
Artificial intelligence in procurement: a systematic and AI-assisted literature review

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Abstract

Purpose – This study investigates the application of artificial intelligence (AI) within global procurement processes. It builds upon prior literature and offers novel methodological insights while pinpointing trends and outlining research gaps for future investigations.

Design/methodology/approach – The study combines a bibliometric literature review using VOSviewer with an AI-assisted review process. AI tools, including ChatGPT, are integrated into selected stages of the review and examined alongside researcher-driven approaches to assess their usefulness and limitations in supporting systematic literature analysis.

Findings – The results indicate a shift in AI use in procurement from isolated automation toward more strategic integration. The literature increasingly focuses on strategic areas such as supplier management, while comprehensive implementation frameworks remain limited. The analysis of AI-assisted reviewing suggests that such tools can support efficiency and consistency, but their application remains sensitive to conceptual ambiguity and requires human oversight, particularly in classification tasks.

Originality/value – This study offers two distinct contributions to the literature. First, it provides a focused analysis of how research on AI in procurement has evolved since previous systematic literature reviews (SLRs), emphasising studies that examine real-world implementation and effectiveness rather than merely discussing willingness or barriers to adoption. Second, it provides an exploratory assessment of AI-assisted reviewing as an emerging methodological approach, highlighting both its potential and its current limitations.

Keywords Procurement, Purchasing, Artificial intelligence, Machine learning, LLM-Assisted review, Digital procurement

Paper type Research article

1. Introduction

The recent global developments, marked by geopolitical disturbances and increasing uncertainty, have demonstrated the vital role of supply chain management – and procurement in particular – in ensuring organisational resilience (Ivanov and Dolgui, 2020). Procurement is no longer viewed merely as a cost-rationalising function but as a strategic capability that enhances competitiveness, adaptability, and agility. It contributes to quality assurance, cost

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management, supplier relationship development, and innovation generation. As procurement becomes an increasingly central element of corporate value creation, firms are turning to advanced digital solutions to accelerate data analysis and support more informed strategic decision-making. Among these solutions, AI-powered tools have gained prominence for their potential to strengthen resilience and support organisational performance (Belhadi *et al.*, 2024; Wamba-Taguimdje *et al.*, 2020).

Artificial intelligence has become a defining topic across managerial domains, including risk management, market analysis, and marketing – any area that requires iterative analysis of large and complex datasets (Duan *et al.*, 2019). In procurement, AI is increasingly associated with two main advantages: the automation of repetitive, low-value tasks and the potential to support more data-informed decision-making processes. AI applications support both sourcing and supply activities by categorising spend data, identifying excessive costs, analysing purchasing patterns, aligning supply with demand, and reducing phenomena such as the bullwhip effect. AI-enabled contract analysis tools accelerate negotiations, while chatbots and virtual assistants streamline routine operational tasks. At the same time, the boundary between AI and broader digital technologies remains fluid, which creates challenges for conceptual clarity in both research and practice.

Since 2020, research on AI in procurement has accelerated, driven in part by the COVID-19 pandemic and the resulting disruptions to global value chains. Digitalisation emerged as a response to operational bottlenecks, prompting renewed academic and managerial interest in AI adoption. Guida *et al.* (2023) provided a comprehensive review and systematic framework of literature published up to December 2020, offering insights into expectations surrounding AI in the procurement function. However, their work does not capture the surge of research that emerged after the pandemic, nor the rapid evolution of AI technologies during this period. Building on their framework, our study examines how these expectations have evolved in light of recent developments and whether new patterns and research directions have emerged. Following Guida *et al.* (2023), we focus on the strategic purchasing process as conceptualised by Spina *et al.* (2013), enabling a structured comparison of the procurement phases and activities addressed in recent literature.

Beyond updating the substantive understanding of AI in procurement, this study also explores the methodological potential of AI tools in supporting systematic literature reviews. The increasing scale of academic output poses challenges for traditional review methods, which require extensive manual classification and synthesis. To address this, we integrate AI-based tools into the review protocol and examine their usefulness alongside researcher-driven approaches. In doing so, we respond to recent calls by Marzi *et al.* (2025) for incorporating advanced digital tools into scholarly workflows, while explicitly treating AI-assisted reviewing as an emerging and still evolving approach rather than a definitive solution.

Against this backdrop, the aim of this study is twofold: first, to update and systematise current knowledge on how AI is conceptualised and applied within procurement processes; and second, to explore how AI tools can support key steps in the literature review process and what insights and limitations emerge from their use. This dual focus allows us to connect substantive developments in AI-enabled procurement with methodological reflections on the evolving role of AI in research practice. To operationalise these objectives and structure the analysis, we formulate the following research questions:

- RQ1. How has the academic literature conceptualised and applied AI across procurement processes, and what trends emerge?
- RQ2. How can AI tools support key steps in a systematic literature review in this domain, and what limitations emerge from their use?
- RQ3. What insights emerge from combining human and AI-driven classification of procurement research?

2. Methodology

The systematic literature review was conducted to address the study's overarching aim: examine how AI is conceptualised and applied across procurement processes and to explore the role of AI tools in supporting key stages of the review process. These objectives are translated in the three research questions, which guide the structure and logic of the methodological approach.

To establish a solid conceptual and methodological foundation, we began by reviewing existing studies and prior systematic literature reviews in procurement, supply chain management and artificial intelligence. This preparatory phase helped to clarify the relevant terminology, scope and conceptual boundaries and informed the development of the review protocol.

In designing this protocol, we followed established SLR guidelines and complemented them with snowball sampling (Denyer and Tranfield, 2009) to ensure comprehensive coverage of the field. This combined approach enabled us to formulate a precise search strategy, define transparent inclusion criteria and structure the subsequent stages of the review in a systematic and replicable manner. The full sequence of methodological steps is presented in Figure 1.

The review process was structured into three distinct phases to ensure methodological rigor and transparency. Phase 1 – Planning was entirely human-led and involved selecting keywords, extracting papers from relevant databases, and cross-comparing results to eliminate duplicates and merge overlapping entries. As they are already highly automated by database functionalities, additional AI assistance was deemed unnecessary. Phase 2 – Conducting the Review was AI-enhanced; abstract screening was performed simultaneously by AI and human reviewers to identify studies specifically addressing the application of AI in procurement. After determining the final sample of 89 papers, full-text screening was conducted with AI support, where the primary task for AI was to classify papers according to specific steps in the purchasing process – strategic or operational. Phase 3 – Reporting and Dissemination combined AI and human efforts in conducting bibliometric analysis and descriptive synthesis.

2.1 Developing the review protocol

The review protocol was established following the principles of the key scoping study defined by Arksey and O'Malley (2005), which served as a preliminary exploration of the literature at the intersection of artificial intelligence and procurement. This initial examination enabled us to refine the scope of the study and develop a protocol aligned with the research questions posed in the introduction. These questions focus on (1) how academic literature conceptualises and applies AI across procurement processes, (2) how AI tools can support key steps in a systematic literature review and what limitations emerge from their use, and (3) what additional insights arise from combining human and AI-driven classifications of procurement research.

On this basis, we established a structured review protocol that defined the search strategy and inclusion criteria. We included only peer-reviewed journal articles to ensure high-quality evidence. The time frame was set from January 2000 to March 2025 to capture both early developments and the rapid acceleration of AI-driven procurement research in recent years. Only publications in English were considered, reflecting the dominance of this language in the field.

To operationalise the search strategy, we developed a comprehensive query for Scopus and Web of Science (WoS). These two databases were selected because they jointly index more than 90% of the high-impact journals in supply chain management, operations management, and related managerial fields, ensuring robust coverage of the scholarly outlets in which AI-in-procurement research is most frequently published (Visser *et al.*, 2021). Scopus provides a wide interdisciplinary reach, while WoS offers stringent curation and depth in established management and operations research journals. Relying on both databases, therefore maximises breadth and depth simultaneously, reducing the likelihood of systematic omissions.

