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Investigating the Impact of Artificial Intelligence on Procurement &
SCM Strategies
A study of the International Automotive Sector

Cranfield School of Management
Logistics and Supply Chain Management

MSc
Academic Year: 2024 - 2025

Supervisor: Dr. Farooq Habib
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This thesis is submitted in partial fulfilment of the requirements for
the degree of MSc

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Academic integrity declaration

I declare that:

- the thesis submitted has been written by me alone.
- the thesis submitted has not been previously submitted to this university or any other.
- that all content, including primary and/or secondary data, is true to the best of my knowledge.
- that all quotations and references have been duly acknowledged according to the requirements of academic research.

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Abstract

Purpose of the research

The purpose of this research is to explore the impact and role of artificial intelligence in the procurement and supply chain operations of the international automotive sector. More specifically, this research aims to explore key artificial intelligence applications in the supplier selection, evaluation and supply chain resilience operations, identify key barriers to AI implementation, analyze key strategic benefits and tactical measurable impacts derived from AI adoption, and develop key implementation recommendations.

Methodology

This research adopts systematic literature review methodology, including its major five steps: planning, screening, searching, extraction & synthesis and reporting of the descriptive and thematic findings. In total, it employs 70 academic sources and 14 industrial sources.

Key Findings

In general, automotive supplier selection and supply chain resilience are significantly impacted by the use of artificial intelligence, but the set of applied tools and practices remains limited. Although advanced technologies such as GenAI and NLP are already being applied selectively in the supplier selection and evaluation process, basic machine learning applications remain the key tools at this stage. In terms of supply chain resilience, deep learning tools are the primary technology in use, while GenAI is employed fragmentally. On the path to AI implementation, organisations face many organisational, regulatory and technical barriers, but with proper data and change management, technical architecture setup, high-ROI use cases prioritisation, and effective AI governance, the effect of AI implementation is significant, resulting in improved supply chain resilience, a more accurate, scalable and reliable supplier selection process and significant time and cost savings.

Practical value

This work has a high practical value, as it not only provides an overview of the main AI applications in supplier selection, evaluation, and resilience, but it also represents a multi-phase structured framework for AI implementation based on the synthesis of academic and industrial sources, taking into account the main barriers and steps for mitigating them.

Keywords: Supplier Selection; Supplier Evaluation; Supply Chain Resilience

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List of Abbreviations

AI	Artificial Intelligence
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
API	Application Programming Interface
BCG	Boston Consulting Group
BERT	Bidirectional Encoder Representations from Transformers
CRM	Customer Relationship Management
DAI	Distributed Artificial Intelligence
DEMATEL	Decision Making Trial and Evaluation Laboratory
DL	Deep Learning
DRL	Deep Reinforcement Learning
EBSCO	Elton B. Stephens Company
ELECTRE	ELimination Et Choix Traduisant la REalite
ERP	Enterprise Resource Planning
EU	European Union
EU AI Act	European Union Artificial Intelligence Act
EV	Electric Vehicle
FIS	Fuzzy Inference System
G7	Group of Seven
GA	Genetic Algorithm
GAC	Guangzhou Automobile Group
GDPR	General Data Protection Regulation
GPT	Generative Pretrained Transformer
HR	Human Resources
IBM	International Business Machines Corporation
ID3	Iterative Dichotomiser 3

IT	Information Technology
JV	Joint Venture
KPI	Key Performance Indicator
LIME	Local Interpretable Model-agnostic Explanations
LLM	Large Language Model
LSTM	Long Short-Term Memory
M&A	Mergers and Acquisitions
MAS	Multi-Agent Systems
MCDM	Multi-Criteria Decision-Making
MENA	Middle East and North Africa
ML	Machine Learning
MLP	Multilayer Perceptron
NEV	New Energy Vehicle
NER	Named Entity Recognition
NLP	Natural Language Processing
OECD	Organisation for Economic Co-operation and Development
OEM	Original Equipment Manufacturer
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RBFNN	Radial Basis Function Neural Network
RE	Relation Extraction
RFECV	Recursive Feature Elimination with Cross-Validation
RFI	Request for Information
RFP	Request for Proposal
ROI	Return on Investment
RPA	Robotic Process Automation
RPN	Risk Priority Number
SCM	Supply Chain Management

SCREM	Supply Chain Resilience Estimation Model
SHAP	SHapley Additive exPlanations
SLR	Systematic Literature Review
SMEs	Small and Medium-sized Enterprises
SoC	System-on-Chip
SPGM	Sum-Product Graphical Model
SVM	Support Vector Machine
TCO	Total Cost of Ownership
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
TTR	Time-to-Recover
TTS	Time-to-Survive
UK	United Kingdom
VIKOR	VlseKriterijumska Optimizacija I Kompromisno Resenje
VUCA	Volatility, Uncertainty, Complexity, Ambiguity
WEF	World Economic Forum
XAI	Explainable Artificial Intelligence

List of Key Definitions

Term	Definition
Artificial Intelligence	Artificial Intelligence refers to computer systems capable of performing tasks that typically require human intelligence, such as learning, reasoning, problem-solving, and decision-making
Supplier Selection and Evaluation	Supplier selection and evaluation refers to the structured process of identifying, assessing, and choosing suppliers based on predefined set of criteria
Supply Chain Resilience	Supply chain resilience is the capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them

1 CHAPTER 1: INTRODUCTION

1.1 Chapter Overview

This chapter covers the research motivation, context and background. It outlines the research problem and explains why AI-based methods are becoming more and more relevant in the automotive supply chain and procurement. The chapter consists of six main sections, which include the research problem, research background, research objectives, research questions, research scope, and an outline of the thesis structure.

