below.
Aim: To synthesise evidence from the recent literature on the role of AI in enhancing supply chain efficiency.

METHODOLOGY
The search term used was "AI methods for supply chain management impacting supply chain efficiency." Using this search term, Google Scholar was searched to identify papers. The papers identified from Google Scholar were screened and selected repeatedly using the PRISMA flow process (appended) applying the inclusion and exclusion criteria listed in Table 1.

Table 1. Inclusion and exclusion criteria.

Inclusion criteria	Exclusion criteria	Remarks
Full texts	Abstracts	Abstracts may be included if they contain relevant information.
English	Other languages	Although translations are possible, they may not express the contents properly.
Published during 2020-2024	Earlier years	Some classical papers referred in the selected papers may be used, but not included in the list of reviewed papers.
	Dissertations	Being guided works, they may not reflect the author's views.
	Books	If full texts are available, they will be considered or selected chapters may be included.
	Book sections	If full texts are available, they will be considered.
	Editorials, comments on some papers, opinions	All will be excluded.
	Papers for which adequate reference details are not available.	Even if they contain useful information, the difficulty of citing properly excludes these papers.

A target of 25 papers was set for this review considering the permitted length of the paper.
Along with the textual description of the selected papers, an Excel spreadsheet was made containing reference details, aim, method, theory or framework used, findings, limitations and quality ratings as per the following parameters.

Citations per year
The number of citations is available for most papers in Google Scholar. However, the years of their publications are different. To compare the quality of papers based on the number of citations the total number of citations was divided by the number of years from publication to 2024. Thus, the average number of citations per year was used as a quality measure.

Adequacy of evidence assessment
Whether the evidence presented is adequate to reach the stated conclusion was qualitatively assessed using 1 (lowest) to 5 (highest) levels of adequacy.

Risk of Bias (RoB)
The National Toxicology Program's Office of Health Assessment and Translation (NTP OHAT) risk of bias (RoB) tool was used. This tool assesses RoB based on the criteria to select study participants, confounding, measurement of exposure and outcomes, follow-up of study participants, adequacy of the reporting of outcomes, and pre-specification of study analysis/study protocol. RoB was rated as 1 (lowest) to 5 (highest).

Grade
Certainty of evidence was evaluated by the Grading of Recommendations Assessment, Development and Evaluation (GRADE) framework. This was assessed as 1(lowest) to 5 (highest).

CCAT
Crowe Critical Appraisal Tool (CCAT; version 1.4) was used as a quality index of papers. CCAT consists of preliminaries, introduction, design, sampling, data collection, ethical matters, results, and discussion as the assessment items. The range of scores is 0 (lowest quality) to 5 (highest quality).

Overall quality
This score was obtained by adding the scores of mean citations per year, adequacy of evidence, GRADE and CCAT, subtracting the risk of bias from it, and then dividing the net sum by 5. That is-
Overall quality = (Citations+ Evidence adequacy + GRADE+ CCAT- RoB) /5.

Synthesis of literature
The data collected in the Excel spreadsheet were used for some quantitative synthesis across the papers to discover general trends. The detailed discussions were based on these and other qualitative aspects. Similar findings across different papers were pooled together and differentiated from contradictory findings to achieve the desired level of synthesis. In the results section, each paper is described in detail cross-referring to earlier concepts or frameworks if relevant. The PRISMA flow diagram is appended.
The selected papers are described in the next (Results) section. This is followed by the Discussion section which mainly deals with the analysis of some trends identified from the Excel entries. Then the main points of the review are summarised in the Conclusion section. Some limitations of this review are mentioned in the final section.