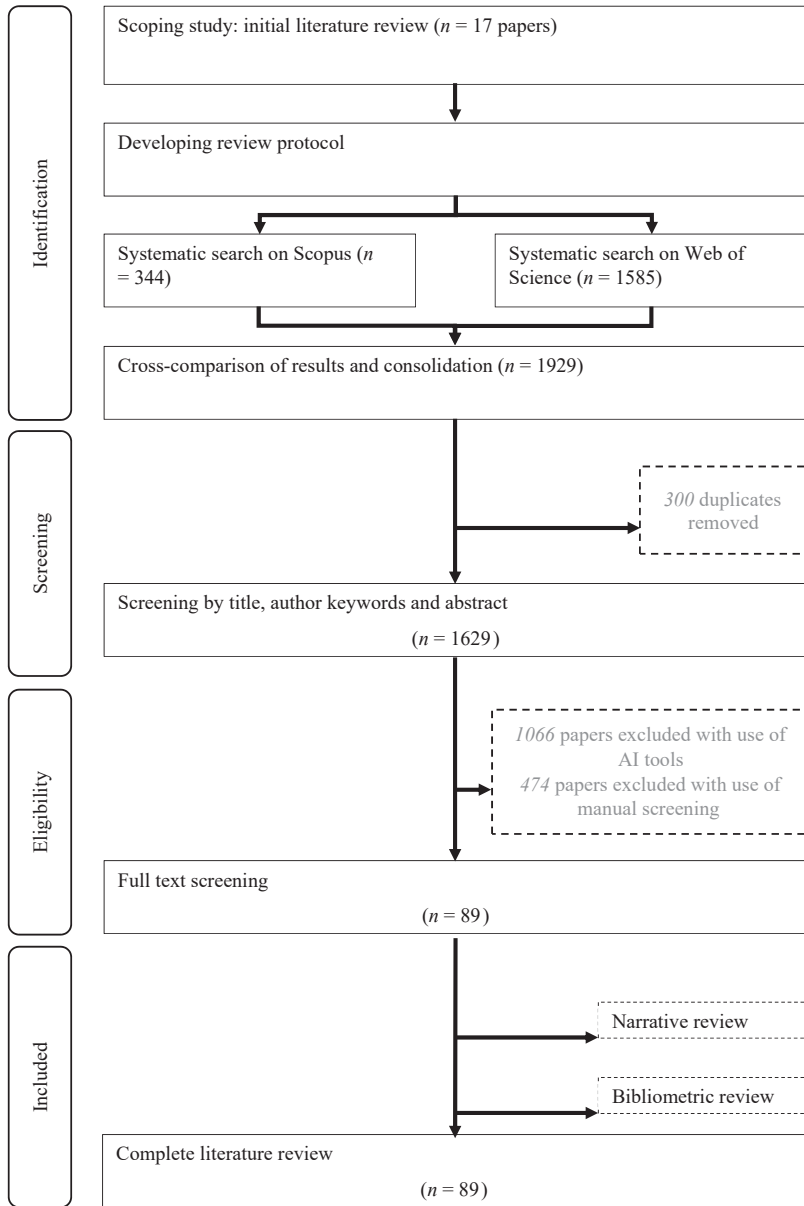


Figure 1. Literature review process. Source: Authors’ own work based on [Moher et al. \(2009\)](#)

Because terminology related to AI remains broad and sometimes ambiguous, we first reviewed 17 purposely selected papers representing key prior literature on AI applications in procurement and supply chains. This allowed us to delineate a keyword set that maximises coverage and while reducing the likelihood of omitting relevant studies, even if the term “AI” did not explicitly appear. We searched both databases for the string of keywords [“artificial intelligence” OR “AI” OR “machine learning” OR “deep learning” OR “neural network*” OR

“natural language processing” OR “expert system*” OR “intelligent agents” OR “robotics” OR “automation” OR “decision support systems” OR “knowledge based systems” OR “fuzzy logic” OR “genetic algorithms” OR “swarm intelligence” OR “reinforcement learning” OR “data mining” OR “predictive analytics” OR “big data” OR “internet of things” OR “cloud computing” OR “unsupervised learning” OR “supervised learning” OR “computer vision” OR “natural language processing” OR “nlp” OR “support vector machine” OR “svm” OR “self-learning” OR “self learning” OR “transfer learning” OR “cognitive computing” OR “logic programming”] AND [“supply chain*” OR “value chain*” OR “supply network*” OR “demand chain” OR “alliance” OR “procurement” OR “purchas*” OR “sourc*”] in title, author keywords and abstracts.

The initial search yielded many irrelevant papers. To narrow the results, we restricted the search to subject areas most closely aligned with our research focus (“Business and Management” in Scopus; “Management”, “Operations Research and Management Science” and “Multidisciplinary Sciences” in WoS). Unlike previous reviews (Guida *et al.*, 2023; Wynstra *et al.*, 2019), we deliberately chose not to limit the search to a predefined set of supply chain journals, as this would exclude interdisciplinary studies where AI-enabled procurement insights frequently appear. As the search was conducted across two databases, the preparation phase required a manual cross-checking and consolidation of all retrieved records to ensure completeness and avoid duplication.

2.2 Conducting the review

All papers retrieved from the consolidated dataset were screened based on their titles, abstracts and author keywords. Consistent with Denyer and Tranfield (2009), we acknowledge that the application of inclusion and exclusion criteria can introduce subjectivity. To reduce potential bias – particularly relevant for RQ2 and RQ3 – we incorporated AI tools into the initial filtering stage. Using ChatGPT 4.0, we conducted an automated preliminary screening, which excluded 1,066 papers that clearly did not meet our criteria (cf. Table A1 in the Appendix for exact prompting). We applied explicit inclusion and exclusion criteria during abstract screening. To be included, a study had to clearly describe how AI was used within a procurement context; mere references to AI-related buzzwords were insufficient, and likewise, any descriptions of purchasing processes without an AI component were excluded. Methodological criteria were also applied. We excluded literature reviews and papers that did not provide any empirical evidence of AI implementation in procurement. Conceptual papers were included only when they incorporated empirical material demonstrating AI use in procurement. The remaining 474 papers were then independently assessed by all authors, who reviewed each record to clarify uncertainties and resolve disagreements.

Following this multi-stage screening procedure, 89 papers were selected for full-text analysis. These papers formed the basis for the subsequent components of the study. To address the first research question – how AI has been conceptualised and applied across procurement processes – we conducted a bibliometric analysis and a qualitative mapping of AI applications. For the second research question – how AI tools can support key steps in a systematic literature review and what limitations emerge from their use – we compared AI-assisted screening and categorisation outcomes with the researcher-driven assessment. Finally, to answer the third research question – what insights emerge from combining human and AI-driven classifications – we analysed points of convergence and divergence between both approaches and explored the additional interpretive value produced through their integration.

3. An AI-supported analysis

While reviewing the papers, we employed a multi-step approach that combined advanced AI supported analysis with expert evaluation to assign the papers from our consolidated list to the

respective steps of the strategic and operational purchasing process (cf. [Guida et al., 2023](#)). To ensure a thorough understanding of the content, we systematically generated concise summaries highlighting the principal findings of each paper. The outcomes of this process were documented in a shared master file, which facilitated the subsequent manual validation and analysis within the research team. Attention was paid not only to papers that were inconsistently assigned across iterations, but to the entire sample. This dual approach enabled us not only to conduct the SLR, but also to assess the usefulness and reliability of AI-powered tools in supporting the literature review process. Ultimately, 89 papers served as the basis for our analysis, conducted with the assistance of ChatGPT.

As a preparatory step, we identified the stages of the strategic and operational purchasing processes. While our classification broadly followed the framework established by [Guida et al. \(2023\)](#), we refined the process steps based on the models proposed by [van Weele and Eßig \(2017\)](#), [Bogaschewsky \(2021\)](#) and the German “Bundesverband Materialwirtschaft, Einkauf und Logistik e.V.”, delineating five key steps for each type of procurement. [Table 1](#) presents a detailed overview of these steps for both strategic and operative purchasing.

Subsequently, we analysed the distribution of the 89 selected papers across the identified steps of the strategic and operative purchasing process. Even if a paper might contribute to more than one process step overall, it normally has a clear primary focus. Thus, we initially concentrated on identifying the main theme. To enhance efficiency and methodological rigor, we employed ChatGPT in a support role – an approach that, to the best of our knowledge, represents a relatively novel application in this context of systematic literature reviews. Unlike

Table 1. 5 steps of the strategic and operative purchasing process and their description

Strategic Step name	Description	Operative Step name	Description
S1. Analysis of demand and market research	- investigation of purchasing volumes, cost structures and market trends to develop procurement strategies	O1. Determination of requirements	- determination of short-term material requirements based on orders, stock levels or production plans
S2. Supplier selection and evaluation	- identification, qualification and evaluation of potential suppliers based on criteria such as price, quality and sustainability	O2. Inquiry and order	- ordering goods or services according to existing contracts or price inquiries from suppliers
S3. Contract and price negotiations	- negotiation of framework agreements, quantity discounts, payment terms and delivery conditions	O3. Delivery monitoring	- checking delivery dates, tracking orders and communicating with suppliers in the event of delays
S4. Supplier management and development	- building long-term partnerships, regularly assessing performance, managing risk and optimising collaboration	O4. Incoming goods and quality control	- checking the delivered goods for quantity and quality, initiating complaints if necessary
S5. Optimisation of the purchasing strategy	- continuous improvement of purchasing processes, cost analyses and introduction of new technologies or methods to increase efficiency	O5. Invoice verification and payment processing	- reconciliation of invoice, order and goods receipt, release of payment