1.1.1 Research Problem

In the current unstable global supply chain environment, automotive supply chains are facing difficult times and unprecedented challenges, including geopolitical disruptions, pandemics, wars, critical component shortages, ESG requirements, supplier vulnerability and fluctuating demand.

The urgency for AI transformation of supply chain processes became evident during the 2021-2022 semiconductor shortage crisis and COVID-19 pandemic, when automotive OEMs experienced severe production halts due to weak upstream visibility and limited supplier flexibility.

In addition to frequent disruptions, automotive supply chains are becoming increasingly complex due to the growing number of suppliers and logistics routes. Furthermore, the diversification of vehicle types, including hybrids and electric vehicles (EVs), as well as the expanding component base, has added complexity to procurement and supply chain processes.

Such new challenges and disruptions have sparked an interest in incorporating AI tools into procurement and supply chain processes and demonstrated the need for strong, AI-powered frameworks that can support both supply chain resilience and supplier evaluation.

1.1.2 Research Background

Traditionally, supplier selection and evaluation in the automotive industry have relied on AHP and MCDM decision-making frameworks, with limited use of basic machine learning techniques for supplier classification (Luthra et al., 2017; Jain et al., 2018). AHP allowed effectively digitising experts' evaluation judgements and obtaining the criteria rankings. MCDM techniques (TOPSIS, ELECTRE, VIKOR, DEMATEL) allowed ranking suppliers based on the final score and producing the overall supplier ranking. Depending on the chosen method, each decision was based on specific rules.

Despite the certain reliability of MCDM approaches and their heterogeneity, it is important to note that their functionality remains very limited. First, MCDM models are static and only tend to be effective when applied to limited datasets, where both the number of criteria and the number of suppliers are minimal. However, they are ineffective when processing massive amounts of data, particularly in real time. These methods are mainly applicable in pilot or academic projects, but their scalability for the industrial level is also limited.

Furthermore, MCDM tools are not able to identify and extract patterns and non-linear relationships based on historical data since they rely entirely on predefined criteria and depend on the subjectivity of expert judgements. In contrast, artificial intelligence has a much broader range of functionality, going beyond simply ranking suppliers. It can handle various data formats, including numeric, textual, visual, and unstructured data. As a result, organisations are turning toward AI-driven frameworks.

In this research, we examine a wide range of AI approaches for supplier selection, evaluation and resilience management in the automotive supply chain.

1.1.3 Research Objectives

The research objectives of this work are as follows:

1. To examine the applications of artificial intelligence in enhancing supply chain resilience and in improving supplier selection and evaluation within the automotive industry.
2. To identify and assess the critical challenges, barriers, and limitations in implementing AI solutions for supplier selection, evaluation, and supply chain resilience enhancement in the automotive sector.
3. To examine the benefits and measurable impacts from adopting AI technologies in enhancing supply chain resilience and improving supplier selection and evaluation
4. To recommend strategies for implementing AI-driven supplier evaluation, selection and resilience frameworks in the automotive industry.

1.1.4 Research Questions

This work addresses the following research questions:

1. What are the key AI applications currently used to enhance supplier selection, evaluation, and supply chain resilience in the automotive industry?
2. What are the critical challenges, barriers, and limitations in implementing AI technologies for supplier selection, evaluation, and resilience improvement?
3. What are the measurable benefits and impacts of adopting AI tools in supplier management and supply chain resilience?
4. What are the recommended strategies for successfully implementing AI-driven frameworks for supplier evaluation, selection, and supply chain resilience in the automotive sector?

1.1.5 Research Scope

This study focuses on the use of AI and machine learning techniques in supplier selection, evaluation, and supply chain. It considers their benefits, barriers, and phases of AI implementation. It addresses both the pre-contract and post-contract procurement phases, with a major focus on OEMs and Tier-1 suppliers.

The geographical focus is global, with particular emphasis on European and Asian automotive sectors.

1.1.6 Thesis Structure

Chapter 2 describes the methodology of the SLR process. Chapter 3 discusses the literature review's descriptive findings as well as the important characteristics of the collected data. Chapter 4 discusses key thematic findings from the literature review, including AI applications, barriers to adoption, benefits and measurable impacts, and implementation phases. Chapter 5 discusses the material, synthesises and interprets the thematic findings, also covering major research gaps based on the literature reviewed. Chapter 6 outlines key practical recommendations and managerial implications for AI implementation. Chapter 7 refers to conclusions, showing how the research objectives have been met.

2 CHAPTER 2: METHODOLOGY

2.1 Chapter Overview

This chapter describes the five main steps of the SLR process. The planning stage includes forming the review panel, mapping the field of study, and producing a review protocol. The planning and screening stages include the development of search strings, selection of key databases, and the formation of inclusion and exclusion criteria. The remaining stages include screening of the selected literature, conducting data extraction according to a predefined data extraction format, synthesis of key thematic findings across key research objectives and reporting the findings.

2.2 Forming the Review Panel

The review panel for this study included the researcher and the academic supervisor, Dr. Farooq Habib. The panel approved the project's initial scope and offered guidance on the development of the research objectives and research questions. The development of the search strings, selection of databases, and definition of inclusion and exclusion criteria were carried out independently by the researcher and approved by review panel.

2.3 Mapping the Field of Study

Based on the project title, four key search terms have been identified: artificial intelligence, supplier selection, supplier evaluation and supply chain resilience.