RESULTS
A survey of 279 firms of different sizes and sectorsfrom Morocco, France and India by Belhadi, et al. (2024) showed a short-term direct impact of AI on supply chain performance (SCP), the use of its information processing capacities to build supply chain resilience will have a long-term impact on the performance. Organisational information processing theory was used as the theoretical framework in this paper. A literature review by the authors showed that AI information processing capabilities can be used for the exploitation, expansion and exploration of massive data for various purposes. The limitations were dependence on one theory could bias the survey constructsand the impact of the COVID period on cross-sectional research.
The optimisation ofsupply chains in the U.S. has become increasingly critical in the wake of globalisation, market volatility and the recent disruptions caused by the COVID-19 pandemic. A survey of 180 US firms across different sectors and semi-structured interviews with 20 supply chain leaders was conducted by Shil, et al. (2024). Companies leveraging AI in their supply chain operations increased their efficiency by 7-8 units compared to 5.5 units (out of 10)for traditional methods and reduced their costs by 12-18% compared to 5.5% for traditional methods. The AI methods measured were predictive analytics, machine learning and automation. They also increased decision-making speed. Order fulfilment rate increased from 75% for traditional methods to about 90% for AI methods. The inventory turnover rate was 6.8 to 7.5 units for AI methods compared to 4.5 units for traditional methods. Supply chain agility increased from 0.6 units for traditional methods to 0.8 to 0.9 units for AI methods. The cost associated with traditional methods was $350000 against $250000 to $300000 with AI methods. There was an operational cost reduction of 20% and an inventory management cost reduction of 37.5%by AI implementation. However, issues of data management and challenges of integrating AI with the current systems were highlighted by some interviewees. The limitations of this study were the mismatch betweensome variables of quantitative and qualitative methods and cross-sectional studies. Additionally, the sample size of 180 may not be adequate for validity and generalisation.
Based on a survey of 351 Pakistani manufacturing and logistics firms,Nwagwu, et al. (2023)observed a significant influence of AI methods on the supply chain performance of these firms. Supply chain

collaboration partially mediated the relationship between AI and SCP. One limitation of this study may be the inclusion of interns and metrics in the survey participants as their knowledge of supply chain and AI might be very low to answer the survey items precisely.

Rathor (2023)explored how ChatGPT and AI may be used together to increase operational performance, promote sustainable development, and earn money from data that has been acquired. A survey of 159 US firms revealed no effect of using ChatGPT with AI on customer service, improved warehouse management or optimising route planning on sustainable SCM. The sample size of 159 may not be adequate for validity and generalisability.

A review of 127 papers by Ganesh and Kalpana (2022) showed that intelligent risk management facilitated by AI can improve supply chain resilience as it makes supply chains smarter. The authors proposed a risk management framework for further research.

Semi-structured interviews with 31 supply chain specialists conducted by Modgil, et al. (2022)revealed that AI-facilitated supply chains developed both structural and network resilience of supply chains during the COVID pandemic. Supply chains that are resilient in fluctuating environments and during significant disruptions like the pandemiccould identify risks, localization levels, failure modes, and data trends, assess (evaluating what-if scenarios, actual customer demand, conducting stress tests, and understanding constraints), reorganise (implementing automation, realigning the network, enhancing tracking efforts, addressing physical security risks, and exercising control) and quickly implement (setting operational guidelines, managing contingencies, responding to demand fluctuations, and alleviating supply chain shocks) their operations.Organisational information processing theory was used in this study.

Presenting a table showing the relationship between AI methods and their application in SCM,Helo and Hao (2022)analysed secondary data to observe that AI applications were used in SCM by firms for sales configuration, production planning and control, quality of products andspare parts and maintenance orders.

The study by Kasaraneni (2021) highlighted the transformative impact of AI-driven supply chain collaboration platforms in the retail industry through case studies of notable global companies. Technologies like machine learning, predictive analytics, and advanced data integration enhance coordination among stakeholders and lower operational costs. Key insights include AI's role in improving inventory management, optimising logistics, and fostering effective collaboration among the parties involved. Advanced demand forecasting and inventory strategies can significantly decrease stockouts and excess inventory. Furthermore, AI applications in logistics aid in dynamic route planning and cost reduction, leading to more efficient transportation. Despite these advantages, challenges such as data complexity and integration issues were noted.