Source(s): Authors’ own compilation based on [Bundesverband Materialwirtschaft, Einkauf und Logistik e.V. \(2016\)](#), [Van Weele and Eßig \(2017\)](#), [Bogaschewsky \(2021\)](#)

specialised tools (e.g. Abstrackr or Rayyan), we let the AI code the articles. We have applied 3 versions of AI-powered tools, namely ChatGPT 4.0, ChatGPT 4.5 and ChatGPT4.5 with its Deep Research functionality activated [1] to allocate the papers to the appropriate step within the purchasing framework. Deep Research refers to an additional ChatGPT functionality that can be activated by the user in the prompt interface. According to OpenAI, this feature enables more precise and in-depth analyses by enhancing reasoning capabilities and improving reliability. To test this and to identify possible differences, we applied both separately: ChatGPT 4.5 only as well as ChatGPT 4.5 and Deep Research functionality activated. We selected ChatGPT’s Deep Research mode because it was a stable, well-documented, and data-secure tool at the time of our study (data extraction February – March 2025; analysis April–July 2025), whereas alternative models such as DeepSeek – released only in January 2025 – did not yet offer sufficient transparency or verifiable data-handling safeguards. Our aim was not to compare LLMs but to rely on one reliable and well-understood model, with future comparative work falling outside the scope of this study. Further details regarding its use in this study are provided in the [Appendix](#). The outcome of this classification is presented in [Table 2](#).

The initial analysis with ChatGPT 4.0 revealed that most of the papers – 64 out of the original 89 (approximately 72%) – primarily focus on strategic aspects of the purchasing process. Among these, the most frequently addressed steps were the more general strategic stages: S4 and S5. Within the operative process, step O2 (inquiry and order) emerged as the most discussed, due to its critical role in procurement activities. In a subsequent step, we utilised ChatGPT version 4.5 solely to conduct a semantic analysis (details can be found in the [Appendix](#)) of the papers to validate or, where appropriate, revise the initial classifications.

This second iteration revealed an even stronger emphasis on strategic purchasing, with nearly 80% of the papers assigned to strategic process steps – particularly step S4, which stood out as the most frequently referenced. In terms of consistency between versions, ChatGPT 4.0 and 4.5 produced identical classifications for 65 out of the 89 papers (73%). In 15 cases, the assignment shifted primarily from S5 to either S4 or S1, while three papers were reclassified from operational (Ox) to S5. Notably, approximately 25% of the reclassifications involved a shift from an operative to a strategic process step.

Given the significant number of changes between iterations, we conducted a third analysis using ChatGPT 4.5 with having activated its “Deep Research” feature. In this phase, the model was again tasked with assigning each paper to one of the ten defined process steps and explicitly comparing its classification with that of the previous round. Where discrepancies arose, ChatGPT was required to provide a justification for the reclassification. Consistent with

Table 2. Number of papers assigned to each process step based on different usage of ChatGPT models and final manual evaluation

Process step	ChatGPT 4.0	ChatGPT 4.5 “only”	ChatGPT 4.5 with deep research functionality activated	Final number of papers addressed
O1	4	5	8	7
O2	10	7	5	5
O3	4	4	3	3
O4	2	2	1	1
O5	5	1	5	0
S1	5	8	5	3
S2	11	11	11	10
S3	13	13	10	12
S4	17	32	14	13
S5	18	6	27	35

Source(s): Authors’ own work

earlier findings, this round confirmed that most papers (approximately 75%) address strategic process steps. Roughly 55% of the classifications in this round were consistent with those from the previous iteration (version 4.5 without Deep Research functionality activated), and ca. 46% (41 papers) matched the initial classifications from version 4.0. Overall, 38 papers (42.7%) were assigned to the same process step across all three analytical runs.

We have studied the inconsistencies within the paper allocation under various AI-iterations to understand the differences. For most papers, the final classification was to step S5. These papers typically address overarching topics such as the implementation of Robotic Process Automation (RPA) in procurement, reflecting a broader and more integrative focus that spans multiple process steps rather than focusing on a single one. This implies that relying on isolated “bullet points” from abstracts or selected text passages can be misleading, as the overall context must be considered. Importantly, the AI-assisted analysis did not exhibit commonly acknowledged AI errors such as hallucinations. Instead, the observed inaccuracies were boundary-related rather than conceptual or out-of-scope. While the AI correctly understood constructs and definitions, it occasionally struggled with interpretation when elements belonging to multiple categories appeared within the same context. Moreover, most reclassifications represented minor adjustments – i.e. shifts between adjacent process steps – within the same overarching domain (strategic or operative), rather than fundamental changes in categorisation. This last iteration with ChatGPT 4.5 and Deep Research iteration revealed a slight shift in the distribution of papers assigned to operative process steps.

However, since the AI-usage for SLR is still in the testing phase, it was necessary to validate ChatGPT’s results through manual verification. This process also involved a comprehensive manual analysis of all papers, conducted by all authors through a full-text review. The verification was overseen by four senior researchers with extensive experience in supply chain research, and each researcher worked individually to ensure independence and rigor. The first step was to validate the accuracy of AI classifications. To do so, a randomly selected subset of those 38 papers that had been consistently assigned to the same process step across all three AI runs was examined, confirming correct assignment with no reported issues. Consequently, as the second step, attention was directed toward papers that were not consistently classified across all three iterations. This means, 51 papers (the total number of 89 papers with exclusion of the 38 papers which were assigned identically in all three iterations) were manually reviewed comprehensively and finally assigned by the authors (see [Table 2](#)). The consolidation of these decisions occurred during an online meeting, where individual assignments were compared and discrepancies discussed, including the underlying reasons. Most of the discrepancies were not due to incorrect categorisation, but rather to the fact that a paper could fit into more than one category; therefore, the focus had to be determined, as studies can take a broader perspective. Since the AI model was constrained to make a single assignment, this requirement occasionally led to divergence from human judgment or alternative AI-powered tools. Following this final verification, we found that ChatGPT version 4.5 with activated Deep Research functionality, i.e. the third iteration which we performed, had correctly classified more than 77.5% of the papers (69 out of 89), i.e. all 38 papers that maintained consistent classification across all runs, as well as 31 papers that were assigned to different process steps in one or more previous runs (version 4.0 or version 4.5 only). The remaining 20 papers were found to be misinterpreted, and the classifications required correction. The manual cross-check corroborated the earlier findings: strategic purchasing processes are addressed more frequently than operative ones, with many studies adopting a broad, overarching perspective. This likely explains why ChatGPT produced misinterpretations in the final run: the distinctions between certain process steps are sometimes minimal, for example, between S4 and S5, and the overarching focus has to be identified. As a result, statistical methods such as semantic analysis may lead to incorrect conclusions. Accurate classification requires detailed domain knowledge and a thorough review of the entire paper rather than relying solely on abstracts or isolated phrases, which can be misleading. Fortunately, no clear cases of factual hallucinations were identified in our

setting. Consequently, the previously drawn conclusions remain valid. Finally, we estimated error decomposition rates to assess the consistency and accuracy of its classifications (Table 3.). While the majority of errors (ca. 70%) occur within the same level, a substantial share (up to 31%) reflects cross-group confusion between O and S categories. Notably, cross-group errors are highly asymmetric, dominated by S→O misclassification, indicating systematic difficulty in recognising more complex S-level instances. The Deep Research model reduces overall error and eliminates O→S misclassification entirely, yet S→O errors persist.

To calculate the success rate, a slightly adjusted Tversky Index has been used: to evaluate the accuracy of categorical assignments, the task is conceptualised as a multiclass classification problem. For each outcome category i , we quantify classification performance using a score derived from established similarity measures in statistical pattern recognition.

Let:

- (1) TP_i = number of correctly assigned observations (true positives)
- (2) FP_i = number of observations incorrectly assigned to outcome i (false positives)
- (3) FN_i = number of observations that should have been assigned to outcome i but were not (false negatives)
- (4) EP_i = number of excess assignments beyond the number of true instances (over-assignments), defined as:

$$EP_i = \max(P_i - A_i, 0)$$

where P_i is the number of predicted assignments and A_i is the number of actual observations in the category i .

Consequently, the score for category i is defined as:

$$S_i = \frac{TP_i}{TP_i + FN_i + FP_i + EP_i}$$

This ensures that the score is bound by 1 and penalises both under-assignment and over-assignment. This scoring function corresponds to a weighted variant of the Tversky index. Our scoring function can be understood as a special case of the Tversky index in which false positives and over-assignments receive greater weight than false negatives with fixed parameters $\alpha = 1$ and $\beta = 2$.