These key terms were then used to map out the field of study.

Figure 2-1 illustrates the three key thematic pillars in this automotive industry study using a Venn diagram: Supplier Selection and Evaluation, Supply Chain Resilience, and Artificial Intelligence. Each pillar is assigned a primary circle.

The overlapping areas represent the core focus of this study – the intersection of Artificial Intelligence, Supplier Selection & Evaluation, and Supply Chain Resilience in the automotive sector.

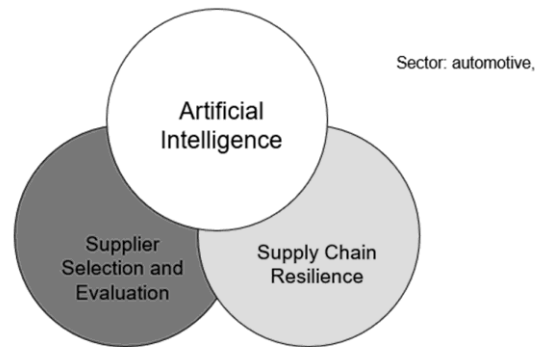


Figure 2-1: Sectoral Venn Diagram (Source: Author, 2025)

2.4 Producing the Review Protocol

The literature review followed a structured protocol based on the research objectives and questions. The protocol included the following components: Search Strings, Databases and Sources, Inclusion and Exclusion Criteria, Quality Appraisal Method.

2.5 Search Strings

For this review, the following search strings were applied to identify relevant academic articles: ("artificial intelligence" OR "machine learning") AND ("supplier evaluation" OR "supplier selection" OR "supplier performance" OR "supply chain resilience" OR "disruption prediction") AND ("automotive industry" OR "automotive sector" OR "automotive supply chain") AND ("artificial intelligence adoption" OR "artificial intelligence barriers" OR "artificial intelligence benefits") AND ("AI scaling" OR "AI deployment") AND ("data infrastructure" OR "technical infrastructure").

Table 2-1: Search String Formation

AI Terms		Supplier Terms		Industry Terms		Adoption / Barriers Terms		Not related terms
"artificial intelligence" OR "AI" OR "machine learning"	AND	"supply chain resilience" OR "disruption prediction" OR "supplier evaluation" OR "supplier selection" OR "supplier performance" OR "supplier scouting"	AND	"automotive industry" OR "automotive sector" OR "automotive supply chain"	AND	"AI adoption" OR "AI barriers" OR "AI challenges" OR "AI scaling" OR "AI deployment" OR "AI implementation" OR "data infrastructure" OR "technical infrastructure"	AND NOT	"MCDM" OR "AHP" OR "DEMATEL" OR "VIKOR" OR "TOPSIS" OR "ELECTRE"

Source: Author, 2025

The search strategy also included targeted strings for specific AI subdomains and techniques such as supervised learning, unsupervised learning, deep learning, and generative artificial intelligence. Additional search strings focused on barriers to AI implementation, implementation benefits and measurable impacts, and various stages of AI adoption. Search strings related to MCDM tools for supplier selection and evaluation have been excluded since the focus of the thesis is on artificial intelligence.

2.6 Databases and Journals

The following databases were selected due to their relevance for this area of research. The initial search was conducted via Google Scholar, which provided a broad foundation of potentially relevant sources. Additional searches were performed using several specialised databases, including EBSCO, Scopus, Web of Science, IEEE Xplore, arXiv, Wiley Online Library, Taylor & Francis Online, Emerald Insight.

2.7 Screening

The screening of academic literature was conducted using the databases outlined in Section 2.6. The PRISMA flow diagram was applied to the screening process.

In total, 1,541 records were found through Google Scholar, Scopus and other databases. After removing duplicates and applying title and keyword screening, 224 academic sources were identified. The exclusion criteria were then applied, resulting in the removal of 28 articles from the research scope (conference papers, book chapters, and articles covering other industries). Finally, 196 articles were selected for full-text review, resulting in 70 articles being included in the final analysis.

In addition to the 70 academic articles selected for review, 14 industrial sources from top-tier consulting agencies and corporations were also included in the research scope.

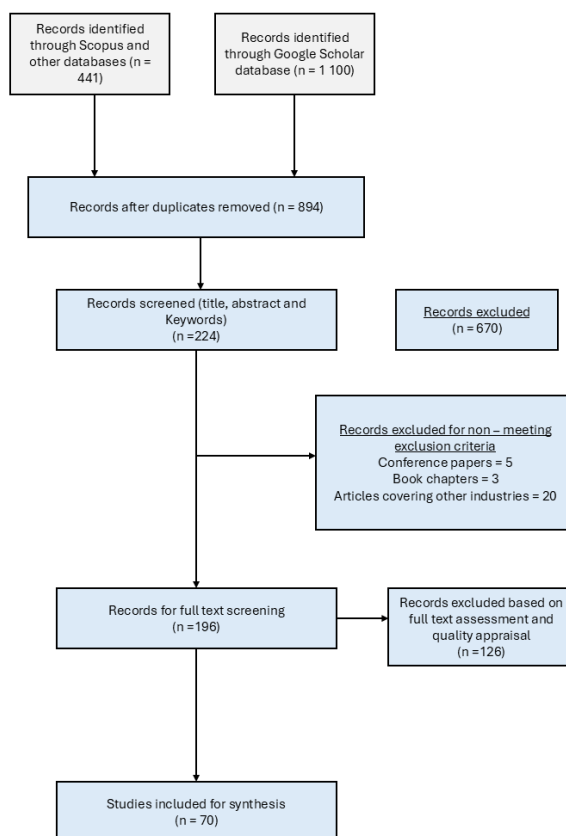


Figure 2-2: PRISMA flow diagram (Source: Author, 2025)

2.8 Inclusion and Exclusion Criteria

The inclusion criteria for this review were as follows: only articles written in English were considered. The publication period was set from 2016 to 2025; studies published prior to 2015 were excluded. The studies needed to be related to supply chain resilience, supplier selection, or supplier evaluation. The exclusion criteria included non-English publications. Peer-review status of the academic source was not used as an exclusion criteria due to the limited number of relevant AI-related studies in this field. The review considered academic journal articles, industry reports, and web-based articles, while conference proceedings and books were excluded.