A survey of 279 Indian agro-industries byNayal, et al. (2022) showed that AI adoption by these firms was influenced by process factors, information sharing, and supply chain integration (SCI). Supply chain risk mitigation(SCRM) induced by the COVID pandemic was positively influenced by AI. There was no effect of the technological,organisational and environmental factors on AI. The Technology-Organisation-Environment (TOE) framework was used in this study. Possible response bias, the use of one theory and missing some important variables were mentioned as the limitations of this study.

To examine how firms employ AI and consider the opportunities for AI to enhance supply chain resilience by developing visibility, risk, sourcing and distribution capabilities during the COVID pandemic,Modgil, et al. (2022)conducted semi-structured interviews with experts from the e-commerce supply chain. The authors identified five critical areas of AI contribution to enhanced supply chain resilience. These were transparency, ensuring last-mile delivery, offering personalised solutions to both upstream and downstream supply chain stakeholders, minimising the impact of disruption and facilitating an agile procurement strategy. Dynamic capabilities theory was used in this study. The experts expressed some points regarding AI use for risk management during uncertainties like the COVID-19 pandemic.Under the pandemic conditions, AI can play a critical role in aligning demand and supply to avoid the impact of disruption. During prolonged supply chain disruption, firms can use AIto increase their information processing capabilities leading to improved supply chain resilience by synchronising manufacturing and inventoryplanning. Under uncertain conditions, AI can help identify the most efficient local suppliers to reduce supply chain risks due to the emphasis on resilience in sourcing. Duringsocial distancing, AI facilitates the digital delivery of products to customers at the right time, right place and in the right quantity for customer satisfaction.During pandemic-type uncertainties, AI offers a higher degree of flexibility and automation enabling firms to quickly adjust to the changing environment and improve supply chainperformance by mitigating the disruption risk.

Management scholars hold differing views on the balance between responsiveness and efficiency. Nevertheless, organisations must be both agile and resilient to handle unforeseen events such as disasters effectively. Earlier research has utilised the resource-based view or dynamic capability view to analyse how the integration of resources and capabilities—such as technology, agility, and resilience—affects performance. However, based on some recent academic discussions, Dubey, et al. (2022) contended that traditional organisational theories like the resource-based view and dynamic capability view, are inadequate for explaining the performance of humanitarian supply chains. Humanitarian organisations are not convinced aboutthe need to adopt AI-driven big data analytics capability (AI-BDAC) for their decision-making process. Using a practice-based and contingency approach, the authors surveyed 171 international NGOsand 17 semi-structured interviews with managers of these NGOs to find AI-BDAC a significant determinant of agility, resilience and performance. AI-BDAC positivelyinfluenced agility, resilience and performance. Agility and resilience positively influenced performance. The interactive effects of agility withinformation complexity and resilience with information complexity negatively influenced performance. There was a reduction in the level of information complexity (IC) on the paths connecting agility, resilience, and performance in the humanitarian supply chain. These findings indicate that the supply chain designs of humanitarian organisations are different from commercial organisations. Therefore, in these cases, practice-based approaches are more valid than the theories of resource-based view or dynamic capabilities.

A review by Tirkolaee, et al. (2021) showed that ML methods can be used for selecting and segmenting suppliers, predicting supply chain risks, and estimating demand, sales, production, inventory management, transportation and distribution, sustainable development (SD), and circular economy (CE). The authors did not explain the method of selecting the papers or the number of papers used in the review.

A systematic review of 64 papers by Toorajipour, et al. (2021) showed many trends. Of the many available AI methods, the most used is artificial neural networks(ANNs). This is used for pattern classification, approximation, optimisation, clustering, function, prediction, retrieval by content and process control. The second most commonly used technique is fuzzy logic(FL), a multiple-valued logic that uses the concept of partial truth. The third most used technique is agent-based multi-agent system(ABS/MAS), which has manyapplications in SCM. This techniqueperceives the surrounding environment to act autonomously and proactively to solve a specific problem. Agents are extensively used in SCM to solve many problems in planning, designing and simulation of supply chain systems, analysis of the complex behaviour of supply chains and negotiation-based collaborative modelling. Other techniques used less commonly are genetic algorithm(GA),case-based reasoning(CBR),and support vector machines (SVM). The authors did not cover all the details of the reviewed studies.