This asymmetry is justified as over-assignment inflates the apparent prevalence of a category and is therefore considered a more severe error: it introduces an incorrect assignment

Table 3. Error decomposition rates for different ChatGPT applications

Model	Total error	Within-group	Cross-group	O → S	S → O
GPT-4.0	35	24 (27.0%)	11 (12.4%)	1 (1.1%)	10 (11.2%)
GPT-4.5	39	30 (33.7%)	9 (10.1%)	3 (3.4%)	6 (6.7%)
GPT-4.5 DR	20	14 (15.7%)	6 (6.7%)	0 (0%)	6 (6.7%)

Note(s): Within-group error refers to misclassifications occurring within the same category level (i.e. O1–O5 misclassified as another O category or S1–S5 misclassified as another S category). Cross-group error refers to misclassifications between the two levels, i.e. O categories incorrectly classified as S categories (O → S) or S categories incorrectly classified as O categories (S → O)

Source(s): Authors' own work

to the predicted class, and it simultaneously distorts the empirical class distribution by inflating the apparent prevalence of that class.

We calculated macro-F1 and Cohen's Kappa (Table 4) to complement the Tversky index and deepen the overall reliability assessment. Macro-F1 captures how well each model performs across all stages by averaging the F1-scores for every class, ensuring that both frequent and infrequent purchasing-process stages contribute equally to the final metric. Cohen's Kappa provides a stricter perspective by estimating the level of agreement between the model and human annotations after adjusting for chance, which is especially important in imbalanced datasets where apparent accuracy can be misleading.

Using these measures, we find that ChatGPT 4.0 and ChatGPT 4.5 perform at comparable levels, with macro-F1 values of 0.6264 and 0.6136 and Cohen's Kappa scores of 0.5362 and 0.4985, indicating moderate reliability. The addition of Deep Research to ChatGPT 4.5 indicates an improvement: macro-F1 increases substantially to 0.8630, and Cohen's Kappa rises to 0.7243 (cf. Table 4.), approaching substantial agreement beyond chance. This demonstrates that Deep Research is associated with higher classification consistency across purchasing-process stages, although some degree of human judgment remains necessary for ambiguous cases.

This combined approach – integrating AI assistance with expert validation – not only ensured the accuracy of the results but also facilitated an efficient and streamlined review process. These outcomes provided a solid foundation for the subsequent in-depth analysis.

4. Bibliometric analysis

4.1 Publication years and citation counts

Research on the use of AI in Supply Chain Management is relatively recent. The first paper that falls within the scope of the review dates from 2002 (Kashiwagi and Byfield, 2002). However, until 2020, research on AI was negligible, with one or two papers published per year. Research has been evolving ever since, significantly increasing from 2019 onwards and peaking in 2023 and 2024 with 22 papers each, showing growing interest in the field. This upward trend is expected to continue, as evidenced by six papers already published by March 2025.

Given the newness of the topic, citations are relatively low, with some notable exceptions. Figure 2 gives a summary overview of citation counts and the number of papers per year after 2002. Publications before 2018 are negligible, with the notable exception of 2011, when the highly cited paper by Grilo and Jardim-Goncalves (2011) was published and 2009, which saw the publication of a paper by Lam *et al.* (2009). Like all other articles published until 2011, both papers deal with procurement, pointing to the importance of this topic for AI applications.

Citations peak in 2022 with the publication of several highly cited papers by Modgil *et al.* (2022) (218 citations), Enrique *et al.* (2022) (75 citations) and Flechsig *et al.* (2022) (74 citations). There are a few very influential articles (cf. Table 5.) with only 3 reaching more than 100 citations.

Table 4. Macro-F1 and Cohen's Kappa reliability values

	ChatGPT 4.0	ChatGPT 4.5	ChatGPT 4.5 with deep research functionality activated
Macro-F1	0.6264	0.6136	0.8630
Cohen's Kappa	0.5362	0.4985	0.7243

Note(s): Macro-F1 (excluding zero-support categories) confirms that the Deep Research model substantially outperforms the other configurations. The exclusion of O5 avoids artificial penalisation due to dataset composition and ensures that the metric reflects performance on observed categories only

Source(s): Authors' own work

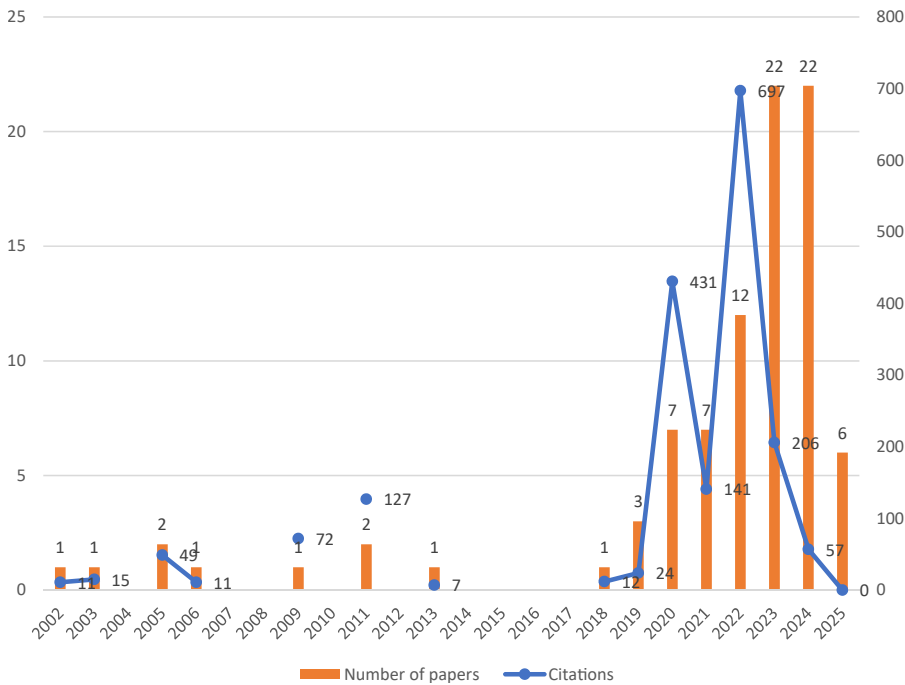


Figure 2. Citation counts and number of papers. Source: Authors' own work

Table 5. Top 10 most influential articles

Author	Journal	Total citations	Av. Citations p.a. (rounded)
Modgil et al. (2022)	International Journal of Logistics Management	218	73
Bag et al. (2020)	Resources Conservation and Recycling	205	41
Grilo and Jardim-Goncalves (2011)	Automation in Construction	111	8
Sachan et al. (2020)	Expert Systems with Applications	98	20
Enrique et al. (2022)	International Journal of Production Economics	75	25
Flechsig et al. (2022)	Journal of Purchasing and Supply Management	74	25
Lam et al. (2009)	Automation in Construction	72	5
Allal-Chérif et al. (2021)	Journal of Business Research	72	18
Benitez et al. (2022)	Supply Chain Management- an International Journal	64	21
Hendriksen (2023)	Journal of Supply Chain Management	59	30

Note(s): Citations and calculations as of the end of 2025

Source(s): Authors' own work

However, since the paper by [Grilo and Jardim-Goncalves \(2011\)](#) was published in 2011 already, i.e. nearly 15 years ago, we additionally considered the average yearly citations. Interestingly, while [Hendriksen \(2023\)](#) ranks only tenth in total citations, it ranks third in terms of average citations per year, suggesting a relatively strong and recent scholarly impact.

Notably, two publications stand out for their exceptionally high average annual citation rates: [Modgil et al. \(2022\)](#) and [Bag et al. \(2020\)](#). [Modgil et al. \(2022\)](#) offer a timely and comprehensive review of supply chain resilience – an area that has gained heightened importance in the wake of the COVID-19 pandemic. Their study not only identifies critical AI capabilities necessary for resilient supply chains but also proposes a structured framework for leveraging these capabilities. [Bag et al. \(2020\)](#) address the intersection of procurement and the circular economy, which is another current megatrend. Their research constitutes a comprehensive foundation for future research as it examines various stages of the procurement process (e.g. strategy, planning) and assesses their current level of development. These insights offer important implications for answering our RQ3, since they highlight the evolving demands and priorities in sustainable and technology-driven supply chain management.

4.2 Regional distribution of journals and authors

Given the novelty of the topic, only a limited number of influential journals are represented among the 89 articles reviewed. The leading journal is *Automation in Construction* from the Netherlands (Europe), with nine published papers primarily focused on purchasing strategy and supplier management. Interestingly, literature reviews centered on procurement journals tend to exclude this publication. Four papers were published in *IEEE Access* (USA), primarily addressing delivery monitoring. Additionally, four other journals – *Computers in Industry* (Netherlands), *Journal of Purchasing and Supply Chain Management* (UK, Europe), *Supply Chain Forum* (UK), and *Supply Chain Management – An International Journal* (UK) – each published three papers. The remaining articles were distributed across 58 different journals, further highlighting the newness of the topic.