Table 2-2: Summary of the Inclusion/Exclusion Criteria

Inclusion Criteria	Exlcusion criteria
Only articles written in English	Non-English publications
Publication period: 2016-2025	Publication period before 2015
Studies must relate to supply chain, supplier selection, or supplier evaluation	
Industries with complex supply chains such as aerospace, logistics, electronics	Other industries
Academic articles, industry reports, web-site articles	Conference papers, books

Source: Author, 2025

2.9 Quality Appraisal

The eighty-four selected academic and industrial sources were assessed against multiple quality criteria appraisal criteria, which are outlined in Table 2-3. Sources with an average quality appraisal score below 2.5 were excluded from the final analysis.

Table 2-3: Quality Appraisal Criteria

	Quality	Quality score				
	Criteria	0	1	2	3	Not Applicable
1	Contribution to the theory	The publication does not provide adequate information to assess this criterion	Weak theoretical base	Partial theoretical base	Strong theoretical grounding; contribution to theory of practice	This element is not applicable for this publication
2	Methodology		Poorly executed; inappropriate quantitative methods	Justified research design; the idea of study is not fully executed	Research design adequately examines the research argument	
3	Data analysis: Sample design and research results		Data sample insufficient; inconclusive research results	Appropriate data sample; adequate results but inadequate explanation	Adequate data sample; well explained research results support theoretical arguments	
4	Implications for practice		Study fails to inform practice of implications	Limited implications for practice provided	Critical implications for practice provided	
5	Level of citations		Absence of citations	Some level of citation present	Comprehensive citation list present	

Source: Habib et al. (2015)

2.10 Data Extraction

Data extraction was conducted using a structured Microsoft Word template that captured both descriptive and thematic findings of each publication. For each reviewed document, the following elements were recorded: (1) author of the article, (2) title of the article, (3) document name, (4) journal title, (5) date of publication, (6) volume, (7) number, (8) page numbers, (9) paper type, (10) geographical location, (11) context or industry, (12) sample size, (13) data collection method, (14) method of data analysis, (15) study characteristics, (16) key findings related to research questions, (17) abstract, and (18) keywords. All data extraction forms are included in Appendix B.

The articles related to the first research question were classified into two categories: those focused on supplier selection and evaluation and those on supply chain resilience. These articles were then subdivided according to their relevance to the stage of supplier selection and evaluation: pre-contract or post-contract. Other articles were distributed according to their relevance to the remaining research questions: barriers towards AI adoption, benefits of AI adoption, and recommendations for implementation.

The extracted data was first analysed descriptively. The descriptive findings show the chronological distribution, authors, journals, organisation field of study, paper type, industrial context, geographical context, and research methodology of selected sources. Subsequently, a thematic analysis was conducted to identify key findings related to the four research questions. Each article was examined in relation to the predefined research objectives and questions using qualitative content analysis.

The findings of the descriptive and thematic analyses are presented in Chapters 3 and 4, respectively, structured according to the research questions.

2.11 Research Ethics

This study does not involve any direct respondents and uses only publicly available academic literature. It does not include collecting or processing personal data. Where necessary, information from case studies or articles is anonymised to comply with the UK Data Protection Act 2018 and GDPR (2018).

To ensure data integrity, a structured and traceable record of all reviewed articles was maintained. No changes were made to the source data, and the findings were interpreted objectively based on the research questions. The research relied solely on publicly accessible academic sources. No legally sensitive, proprietary, or confidential documents were used. All extracted data and notes remain restricted to the research author and supervisor only. No data will be shared with third parties outside the academic scope of this study.

2.12 Chapter Summary

This methodology chapter describes the systematic five-stage approach used to identify and analyse literature that examines the impact of artificial intelligence on procurement and supply chain strategies in the international automotive sector. Through a rigorous process, 84 relevant sources were selected from over 1,500 initial records, establishing a comprehensive foundation for examining AI's role in the automotive supply chain.

The next chapter presents the descriptive findings from the reviewed literature.

3 CHAPTER 3: DESCRIPTIVE FINDINGS

3.1 Chapter Overview

The chapter provides insights into the descriptive findings of the selected sources. It presents the distribution of reviewed papers across the following categories: time, authors, journals, organisational field of study, paper type, classification by industry, geography and research methodology. In total, 70 academic sources and 13 industrial sources have been reviewed.