A bibliometric review of 1076 papers bySharma, et al. (2022)identified five themes of AI applications in SCM. They included supply chain network design (SCND), supplier selection, inventory planning, demand planning, and green supply chain management. The continuing growth of AI in SCM leads to a need for greater exploration of these methods to add value to the supply chain processes. The selection of papers was limited to business journals.

Based on the results of a survey of 168 French hospitals,Benzidia, et al. (2021) observed improvement in green supply chain collaboration and environmental process integration leading to environmental performance. Green digital learning moderated the relationship between BDA-AI and green supply chain collaboration. The authors used organisational information processing theory by integrating BDA-AI and positioning digital learning as a moderator of the green supply chain process for a conceptual model. The model was supported by the findings.

Based on a literature review,Dumitrascu, et al. (2020)identified the five most important performance indicators impacting different subsystems of SCM. This was followed by interviews of 12 senior managers of the automobile industry from Romania, Germany and Denmark. The relationship between issues of SCM subsystems reported by the interviewees and the five key performance indicators was evaluated. A performance evaluation model was developed based on the results of these relationships. The relationship between certain issues of SCM subsystems and the key performance indicators was established. The only limitation was that the multilayer perceptron artificial intelligence data mining algorithm allows for analysing the neuronal network for only one KPI at a time.

A qualitative review byIkevuje, et al. (2024) revealed the benefits of integrating IoT and data analytics to enhance efficiency, reduce costs, and improve the performance of supply chains. The integration may involve data collection, processing, analysis, and decision-making. Emerging technologies like edge computing, blockchain, AI, 5G, and digital twins increase the potential usefulness of AI for supply chains. The key challenges are lack of real-time visibility, inefficient inventory management, operational delays, and risk management.A textual framework was presented to explain these aspects. The absence of a diagram of the framework and no attempt to validate it through empirical tests are the two limitations of this paper.

Pasupuleti, et al. (2024) used historical data on sales, inventory levels, order fulfilment rates, and operational costs from multinational retail corporations. The authors analysed these data using various ML algorithms, including regression, classification, clustering, and time series analysis. The ML applications led to a 15% increase in demand forecasting accuracy, a 10% reduction in overstock and stockouts, a 95% accuracy in predicting order fulfilment timelines and at-risk shipments and enabled customer segmentation based on delivery preferences, leading to more personalized service offerings. The limitations are the dependency on specific data types and the generalizability of the models across different industries or geographical contexts.

To identify critical success factors (CSFs) for AI adoption in healthcare supply chains(HSC),Kumar, et al. (2023) conducted interviews with 17senior officers of Indian healthcare firms and three academics. Rough Step-wise weighted assessment ratio analysis (R-SWARA) was used for ranking CSFs of AI adoption in HSC. The most important factors were the technological (TEC) institutional environment (INV) and organisational (ORG) factors in the order of decreasing importance. The results were validated using feedback from experts from the field. TOE and Human-Organisation-Technology(HOT) frameworks were used to assess the ease of AI adoption in HSC in emerging economies.

A conceptual framework grounded in the TOEH (Technology–Organisation–Environment–Human) theory was employed by Dora, et al. (2022) to identify the critical success factors (CSFs) impacting AI adoption within the Indian food supply chain (FSC). The approach involved two phases. The first phase entailed an extensive literature review to identify CSFs, which were then refined through discussions with industry specialists. In the second phase, the R-SWARA method was applied to assess the relative importance of the identified CSFs for AI adoption in the Indian FSC context. The findings suggest that the key CSFs for AI adoption in FSC include technology readiness, security, privacy, customer satisfaction, perceived benefits, demand fluctuations, regulatory compliance, competitive pressure, and information sharing among partners.