Furthermore, most authors are affiliated with institutions in China (19), followed by the United States (15) and India (13), highlighting the strong presence of these countries in AI-related research. However, when authors are grouped by continent, a different picture emerges. Europe leads with 52 researchers affiliated with European universities, particularly in the GB (8), Germany (7), and Spain (6). As the continent is home to numerous influential global market leaders, European industries – deeply embedded in complex international supply chains – demonstrate a strong interest in advancements in this area. Asia follows with 45 researchers, primarily from China and India, while 17 authors are affiliated with North American universities. A detailed breakdown is provided in [Figure 3](#).

As the distribution of journals and author affiliations suggests, no prominent author clusters or leading individual researchers have emerged as of the time of writing. Only two authors – Grilo (NOVA University of Lisbon, Portugal) and Torres-Berru (International University of Ecuador) – have published more than one paper each. Grilo contributed to two publications ([Grilo and Jardim-Goncalves, 2011](#); [Mehrbod and Grilo, 2018](#)), while Torres-Berru co-authored two others ([Torres-Berru et al., 2023](#); [Torres-Berru and López Batista, 2021](#)).

4.3 Co-citation analysis

To examine the underlying assumptions and theoretical foundations of the field, we conducted a bibliometric co-citation analysis using VOSviewer 1.6.20. The analysis was performed at the reference level, with the minimum number of citations set to three. This yielded 19 distinct references, grouped into three clusters (excluding three papers that lacked connections to the main network; see [Figure 4](#)). Cluster 1 (red in [Figure 4](#)) focuses on changes in supply chain management driven by disruptive technologies. It includes the seminal work by [Teece et al. \(1997\)](#), which introduces the concept of dynamic capabilities as a strategic response to continuously evolving environments. Cluster 2 (blue) comprises foundational literature on Industry 4.0 and digital transformation in procurement, often with references to sustainability. These works highlight the broad impact of digitalisation across supply chains. Cluster 3 (green) contains studies on specific AI applications in procurement and supply chains, offering

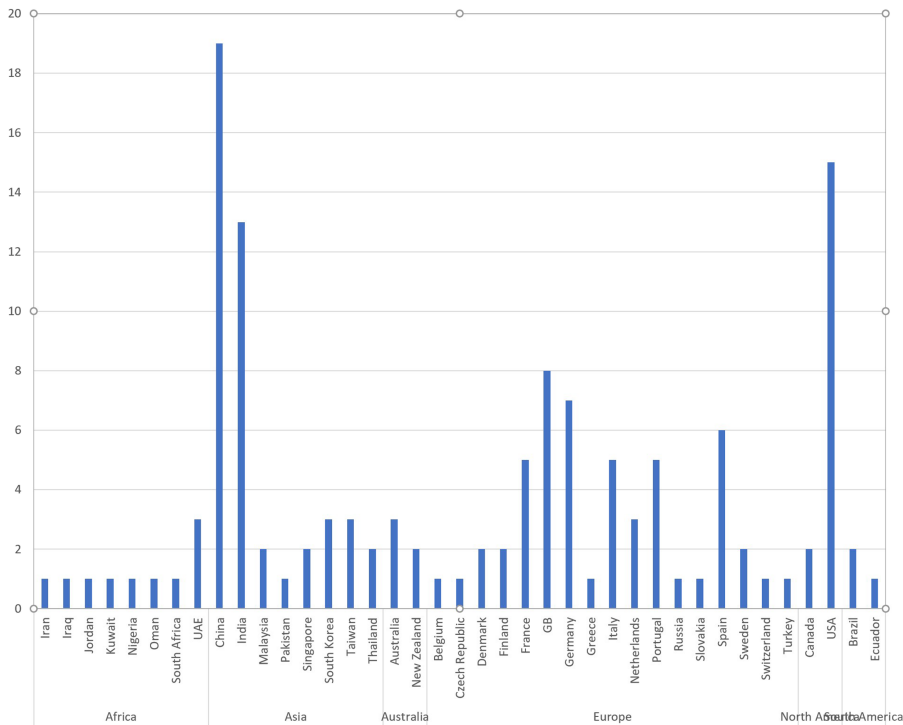


Figure 3. Researcher per country and continent. Source: Authors' own work

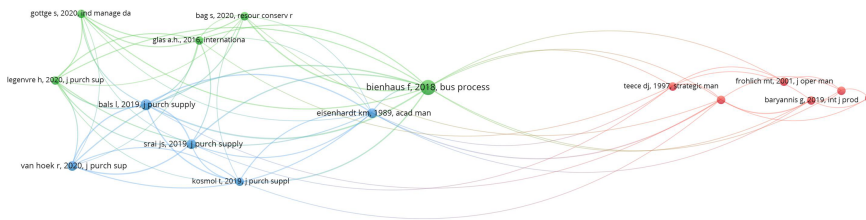


Figure 4. Co-citation analysis, own elaboration in VOSviewer. Source: Authors' own work

use cases and practical examples. It also includes Eisenhardt's (1989) influential paper on case study research, frequently used as a methodological reference in these studies. All three clusters are interconnected through Bienhaus and Haddud (2018) – an early empirical study based on a quantitative survey of procurement professionals, identifying key benefits and barriers to digitalisation. This paper forms the central link in the network, with 14 connections and 9 citations.

Overall, the bibliometric results underscore the emergent nature of the field. The need to lower the citation threshold to just three to generate meaningful clusters indicates that the theoretical foundation is still in its formative stages.

4.4 Research methods employed

As the final step in the bibliometric analysis, we examined the research methods employed across the reviewed papers. Most studies (45) adopt a quantitative research design, while significantly fewer rely on qualitative approaches (17), and only one study uses a mixed-methods framework. Notably, 15 papers are based on use cases, underscoring the relevance of industry-specific solutions that can be directly implemented by companies. Additionally, we identified 11 conceptual papers, indicating that scholars are beginning to develop foundational frameworks to guide future research in this emerging field.

5. Discussion

5.1 Findings on AI implementation in procurement

Our analysis shows that most studies focus on strategic aspects of procurement, particularly purchasing optimisation, supplier management, and supplier development. AI and related technologies are increasingly associated with improvements in process efficiency and decision support. Frequently discussed tools include robotic process automation, machine learning, data mining, and blockchain.

In addition, sustainability has emerged as a growing research theme, particularly in recent publications. Many studies address carbon reduction, green purchasing strategies, and responsible sourcing practices.

(Berneis and Winkler, 2024; Bhattacharjee *et al.*, 2024; Chiu *et al.*, 2024; e.g. Foroughi *et al.*, 2025; Huang and Mao, 2024; Kumar and Zhang, 2024; Niu *et al.*, 2025; Qian *et al.*, 2021; Vaca-Recalde *et al.*, 2024). However, the evidence remains concentrated in a limited number of sectors, primarily construction, public procurement, and manufacturing.

In response to RQ1, the findings indicate a shift in how AI is studied in procurement. While some previously identified trends remain relevant, we observe a notable shift in how AI is studied. Earlier research predominantly focused on task-level automation (e.g. forecasting, spend analysis, supplier selection), whereas more recent studies increasingly explore AI in broader, process-level and strategic contexts. This includes applications related to process optimisation, risk management, and decision support, although such uses remain unevenly developed across the literature.

Our RQ1 related to the research areas that evolved since the publication of the systematic literature review paper by Guida *et al.* (2023) revealed that, indeed, new technologies are being studied. The analysis also shows a shift in the technological focus of the literature. While earlier studies frequently addressed tools such as chatbots and natural language processing, more recent research increasingly considers broader digital technologies, including blockchain and building information modeling (BIM), often in combination with AI-based approaches.

During the review, we were able to prepare a detailed mapping of papers in relation to the procurement process. Therefore, we followed the aforementioned framework introduced by Guida *et al.* (2023) and cross-referenced our findings with theirs to compare how academic interest in specific hotspots has evolved over time. We assigned each paper to a specific phase and sub-phase of the purchasing process and identified functions in which AI-powered solutions were applied. This resulted in the adjusted framework depicted in Figure 5. Since a single paper could address more than one purchasing function, the number of identified functions does not correspond directly to the number of papers. Our analysis focused exclusively on studies published from 2021 onwards and thus serves as a complementary extension to the original framework. As in the previous study, the encircled numbers are scaled according to the node size.