3.2 Classification by Time

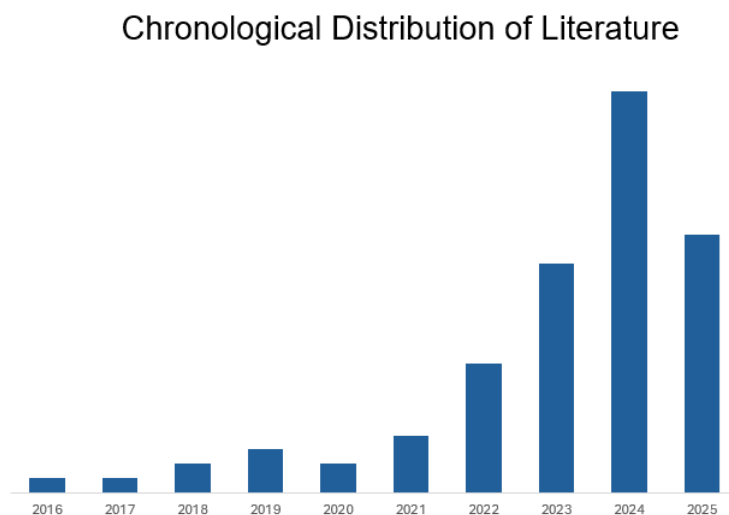


Figure 3-1: Classification by Time (Source: Author, 2025)

The selected studies (see Figure 3-1) were published between 2016 and 2025. The first relevant publication appeared in 2016, and there has been steady growth since 2021. The peak period of publication occurred between 2023 and 2025. This data suggests a significant increase in academic and industry interest in exploring AI technologies for supply chain management and procurement. The high concentration of studies from 2022 to 2025 also indicates that this research addresses the most current trends and approaches to the use of artificial intelligence in procurement and supply chain management.

3.3 Classification by Authors

Across all the sources, 17 articles were written by the single author, 40 articles were written by small groups (2-3 authors), and 27 articles were developed by large groups (more than 3 authors). Several highly recognized scholars, such as Alexandra Brintrup, Michela Guida, Dennis Meyer, Michael Henke, Nada R. Sanders, Francisco Herrera, Remko van Hoek, and Kannan Govinda, stand out due to their significant contributions to the fields of supply chain management, procurement and artificial intelligence.

3.4 Classification by Journals

Table 3-1: List of Journal Articles

Number	Journal Title	Number of articles
1	Journal of Business Research	2
2	Journal of Engineering and Technology Management	2
3	Journal of Purchasing & Supply Management	2
4	Journal of Risk and Financial Management	2
5	Supply Chain Analytics	2
6	Technovation	2
7	Information	2
8	Manufacturing & Service Operations Management	1
9	Transportation Research Part E: Logistics and Transportation Review	1
10	International Journal of Production Research	1
11	Annals of Operations Research	1
12	Computers in Industry	1
13	Journal of Cleaner Production	1
14	Expert Systems With Applications	1
15	Applied Soft Computing	1
16	Future Generation Computer Systems	1
17	Journal of Intelligent Manufacturing	1
18	International Journal of Physical Distribution & Logistics Management	1
19	Supply Chain Management: An International Journal	1
20	Technological Forecasting & Social Change	1

(Source: Author, 2025)

The reviewed articles were published in a wide range of reputable journals from different disciplines, including Operations and Supply Chain, Artificial Intelligence and Computing, Information Systems and Digital Business, Innovation and Technology Management. However, no particular journal was identified as dominant in the literature with a significant concentration of articles.

This study employed the following esteemed journals: Manufacturing & Service Operations Management, International Journal of Production Research, Transportation Research Part E: Logistics and Transportation Review, Annals of Operations Research, Journal of Business Research.

3.5 Classification by Organisational Field of Study

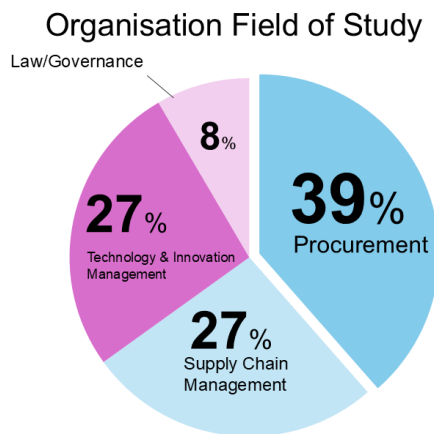


Figure 3-2: Classification by Organisation Field of Study (Source: Author, 2025)

Among the 84 reviewed studies, procurement dominates with 32 studies in total. Supply Chain Management represents the second largest area, with 22 studies. Technology and Innovation account for the same number of sources. A smaller set of studies belongs to Law and Governance (7 studies). One study belongs to the operations management and manufacturing field of study.

In general, the distribution shows a balanced mix that mainly covers procurement, particularly the important steps of supplier selection and evaluation, along with supply chain resilience in the automotive sector. At the same time, the technological aspect of applying and implementing artificial intelligence in procurement and supply chains (27% of the studies) is covered as thoroughly as the supply chain management aspects.

3.6 Classification by Paper Type

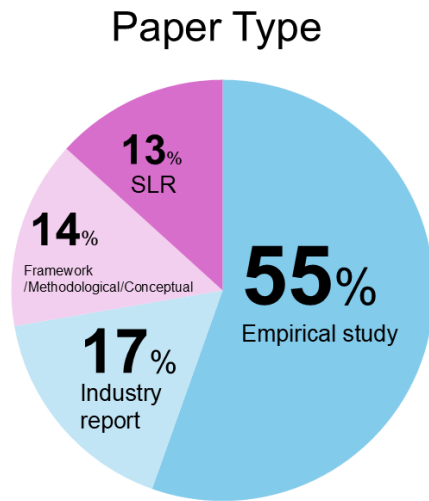


Figure 3-3: Classification by Paper Type (Source: Author, 2025)

Figure 3-3 shows the distribution of paper types across the selected literature. Most articles (55%) are empirical studies, which adds strong practical relevance to this review. Industry, consulting and government reports account for 17%, adding an industry perspective to the current academic landscape. Conceptual/framework papers comprise 14% of the selected literature and were actively used to develop the AI implementation roadmap and to provide practical recommendations. Systematic literature reviews (SLRs) represent 13%, mapping the field.