To identify the significance of AI for creating a sustainable and resilient supply chain against risks like the COVID-19 pandemic,Naz, et al. (2022) conducted a systematic review of 162 papers. Structural Topic Modelling (STM), a big data-based approach, was employed to generate several thematic topics of AI in SC resilience. R-package was used for bibliometric analysis. Based on the review a research framework was proposed. The topics identified from this review were risks associated with SCM, sustainable transportation and logistics, resilience, supplier risk management, data-driven supply chain, decision models, network design, machine learning, the supply chain, optimisation algorithm in SCs and technology management in supply chain firms.

A study on how organisational behavioural mechanisms at the human-technology interface will facilitate AI adoption in SMEs and the subsequent impact of the adoption on sustainable practices and supply chain resilience (SCR) was undertaken byDey, et al. (2024) The authors surveyed 280 Vietnamese manufacturing firms. Structural equation modelling showed that leadership drives AI adoption by creating a data-driven, digital and conducive culture and strengthening employee skills and competencies. AI adoption positively influenced circular economy practices, SC agility and risk management leading to resilience. Managers can use internal organisational employee-centricmechanisms to create value from AI adoption without impeding business value.

A study conducted by Dey, et al. (2024) examined how organizational behavioural dynamics at the human-technology interface can promote the adoption of AI in SMEs and its subsequent effects on sustainability practices and supply chain resilience (SCR). The authors surveyed 280 manufacturing companies in Vietnam. Analysis usingstructural equation modellingrevealed that leadership plays a crucial role in fostering AI adoption by cultivating a data-driven, digital-friendly culture and enhancing employee skills and competencies. The adoption of AI positively impacted circular economy practices, supply chain agility, and risk management, thereby contributing to resilience. Managers can leverage internal, employee-focused organizational mechanisms to derive value from AI adoption without compromising overall business value. The limitations are the restrictions to one country, one sector and only SMEs. Knowledge-based view (KBV) and resource orchestration theory were used in this research.

A mixed approach was used byDubey, et al. (2021) to study alliance management capability (AMC) and artificial intelligence (AI) driven supply chain analytics capability (AI-SCAC) as dynamic capabilities, under the moderating effect of environmental dynamism in Indian auto parts manufacturing firms. The approach consisted of 26 interviews, via Zoom/ Microsoft Teams, with senior-level supply chain managers and a survey of 167 firms. The results showed that alliance management capability mediated by AI-powered supply chain analytics capability enhanced operational and financial performance. Alliance management capability influenced AI-powered supply chain analytics moderated by environmental dynamism.Dynamic capabilities theory was used in this research. The limitations of this

study are the use of cross-sectional data, restricting the role of AMC and the AI-SCAC on organizational performance, one sector in one country and a narrow definition of dynamic capabilities.
A literature review and interviews with 30FMCG experts byNozari, et al. (2022) revealed that the lack of proper infrastructure, security and lack of adequate knowledgeare among the most important challenges of implementing a system based on digital transformation needs. The presence of capable and expert human resources is necessary to understand better the concepts related to the effects of digital transformation, and thus remove these limitations and train experts.
By leveraging a combination of AI and machine learning, along with case studies derived from data collected in Indonesia, Malaysia, and Pakistan, Akhtar, et al. (2023) created a model for detecting Fake News and Disinformation (FNaD) to help prevent supply chain disruptions (SCDs). The authorsused Organisational Information Processing Theory (OIPT) for this study. The methodology involved mixed methods, integrating an AI-ML-driven approach with case study interviews conducted with 16 participants. The dataset for the AI and ML analysis was compiled from 500 pages each of four major online news outlets in Pakistan: Geo News, The Dawn, Express Tribune, and The News. The data on supply chain disruptions was categorised into natural, human-induced, maritime, and mass disruptions associated with FNaD. The themes identified from the interviews were the impact of fake news, dealing with FNaD, FNaD filtering and counter-modelling process on supply chain operations emerged as the first theme from the analysis. These themes validated the model.
Thus, the review of 25 papers above shows many possibilities of using AI alone or in combination with other technologies to enhance supply chain efficiency and associated factors.