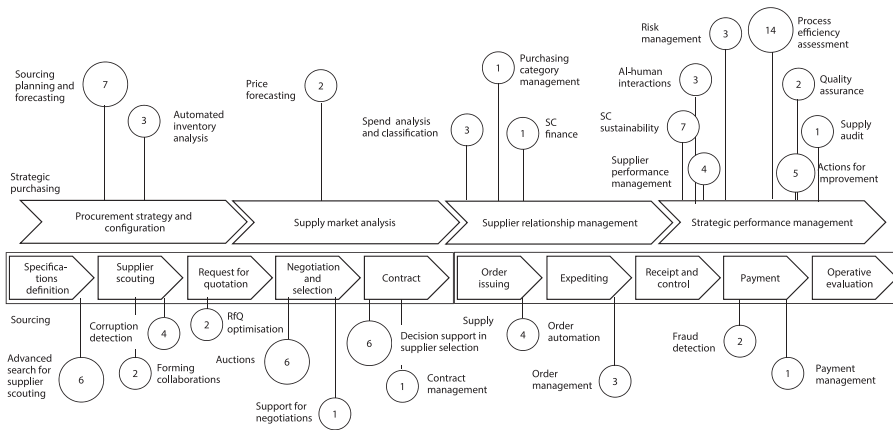


Figure 5. Framework for mapping AI functionalities in procurement process – 2021+ papers. Source: Authors’ own work based on [Guida et al. \(2023\)](#). Note: the number of publications in the analysis does not match the number of topics identified since individual papers could cover more than a single purchasing function

An interesting observation is the shift in academic focus compared to studies conducted prior to 2020. In particular, there is a stronger emphasis on sustainability, reflecting the expanding regulatory landscape shaping procurement strategies across sectors. At the same time, there is a notable increase in research examining the efficiency and application of artificial intelligence, especially in the context of human–AI interaction. This includes a critical examination of the trade-offs involved in delegating tasks to AI, alongside the potential benefits of reallocating human resources away from routine, repetitive activities.

Recent studies also indicate a move toward the strategic implementation of AI across the procurement process, extending beyond isolated, task-specific applications. In parallel, growing attention is being paid to the role of AI as a tool for enhancing transparency, particularly in public institutions, including its potential to mitigate corruption risks. This evolution reflects a broader, more integrated approach to digital transformation in supply chain and procurement management.

While [Guida et al. \(2023\)](#) identify most articles within strategic purchasing as focusing on negotiation and supplier selection, our sample shows a different distribution, with the majority of studies classified under strategic procurement, followed by supplier management and negotiations. This shift can be linked to the disruption of global supply chains during the COVID-19 pandemic, and subsequent crises, including the Ever Given Suez Canal blockage and attacks on commercial shipping in the Red Sea associated with the Houthis. As a result, topics such as nearshoring and supply base reconfiguration have gained prominence, increasingly shaping boardroom discussions on purchasing strategy. These developments were not yet central when [Guida et al. \(2023\)](#) conducted their review. At the same time, their observation regarding the limited presence of a strong process perspective and solid theoretical grounding remains valid. Our findings confirm this gap: only 17 out of the 89 reviewed papers adopt a process perspective, and relatively few studies engage explicitly with theory development. This suggests that, despite the growing practical relevance and expanding scope of AI applications in procurement, the field still lacks deeper theoretical integration and process-oriented explanations.

While performing the review and classification, several avenues for future research became apparent. First, there is a clear need for more studies examining the actual execution of procurement processes. In particular, areas such as quality control, invoice verification, and payment processing remain underexplored. Quality control, for instance, is addressed only

marginally, with limited evidence such as the study by [Niu et al. \(2025\)](#) focusing on improvements in incoming goods quality.

Second, the scarcity of research on invoice verification is particularly surprising given the advanced state of automation in financial and banking processes in other industries. This suggests a disconnect between technological capabilities and their application within procurement, highlighting a promising direction for future empirical and process-oriented research.

Thirdly, the review confirms that comprehensive roadmaps or frameworks for AI implementation in procurement remain largely underdeveloped. Existing research tends to emphasise the potential of AI or focus on individual use cases and their benefits, rather than offering integrated approaches to implementation. [Guida et al. \(2025\)](#) explicitly identify this gap, observing that research has focused on specific applications (e.g. spend analysis or automation of routine tasks) without an integrated framework for broader implementation.

Many studies adopt a case-specific perspective. For example, [Van Hoek et al. \(2022\)](#) document RPA implementation at Maersk's procurement as a standalone success story, yet without generalising these insights into a transferable roadmap. Overall, the literature converges on the observation that, while isolated AI applications are well documented, there is a lack of overarching frameworks or phased implementation pathways to guide procurement organisations through AI-driven transformation. This need is further reinforced by [Van Hoek \(2024\)](#), who calls for more structured guidance for both managers and researchers.

All of these gaps contribute to a certain level of "confusion" among practitioners regarding which AI tools and technologies to adopt, and how to evaluate their effectiveness. A recent mixed-methods review ([Spreitzenbarth et al., 2024](#)) identifies a mismatch between existing literature and expert assessments, indicating that academic focus doesn't reflect practitioners' priorities. This disconnect may contribute to uncertainty among practitioners – procurement professionals lack clear guidance on which AI tools address their specific needs. In parallel, [Van Hoek \(2024\)](#) reports low readiness levels among procurement leaders (only 14% feel they have the necessary talent for future AI adoption), implying uncertainty in executing and evaluating AI initiatives. The literature recognises that without clearer frameworks, practitioners remain unsure which AI solutions to invest in and what performance indicators to use to study AI's impact.

At the same time, the potential of AI to reduce supply chain risk, enhance resilience, and support sustainability remains insufficiently explored, particularly in the context of purchasing strategy. While several studies acknowledge AI's capacity to strengthen resilience, sustainability-related applications in procurement remain underdeveloped. For example, [Modgil et al. \(2022\)](#) propose a framework showing that an AI-enabled supply chain can sense risks, analyse scenarios, reconfigure networks, and rapidly activate responses to disruptions – essentially illustrating how AI builds resilience during crises like COVID-19. Similarly, [Chiu et al. \(2024\)](#) demonstrate AI's role in sustainability by developing an intelligent system for green supplier risk assessment (integrating NLP with lifecycle assessment to evaluate suppliers' environmental risks). These instances confirm AI's utility in managing risk and sustainability. Despite these contributions, broader evidence remains limited. [Spreitzenbarth et al. \(2024\)](#) explicitly identify supplier sustainability as an under-researched area, indicating that this domain is still in an early stage of development and requires further systematic investigation.

Another important gap concerns the limited attention given to small and medium-sized enterprises. Although a substantial number of studies examine AI adoption in large organisations, SME-focused research remains scarce. Only isolated contributions, such as [Liu et al. \(2022\)](#) address SME-specific needs by proposing digital platforms that enable dynamic supply chain collaboration through capacity pooling. Beyond such examples, the literature largely assumes contexts typical of larger firms, leaving open questions regarding how SMEs – often constrained by limited resources and data availability – can effectively implement AI.

This highlights a significant gap related to scalability, resource constraints, and the adaptation of AI tools to smaller organisational settings.

Data-related challenges represent another recurring theme. Multiple studies emphasise that high-quality, well-structured data is a prerequisite for successful AI implementation in procurement. [Van Hoek \(2024\)](#) observes that data availability and quality issues often hinder AI's full potential in procurement. Similarly, [Pathak \(2023\)](#) notes that companies are struggling with the overwhelming volume of data; an inability to extract relevant information from big data makes strategic decision-making difficult and poses risks. These findings confirm that many organisations lack clear strategies for data preparation (e.g. cleaning, categorisation, integration) to support AI tools. While specific papers (e.g. [Guida et al. \(2025\)](#) on spend classification) point to the need for structured data practices, such as spend classification, the literature generally treats data challenges as obstacles rather than offering concrete methodologies for data preparation, integration, and governance. This indicates a clear need for more operationalised guidance in this area.

The human dimension constitutes an additional, yet still underexplored, aspect of AI adoption in procurement. Organisational and behavioral factors, including skills, culture, and change management, are consistently identified as barriers to implementation. [Van Hoek \(2024\)](#) emphasise that a lack of analytical capabilities and resistance to change significantly hinder AI adoption. Empirical evidence, such as the multi-case study by [Colombo et al. \(2023\)](#) further shows that firms implementing AI-driven automation must invest in upskilling employees and redefining roles to fully leverage augmentation effects. These findings suggest that successful AI adoption requires not only technological readiness but also organisational transformation, including training, leadership, and cultural adaptation.