3.7 Classification by Industry

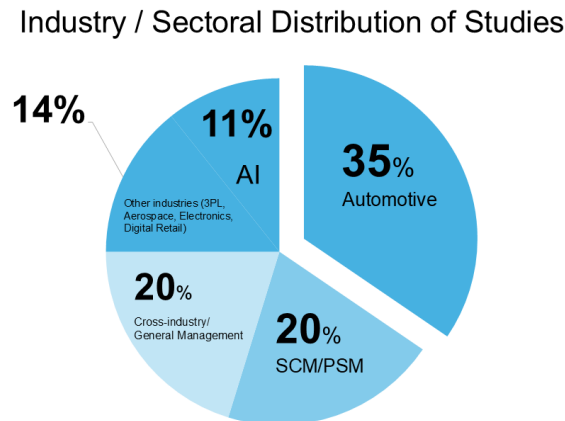


Figure 3-4: Classification by Industry (Source: Author, 2025)

A review of all 55 studies shows that the automotive sector is the single largest focus, with 29 core automotive papers, which further confirms the relevance of the selected literature to the chosen research topic. The remaining publications include 17 general supply chain management (SCM) studies, 17 cross-industry/general management sources, 9 artificial intelligence-oriented sources, and 12 papers related to other industries such as aerospace, electronics, manufacturing, digital retail and third-party logistics. Many studies are at the crossroads of supply chain management, procurement and artificial intelligence, and they do not relate to any particular industry.

3.8 Classification by Geography

Geographical Distribution by Region

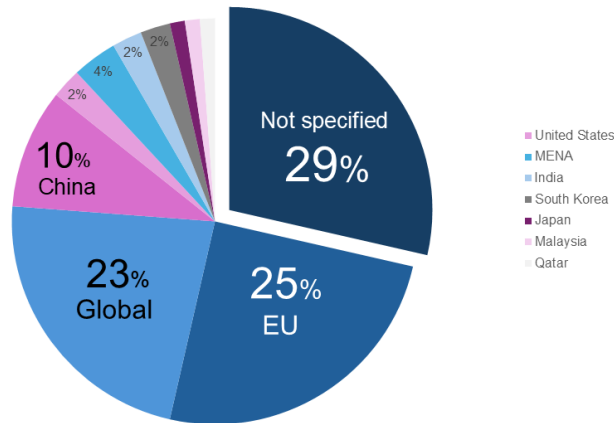


Figure 3-5: Classification by Geography (Source: Author, 2025)

Figure 3-5 shows the geographical distribution of selected literature. Twenty-four studies are not tied to any specific country. The geographical scope of the 19 studies is global. Europe represents the largest share with 21 studies, followed by China (7 studies), then the United States (2 studies), MENA (3 studies), India (2 studies) and South Korea (2 studies). This geographical distribution covers most regions with a developed and well-established automotive sector (EU, China, the United States, India, South Korea, Japan, Morocco), both in the manufacturing and sales and service segments. Studies that are not tied to any specific country are primarily conceptual frameworks.

3.9 Classification by Research Methodology

Among the 84 studies, quantitative modelling methods and surveys account for 44%. Mixed-method designs constitute only 2%. Qualitative cases make up only 13% (11 sources). Systematic literature reviews constitute 15% of all sources. Conceptual/framework papers account for 9%, and practical industry/policy reports comprise 16% (14 papers).

3.10 Chapter Summary

This chapter examines the descriptive findings of the selected literature, including publication timeline, journals, organisational field of study, paper type, industrial and geographical classification. Most sources date from 2021 onwards and capture the latest changes in the fast-moving and dynamic field of artificial intelligence. The sources provide a balanced mix of supply chain/procurement and technological research. Furthermore, the majority of sources focus specifically on the automotive sector, making the review highly relevant to the research objectives.

4 CHAPTER 4: THEMATIC FINDINGS

4.1 Chapter Overview

This chapter reports the main findings that are relevant to answering the research objectives.

The findings cover the use of artificial intelligence in supplier selection and evaluation in the automotive industry. The findings also cover the role of AI in strengthening supply chain resilience, particularly in preventing and recovering from disruptions and detecting anomalies. In addition, the main findings on barriers to AI adoption and key benefits of AI implementation will be presented. Finally, the chapter presents the main recommendations for adopting AI in procurement and supply chain processes.

4.2 Key applications of AI and ML in the supplier selection, evaluation and supply chain resilience

4.2.1 Supplier Relationship Mapping and Strategic Supplier Early Identification

In order to map the supply chain for EV batteries, AlMahri et al. (2024) developed a GPT-powered framework that incorporates NER and RE tools to automatically extract entities and relations between suppliers. The framework provides visibility down to the third-tier supply chain level and could be an excellent starting point for locating strategic automotive suppliers and alternatives.

Feng et al. (2024) used GPT-NER/LLM-KG tool for firm entity recognition and for mapping the Chinese automotive SoC supply chain network. The supplier data extracted via NER tools could be augmented with the use of machine learning techniques.

Hong et al. (2018) segmented core suppliers using corporate e-invoice data from a Korean auto parts manufacturer using the Random Forest algorithm. The percentage of critical items, transaction frequency/cycle, total cost of purchase,

and partnership duration were the main criteria used to categorize core suppliers versus non-core.