Discussions

Various trends of research observed in the reviewed papers are discussed below.

Topics and papers

The distribution of papers dealing with different topics related to AI and supply chains is given in Table 2.

Table 2. Frequency of reviewed papers according to topics.

Topic	References	Frequency	Remarks
Performance and efficiency	Belhadi et al. 2024; Shil et al. 2024; Rathor, 2023; Dumitrascu, et al., 2020; Pasupuleti, et al., 2024; Ikevuje, et al., 2024.	6	It is difficult to separate the two in some papers.
Collaboration (Green also)	Nwagwu, et al., 2023; Kasaraneni, 2021; Benzidia et al. 2021; Dubey et al. 2021	4	
Resilience	Ganesh & Kalpana, 2022; Modgil et al. 2022; Modgil et al. 2022; Dubey et al. 2022 (agility also); Naz et al. 2022; Dey et al. 2024	6	
SC design and benefits	Sharma et al. 2022; Tirkolaee et al.2021	2	Sharma et al. dealt with SC design. Tirkolaee et al. dealt with benefits.
Factors	Helo & Hao, 2022; Kumar et al. 2023; Dora et al. 2022	3	All types of factors.
AI methods	Toorajipour et al.2021	1	Many methods of AI.
Others	Nayal et al.2022; Nozari et al. 2022; Aktar et al. 2023	3	Issues, challenges and solutions.
COVID-19	Belhadi et al. 2024; Shil et al. 2024; Modgil et al. 2022; Nayal et al. 2022; Modgil et al. 2022; Naz et al. 2022;	6	Mentioned as a supply chain disruption or risk factor.

Performance and its efficiency, resilience and mention of COVID dominated the topics with six papers each. Collaboration, including green collaboration, was discussed in four papers. Three papers discussed various types of factors related to AI and supply chains.

Temporal trends

The frequencies of reviewed papers in different years are shown in Fig 1. The number of papers increased only from 2020 to 2022. Then, it declined in 2023 before a slight rise in 2024.

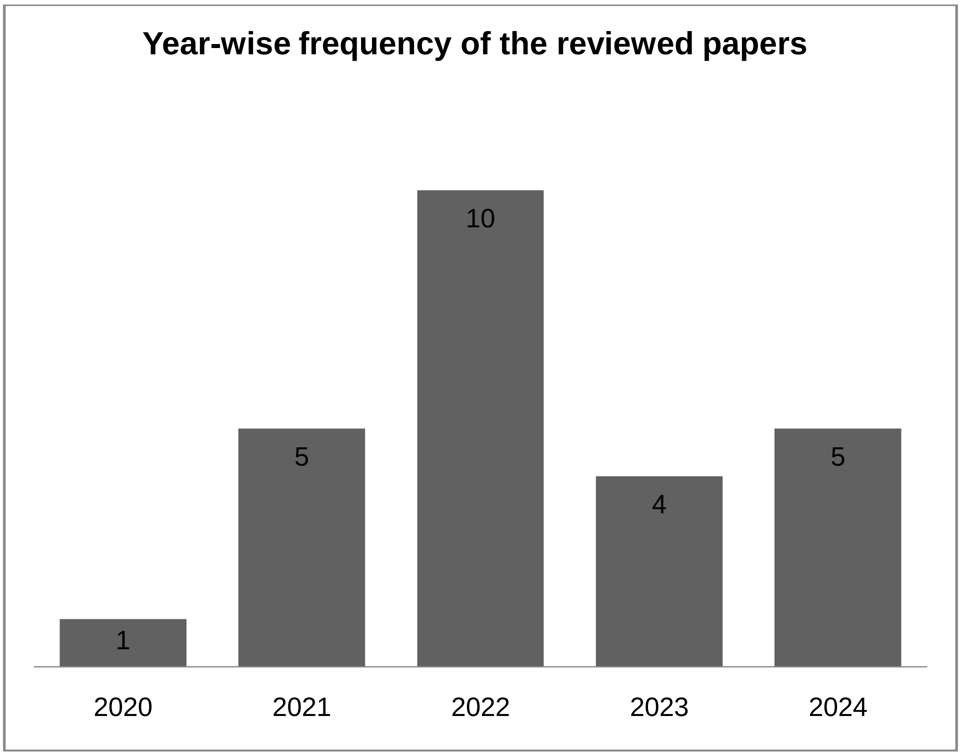

Figure 1: Year-wise frequency of reviewed papers.