Finally, the review identifies several emerging areas for future research, including AI-supported contract negotiation and enhanced buyer-supplier collaboration. While initial studies suggest that AI can support negotiation processes and improve transparency, full automation remains limited and dependent on human oversight. For example, [Schulze-Horn et al. \(2020\)](#) demonstrate that AI-driven mechanism design can facilitate complex negotiations and potentially shift bargaining power in favor of buying organisations. At the same time, studies such as [Viale and Zouari \(2020\)](#) show that automation tools like robotic process automation can improve relationship quality by relieving employees from routine tasks, thereby enabling greater focus on strategic interaction. Overall, while AI shows clear potential to streamline negotiation and strengthen collaboration, fully automated relationship management remains neither feasible nor desirable at the current stage.

Altogether, the systematic literature review not only captures the current state of research but also highlights substantial gaps across multiple dimensions, including theory development, process orientation, data management, organisational readiness, and SME applicability. These gaps point to a broad and evolving research agenda that extends beyond isolated applications toward more integrated and context-sensitive approaches to AI in procurement.

5.2 Findings on AI implementation in SLR

[RQ2](#) and [RQ3](#) address the use of AI during the literature review process. In fields such as medicine, where researchers work with large and heterogeneous datasets, prior studies have explored how AI can support different stages of systematic reviews. However, such applications remain less developed in the context of Supply Chain Management. Existing evidence suggests that AI is most commonly used in the title and abstract screening phase, as well as in literature search ([Ofori-Boateng et al., 2024](#)). Unlike these approaches, this study does not involve training a dedicated model (e.g. [Pilz et al., 2024](#)) nor develop a specific tool (e.g. [van de Schoot et al., 2021](#)). Instead, we examine how readily available AI tools can support the review process without requiring advanced programming or IT capabilities.

Consistent with prior research, the findings indicate that AI can serve as a useful support tool, although it cannot replace human involvement. The scoping phase may benefit from AI-supported functionalities embedded in databases, and screening activities can be accelerated when tasks are clearly defined. While no clear cases of factual hallucinations were identified in our setting, classification outcomes were sensitive to conceptual ambiguity, and human oversight remained essential for final evaluation. The results also suggest that the ChatGPT 4.5 Deep Research mode is associated with higher classification consistency compared to earlier configurations.

With regard to [RQ3](#), the findings indicate that AI tools are less effective in later stages of the review process, particularly in reporting and synthesis. At this stage, AI appears to function more effectively as a source of analytical prompts that support researcher reflection and discussion, rather than as a generator of complete and coherent conceptualisations.

Addressing [RQ2](#) and [RQ3](#) provides further insight into the role of AI across different phases of the SLR process. In the planning stage, the process remains primarily human-led, although AI may support activities such as keyword generation. In the conducting stage, both initial and in-depth screening can be facilitated through structured prompting. In contrast, in the reporting and synthesis stage, AI contributions remain limited and require substantial researcher involvement. Overall, the findings suggest that AI tools are best understood as complementary instruments that can support selected stages of the review process, rather than replace human-led approaches.

Finally, the study contributes to process-oriented perspectives in Business Process Management by extending the framework of [Guida et al. \(2023\)](#) a structured synthesis of AI-related applications across procurement stages. Rather than advancing a standalone theoretical model, the study provides insights that may inform further development of process-based approaches to digital transformation in procurement.

6. Concluding remarks and implications

6.1 Theoretical implications

This study addresses the concerns raised by [Guida et al. \(2023\)](#), who noted that discussions around AI implementation in managerial contexts were predominantly abstract and oriented toward an indefinite future. By contrast, our research contributes to the literature by synthesising empirical evidence of how AI is already being employed in practice. Nevertheless, these instances are characterised by a high degree of fragmentation, confined largely to specific industries or narrowly defined contexts. This highlights a persistent gap in literature: the limited availability of integrative, cross-sectoral theoretical framework that could guide strategic AI integration within procurement and related managerial functions. Such fragmentation limits the scalability, comparability and generalisability of existing insights. Future research could therefore focus on theorising an integrative framework that captures not only technological adoption, but also organisational conditions, human-AI interaction and the processual nature of procurement activities. Developing such a framework would strengthen the theoretical foundations of AI adoption and facilitate more coherent cross-industry applications.

In addition, our findings show that most studies draw predominantly on quantitative designs. Given the complexity of organisational decision-making and the need for practitioners to access applicable and context-sensitive AI tools, future research would benefit from more mixed-method approaches. Combining qualitative insights with quantitative validation could improve understanding of the mechanisms through which AI creates value in procurement, clarify contingencies that influence outcomes and support the development of theories that are both analytically robust and practically meaningful. In addition, emerging economies that often are not home to large-scale industrialised companies and do not provide detailed statistics are an interesting research field for qualitative studies.

From a theoretical perspective, the reference process model ([Figure 5](#), based on [Guida et al., 2023](#)) highlights an imbalance between process design and process execution in the

existing literature. While strategic process stages receive substantial scholarly attention, operational execution and closure activities remain weakly conceptualised, despite their centrality to end-to-end process performance. This asymmetry challenges assumptions in BPM research regarding holistic process coverage and suggests the need to further extend process-oriented perspectives to better account for how digital and AI-enabled processes are governed, monitored, and reconfigured across organisational layers.

Moreover, the study reinforces the relevance of process-oriented thinking in digitally intensive contexts. Prior reviews on AI in procurement and related domains (e.g. Guida *et al.*, 2023) have predominantly adopted functional, technological, or thematic perspectives, which may obscure process interdependencies, sequencing logics, and feedback mechanisms. In contrast, the process-oriented synthesis developed in this study provides a structured view of how AI-related capabilities are positioned within and across process layers and how they shape coordination between strategic and operational activities. In doing so, it highlights structural blind spots – such as under-theorised execution stages and missing feedback loops – that remain less visible in non-process-oriented review approaches.

6.2 Methodological implications

This study also offers methodological insights into the integration of AI tools into academic research workflows. The use of ChatGPT, including its Deep Research functionality, supported the efficiency and scalability of the systematic literature review process by enabling the processing of large volumes of academic texts in a structured and consistent manner. In our setting, approximately 77% of the reviewed papers were aligned with the final human classification, with most discrepancies reflecting boundary cases between adjacent process steps (e.g. S3 vs. S5) rather than fundamental misclassification across broader categories.

At the same time, several limitations became evident. The tools showed sensitivity to nuanced conceptual distinctions, particularly in cases where papers spanned multiple process stages. This indicates that AI-assisted classification remains dependent on interpretive judgment and domain knowledge. Accordingly, human oversight remains essential, especially in tasks requiring contextual interpretation and qualitative evaluation.

These findings suggest that AI tools can support selected stages of the review process, but are not yet suitable for fully autonomous application. Rather than replacing human-led approaches, they are better understood as complementary instruments that can enhance efficiency under clearly defined conditions. From a methodological perspective, this points to the need for further development of transparent validation procedures and standardised reporting practices. Such developments may improve the reliability of AI-assisted methods and support their gradual integration into academic research workflows.

6.3 Practical and societal implications

This review offers several implications that help translate current academic insights on AI in procurement into both practical and societal value. The analysis shows that although AI technologies are increasingly applied across procurement activities, their use remains highly fragmented and often limited to task-specific implementations. As a result, organisations may face challenges in identifying how AI can be meaningfully integrated into procurement processes. By consolidating evidence from recent studies, this review helps bridge the gap between theory and practice and provides evidence-informed insights for organisations exploring AI adoption.

The findings suggest that building solid organisational and data foundations is a key precondition for AI adoption. In particular, prior research highlights the importance of improving the quality, structure, and accessibility of procurement data. The literature also indicates that the role of AI extends beyond the automation of routine tasks. Studies point to its potential to support supplier risk assessment, sustainability evaluations, process transparency

and more informed strategic decision-making. These developments position AI not only as a set of isolated tools, but as an enabler of broader process improvements within procurement.

To further strengthen the practical relevance of the findings, the study translates the fragmented evidence identified in the literature into a process-based managerial roadmap. While prior research predominantly presents isolated use cases of AI in procurement, the analysis reveals recurring patterns that can be systematically aligned with the stages of the procurement process. This allows for a more structured interpretation of how AI applications relate to process stages and organisational conditions.

Table 6 synthesises these patterns by linking procurement process stages with (1) observed AI applications, (2) enabling organisational and data-related requirements, and (3) key risks and constraints. Importantly, the framework is not derived from individual studies but reflects recurring themes across the reviewed literature, particularly with regard to data availability, system integration, and organisational readiness.