4.2.2 Supplier Criteria Definition

Wu, Jia, and Barnes (2023) developed an AI-powered Random Forest-RFECV framework that allows selecting the optimal set of product-based and supplier-based criteria for choosing lithium battery suppliers for forklifts.

4.2.3 Assessment of Vendor Financial Ability

An ensemble of classification was applied by Muniappan and Subramanian (2025) to forecast the financial distress of Indian automobile manufacturers. The study integrated eleven machine learning classifiers through a hard voting mechanism to classify firms as distressed or healthy based on 23 financial ratios. The ensemble of models achieved almost 100% accuracy.

Luo (2022) introduced an ML-driven framework for classifying the financial credit risk of suppliers in the Chinese NEV industry. The model integrates multiple ML classifiers as well as key financial and non-financial indicators, such as debt-paying ability, profitability, and overall supply chain situation.

4.2.4 Automation of RFI and RFP Phases

According to Allal-Cherif et al. (2021), chatbots can automate the initial steps of supplier interaction, including sending RFIs, collecting basic information, and performing supplier prequalification. Cui, Li, and Zhang (2021) used chatbots to automate buyer inquiries for non-critical automotive items such as car accessories on the Chinese B2B e-commerce platform. They also evaluated the impact of AI-based supplier recommendations on initial price quotes.

BMW launched an AI-powered Tender Assistant in close partnership with BCG to support the RFP and tender preparation process. This tool helps the company automatically prepare and adjust tenders, as well as ensure compliance with company's standards and best practices (BCG, 2025).

4.2.5 Supplier Evaluation, Ranking and Risk profiling

Tavana et al. (2016) developed an ANFIS-ANN framework for supplier evaluation and ranking in the automotive industry. The system finds the most significant supplier evaluation criteria and, based on these criteria, predicts supplier scores and ranks suppliers, even if data is incomplete or missing. Zekhnini et al. (2025) proposed a FIS-based model for supplier selection in the automotive industry, where standard selection criteria are supplemented by VUCA selection criteria: resilience, sustainability, and digitalization. The evaluation is performed using 17 sub-criteria that are divided into four main categories, resulting in an aggregated supplier score for each supplier.

Wang et al. (2024) proposed a model that used SPGM tool to aggregate experts' opinions into sustainability scores and applies a genetic algorithm to build an optimal supplier portfolio, selecting the most sustainable and cost-efficient supplier for each critical battery commodity within budget constraints.

Pap et al. (2025) proposed a supplier evaluation model based on a wide range of parameters aggregated into key categories (such as TCO and reliability). Suppliers are classified into three levels (Recommended, Acceptable with Risk, Not Recommended) using the ID3 algorithm, followed by a rule-based mechanism for decision support.

Dumitrascu et al. (2020) developed a performance evaluation system based on the MLP algorithm for automotive manufacturers. The system links supplier-related issues such as long lead times or late deliveries to specific KPIs that should be monitored, for example, perfect order delivery rate. Liu, Yu, and Kim (2023) applied a supplier evaluation and ranking model to eight auto parts suppliers of the Chinese joint venture GAC Toyota, using a radial basis function neural network (RBFNN) that integrated 20 key selection criteria into a single supplier score.

4.2.6 Cost Analysis and Fraud Detection

AI can detect fraud from multiple suppliers in e-procurement platforms, which automotive suppliers commonly use for non-critical items. According to case

study by Bai & Qiu (2023), machine learning algorithms like MLP allow firms to identify and classify procurement fraud with high accuracy.

Schulze-Horn, Hueren, Scheffler, and Schiele (2020) emphasise that, in the automotive industry, AI can also systematically analyze suppliers' cost breakdowns to uncover hidden cost drivers.

In addition, AI can be applied for early cost estimation of materials. For instance, in an empirical study conducted with a German automotive OEM, artificial intelligence is applied to generate forecasted cost estimates for supplied aluminium parts. The model builds its predictions based on a limited dataset available at the contract stage, including the technical specifications and current commodity prices (Bodendorf et al., 2022).

4.2.7 Suppliers Post-Contract Surveillance and Risk Monitoring

Porsche, Audi and Volkswagen launched an AI-powered risk radar to monitor sustainability compliance for their supply chain network, using AI algorithm to scan global media and social platforms across 150 countries, flagging potential sustainability issues across supply chain network (Porsche AG, 2021).

4.2.8 AI for Supply Chain Resilience Enhancement

Supply chain resilience is the ability of a supply chain to adapt to and recover from disruptions such as disasters, wars, blockages, or pandemics.

It can be inferred that machine learning and deep learning techniques, such as One-Class SVM and LSTM Autoencoders, are frequently used to predict supply chain disruptions and detect anomalies in the automotive sector. In the upstream supply chain, models such as LSTM Autoencoders are used to detect lead time anomalies in real time, flagging irregular delays from suppliers before they affect the parts distributor (Amellal et al., 2023). In the downstream automotive supply chain, where the resilience of manufacturing facilities is critical to the entire end-to-end system, more advanced models such as digital supply chain twins can be used. These cognitive models can not only detect anomalies and identify the specific echelons where a disruption has occurred but also predict the time-to-

recovery – the time required to restore normal supply chain operations after the disruption (Ashraf et al., 2024).

More advanced frameworks, such as SCREM proposed by Li et al. (2025), are very useful for predicting unknown-unknown events, including geopolitical shocks, pandemics or wars. The model uses a deep learning architecture that incorporates SHAP-based explainability and survival analysis. SCREM can forecast whether a disruption will occur and estimate the time-to-survive (TTS) – how many days production can continue before failure – only based on internal ERP data, including inventory levels, delays, and usage data.