The above trend may apply only to the papers selected for this review. If several papers were selected, the trend might have been different.

Research methods

The research methods adopted in the reviewed papers are shown in Fig 2. Seven papers (26%) each used surveys, interviews and reviews. Except for one paper combining only a survey and interviews, the remaining papers used other different methods. Others include case studies, secondary data analysis etc.

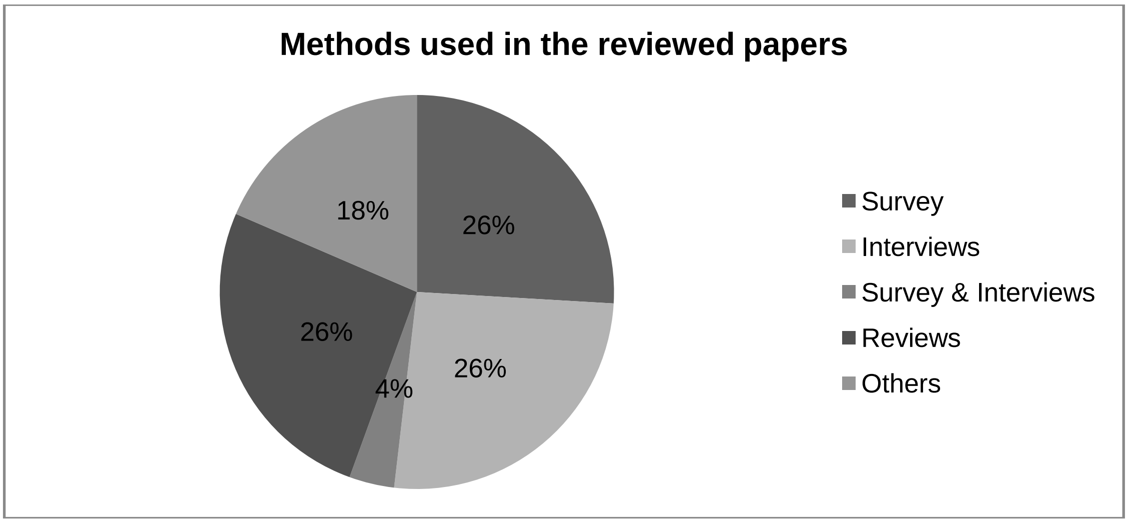

Figure 2: Methods used in the reviewed papers.

Theories used/models proposed
Some papers used theories or models. Others proposed models or frameworks. Their frequencies in the reviewed papers are given in Fig 3.