The roadmap highlights that AI adoption in procurement is inherently processual and cumulative. Early-stage applications, such as spend analysis or demand forecasting, are closely linked to data availability and quality, whereas more advanced applications in supplier

Table 6. Process-based roadmap for AI in procurement

Procurement stage	AI applications	Enabling requirements	Key risks/constraints
S1. Demand and market analysis	Spend analysis, forecasting, market intelligence	Availability of structured historical procurement data; data integration across sources	Data quality issues; difficulty extracting relevant insights from large datasets
S2. Supplier selection and evaluation	Supplier scoring, risk assessment, decision support	Access to supplier data (internal/external); standardised evaluation criteria	Incomplete or inconsistent supplier data; limited transparency of AI outputs
S3. Contracting and negotiation	Contract analysis, support for negotiation processes	Digitised contractual data; formalised negotiation parameters	Legal and interpretative risks; limits of automation in complex negotiations
S4. Supplier management	Performance monitoring, anomaly detection, risk monitoring	Continuous data flows; KPI systems; data sharing with suppliers	Data silos; limited supplier integration; organisational resistance
S5. Strategy optimisation	Decision support, process optimisation, strategic analytics	Cross-functional data integration; analytical capabilities; organisational alignment	Lack of skills; unclear performance metrics; strategic misalignment
O1. Requirements definition	Demand prediction, automated planning	Integration with ERP/planning systems; real-time data inputs	Data inconsistency; system integration challenges
O2. Ordering	Order automation, RPA in purchasing processes	Standardised and digitised workflows	Automation errors; over-standardisation of processes
O3. Delivery monitoring	Tracking, delay prediction, logistics analytics	Access to real-time logistics data	Limited visibility; data latency
O4. Goods receipt and quality	AI-supported quality control (limited evidence)	Digital quality data and inspection systems	Very limited research coverage; underdeveloped applications
O5. Invoice and payment	Invoice automation, fraud detection (very limited evidence)	Structured financial and transactional data	Strong research gap; implementation uncertainty

Source(s): Authors' own work

management or strategic optimisation are associated with higher levels of organisational integration and analytical capability. At the same time, risks evolve across process stages, shifting from data-related challenges to issues related to governance, capability, and alignment issues in more strategic phases. Furthermore, the framework reveals an imbalance in the literature: as AI applications are more developed in strategic stages, while operational stages – particularly quality control and invoice processing – remain underexplored. This points to the need for a more holistic, end-to-end perspective on procurement digitalisation.

To bridge the gap between academic insights and managerial action, the literature suggests several entry points for organisations at early stages of AI adoption. For example, studies frequently describe initial implementations focusing on narrowly defined processes, such as invoice verification or spend categorisation, which allow organisations to build capabilities incrementally. Similarly, prior research highlights the importance of data standardisation, basic digitalisation, and cross-functional coordination in supporting AI adoption. These steps are associated with improved understanding of AI-enabled processes and more effective monitoring of implementation outcomes.

The implications are particularly relevant for small and medium-sized enterprises and organisations in emerging economies, which are underrepresented in the current literature. These firms often face additional challenges related to financial resources, data availability, and analytical capabilities. The literature suggests that modular, low-investment solutions – such as basic forecasting tools, automated data extraction, or robotic process automation – may provide accessible entry points for AI adoption. At the same time, gradual digitalisation and the development of basic data governance practices are frequently identified as important precursors to more advanced AI applications. Participation in shared procurement platforms or digital ecosystems may further support access to capabilities that are otherwise difficult to develop internally.

Additionally, regulatory initiatives such as the European Corporate Sustainability Due Diligence Directive may contribute to the diffusion of best practices across regions, including in relation to AI-enabled procurement processes. However, empirical evidence in this area remains limited, indicating a need for further research.

There are also broader societal implications. In many economies, SMEs play a central role in economic activity, and AI-enabled procurement may contribute increased transparency, reduced corruption risks, and more sustainable sourcing practices. At the same time, public policy may support these developments through investments in digital infrastructure, access to training, and the establishment of data governance standards. In this way, AI adoption in procurement may contribute not only to organisational efficiency, but also to more resilient, transparent supply chains.

Finally, the review offers implications for teaching. The examples identified in this study may support educators in integrating real-world AI applications into procurement and supply chain curricula, thereby strengthening the practical relevance of educational programmes.

6.4 Limitations of the study

While this study provides relevant insights, several limitations should be acknowledged. First, the review is based on publications indexed in Scopus and Web of Science. Although these databases ensure broad coverage of high-quality journals, their classification systems may exclude relevant interdisciplinary contributions. This limitation was partially mitigated through the snowballing procedure described in the methodology.

Second, the study relies on a structured classification of papers into predefined procurement process stages. While this approach enables systematic comparison, it simplifies contributions that may span multiple stages, which may partly explain some classification discrepancies observed in the analysis.

Third, although AI tools like ChatGPT, including its Deep Research functionality, supported the review process by enabling the handling of large volumes of academic texts,

their application revealed several limitations. In particular, classification performance was sensitive to conceptual ambiguity and boundary cases, and instances of misclassification indicate that current AI systems are not yet suitable for fully autonomous use in complex research workflows.

These limitations suggest that AI tools are best understood as complementary instruments that can support selected stages of the research process, rather than replace human-led approaches. Accordingly, their use requires careful integration with expert judgment, particularly in tasks involving interpretation and domain-specific reasoning.

Future studies could further explore hybrid methodologies that combine the efficiency of AI-assisted techniques with the interpretive capabilities of researchers. In addition, the development of more transparent validation procedures and standardised reporting practices may contribute to improving the reliability and acceptance of AI-assisted approaches in academic research.

Table A1. List of prompts used

Phase	Prompt used
Phase 2 – initial screening of the abstracts	<p>You are provided with a file containing a list of research papers extracted from indexed databases. The columns include</p> <p>Column A: Authors Column B: Title Column C: Authors’ keywords Column D: Indexed keywords Column E: Abstract</p> <p>Your task</p> <p>In Column F, indicate whether the paper is related to the use of AI-powered tools in procurement/supply chain (including commonly used synonyms or alternatives such as machine learning, deep learning, predictive analytics, etc.). Use <i>Yes</i> or <i>No</i></p> <p>In Column G, provide a brief justification (2–3 sentences) explaining your decision, based on the title, keywords, and abstract</p>
Phase 2 – analysis of full papers (each of the three iterations separately)	<p>You are provided with a file containing a list of research papers extracted from indexed databases</p> <p>Table A: Contains descriptions of strategic steps (S1–S5) and operational steps (O1–O5) in purchasing Table B: Contains the following columns</p> <p>Column A: Authors Column B: Title Column C: Authors’ keywords Column D: Indexed keywords Column E: Abstract Column F: Findings</p> <p>Your task</p> <p>Review each paper and determine which step it corresponds to (S1–S5 for strategic purchasing or O1–O5 for operational purchasing) based on its primary focus. Enter the assigned step in Column G for the respective row</p> <p>Provide a brief justification (2–3 sentences) in Column H, explaining why you assigned that step, using evidence from the title, keywords, abstract, and findings. Use an interpretative approach grounded in domain knowledge, conceptual understanding, and thematic inference. Rely on qualitative reasoning and conceptual alignment between the thematic focus of each paper and the definitions of the procurement process steps</p>
Phase 3 – reporting	<p>You are provided with a file containing a list of research papers we analysed</p> <p>Table A: Contains descriptions of strategic steps (S1–S5) and operational steps (O1–O5) in purchasing Table B: Contains the following columns</p> <p>Column A: Authors Column B: Title Column C: Authors’ keywords Column D: Indexed keywords Column E: Abstract Column F: Findings Column G: Decision on which step of procurement the paper relates to Column H: Justification for the alignment</p> <p>Your task</p> <p>Review all papers in Table B and identify thematic issues and emerging trends across the studies. Group the papers according to their focus and distinctive features. Provide a structured summary of these themes and trends, highlighting patterns, gaps, and notable directions in the research</p>

Source(s): Authors’ own work

1. Data analysis was conducted using OpenAI's O3-Deep-Research model (version o3-deep-research-2025-06-26, released June 26, 2025), an advanced research system designed for multi-step reasoning and synthesis. According to OpenAI ("Introducing Deep Research", 2025; "Introducing GPT-4.5", 2025), GPT-4.5 is a research preview of OpenAI's largest and most capable chat model to date, featuring broader world knowledge, enhanced pattern recognition, improved alignment with user intent, and higher emotional intelligence than prior versions; it is designed for advanced writing, problem-solving, and programming tasks and is being shared to evaluate strengths and limitations across diverse applications. Deep Research is a new agentic capability within ChatGPT that autonomously conducts multi-step internet research to find, analyse, and synthesise hundreds of online sources into comprehensive reports with clear citations and summaries, enabling results in minutes that would otherwise require hours of manual work. In our approach the model did not have access to the web at any point in the coding process. All inputs were restricted to the dataset we provided.

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