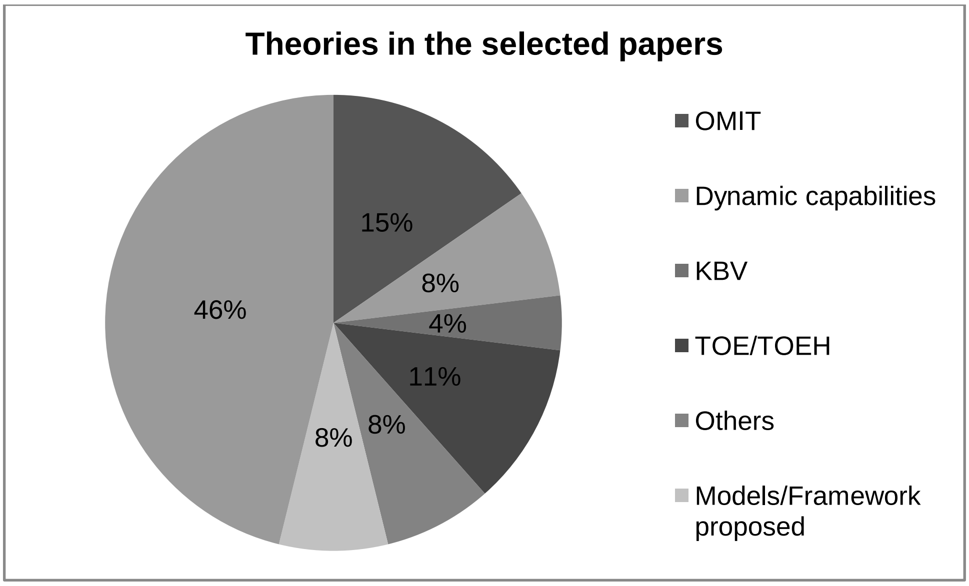

Figure 3: Theories or models used/proposed in the reviewed papers.

Organisational information processing theory (OIPT) dominated with four (15%) of the reviewed papers. No theory was mentioned in 12 (46%) of the papers. Technology-Organisation- Environment framework was used in three (11%) of the papers. Dynamic capabilities theory, proposal of models or frameworks and other different theories were used in two papers (8%) each.

Mention of limitations
Out of 25, 21 mentioned the limitations of their research and four did not.
Quality assessment of papers
As was described in the methodology section, five parameters were used for the assessment of the quality of the reviewed papers.

Citations per year
Out of the 25 papers reviewed, the citations per year were less than 25 for five papers, they ranged between 25 and 50 and above 50for 10 papers each with an overall average of 72.9.The maximum citations of 413 were observed in the case of the paper Belhadi et al. (2024). A paper of the current year receiving so many citations is outstanding. Other papers with high citations were those of Toorajipour et al. 2021 (180 citations) and Modgil et al. (2022) (133 citations). Thus, generally, the reviewed papers were widely received.

Evidence adequacy, Risk of Bias, GRADE and CCAT
The ranges of values for evidence adequacy, RoB, GRADE and CCAT were 4 to 4.8, 2 to 3.5, 4.2 to 4.9 and 4.2 to 4.9 respectively. Out of these, six papers had lower values (4 to 4.3) forevidence adequacy values. RoB values were never higher than 3.5. There were six papers with RoB values 2 and 2.5, showing low levels of risk of bias. Only two papers each had GRADE and CCAT values of 4.2 and 4.3. Others ranged from 4.5 to 4.9. Papers with lower values for all parameters except RoB can be considered lower in quality. In the case of RoB, lower values were better.

Overall quality
Overall quality is the overall effect of the four quality parameters discussed above. The average value of 83.71 obtained for this assessment shows a generally high quality of the reviewed papers. There were only five papers below the overall quality value of 50.
The above quality assessments show that the reviewed papers were moderate to high quality.

Conclusions

The enthusiasm for research on the impact of AI on supply chain efficiency declined since 2022. The most discussed topics in the 25 reviewed papers were performance and its efficiency, resilience and mention of COVID. Collaboration, including green collaboration and various types of factors related to AI and supply chains, received less attention. Very few papers use d mixed methods for their research. Organisational information processing theory and dynamic capabilities theory seem to be more relevant to research on AI's impact on supply chain efficiency. The qualities of the reviewed papers were moderate to high.

Future research on this topic should focus on supply chain efficiency to a greater extent. Green and sustainable chains, collaborations and risks should receive increased attention. They should use mixed methods more. Country comparisons, especially among developed, emerging and developing countries, may be useful. The best practices of using AI for supply chain efficiency should be studied in such multi-country comparisons.

Relying on a single database, targeting a fixed number of papers and setting the period as 2020 to 2024 reduces the scope for selecting many good papers. However, as was said above, the quality of the selected papers was good. The period was chosen deliberately to reflect the latest research trends. These trends were discussed above.

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Appendix - PRISMA Flowchart