Rezki and Mansouri (2024) developed a hybrid classification-regression ML model based on ERP data from a wiring harness manufacturer. The system predicts supplier-related quality issues by identifying which suppliers are most likely to deliver non-conforming parts, estimating the potential number of incidents, and, most importantly, forecasting the total cost of failures.

Researchers have developed an advanced LLM-powered MAS supply chain disruption monitoring system for the automotive industry using the example of Mercedes-Benz (catalyst supplies). The system works as a set of independent multi-agents that monitor newsfeeds, find and classify disruptions according to the risk level, visualize the supply chain network, and offer risk mitigation strategies, including the search for alternative suppliers (AlMahri et al., 2025).

In the article by Regattieri et al. (2024), deep learning is used through the LSTM tool, which, according to historical order data, predicts the punctuality of suppliers of the Italian automaker and serves as the basis for an optimization model for the distribution of orders.

4.3 Key Challenges and Implementation Barriers toward AI Adoption

4.3.1 Data-Centric Barriers

The important bottleneck for AI adoption in the automotive supply chain is data silos, fragmentation, and most critically, the lack of end-to-end data transparency across automotive procurement and supply chain networks. As an example, most OEMs have limited or no access to sub-tier supplier data (2nd/3rd tier), logistics provider data, and external market data, which significantly impairs decision-making in times of disruption (Klee & Janson, 2023).

Poor data quality (particularly data noise, incompleteness, and inaccuracy) remains a major obstacle to the successful adoption of AI, according to Shrivastav (2021). Douimia et al. (2025) underline that data standardisation represents one of the major challenges for ML and DL implementation in automotive manufacturing. To overcome this, they recommend establishing a standard data format and ontology to ensure interoperability across different systems.

For instance, Kumar et al. (2024) indicate that Ford improved data quality during AI implementation by standardising data and using tools for data cleansing and validation.

4.3.2 Organisational and Human-Centric Barriers

Hangl et al. (2022) state that change management and organisational resistance are among the key barriers to the adoption of artificial intelligence in organisations. Zavodna et al. (2024) highlight that employees resist new technologies, do not recognize the benefits of AI, and remain attached to old routines.

The lack of analytical and IT capabilities not only within supply chain firms but also among AI providers limits the effectiveness of ERP integration and hinders the adoption of AI in supplier scouting. Moreover, AI implementation is impacted by a shortage of digital competencies among personnel in the purchasing department (Guida et al., 2023).

4.3.3 Infrastructure-related Barriers

Hangl et al. (2022) conducted a tertiary study analysing 44 systematic literature reviews and found that "technical limitations" represent the second most significant barrier to AI adoption.

4.3.4 Computational Resources and Cloud Infrastructure

Lee et al. (2023) note that companies with access to large amounts of data, equipped with extensive datasets and powerful computing infrastructure, can derive greater benefits from AI adoption. Ghosh (2025) points out that building and maintaining cloud infrastructure is vital for AI projects, with high speed and low latency being key requirements; however, the expense of running AI in the cloud remains a significant obstacle.

Ahmed et al. (2025) note that deep learning models require considerable computational resources, which poses a barrier for many small and medium-sized enterprises (SMEs) that lack the necessary infrastructure to support such technologies.

4.3.5 System Interoperability

Teixeira et al. (2025) underscore that organisations frequently encounter serious integration difficulties when attempting to embed AI into their existing infrastructures due to system interoperability limitations and the rigidity of legacy IT systems. Balan et al. (2025) also note that legacy systems often fail to process data in real time, adapt to rapidly changing conditions, and ensure compatibility with modern data formats; therefore, for the deployment of ML/AI during crises, existing legacy systems should be either updated or replaced with newer, more adaptable systems.

4.3.6 Financial and ROI-related Barriers

According to the literature, uncertainty among automotive firms regarding the ROI of AI adoption greatly hinders further implementation. For instance, Ameye et al. (2023) estimate that in the automotive industry, ROI-related uncertainty is among the highest implementation obstacles and accounts for approximately 36% of the

hesitation to adopt AI. Shrivastav (2022) notes that high upfront costs for AI initiatives can be a significant obstacle to AI adoption in the supply chain, as stakeholders may have other priorities and no dedicated budget for AI investments.

Wang et al. (2025) note that ongoing variable costs, including data collection and cleansing, model training, operational processes, and system maintenance often arise after AI implementation and can be an obstacle to AI adoption.

4.3.7 Regulatory, Compliance, and Legal Barriers

According to Zheng and Brintrup (2025), data privacy and security are primary concerns for AI implementation in supply chain networks, as regulatory frameworks such as the GDPR impose strict requirements on data sharing and necessitate the protection of sensitive information.

Recent industry reports and academic literature highlight that the EU AI Act classifies AI systems according to risk levels, ranging from minimal to unacceptable (high-risk systems) (Botero Arcila, 2024).

For example, a Capgemini report outlines a case in which General Motors procured supply chain analytics solutions powered by artificial intelligence from third-party vendors. From a compliance and legal perspective, such deployments are assessed as “systematic risk” due to the potential non-alignment of many vendors with EU regulations on data privacy, transparency, and accountability (Capgemini, 2024). One major risk is that OEMs may ignore comprehensive legal oversight during vendor selection, resulting in serious legal consequences and large penalties.

Some researchers note that the system of AI regulation around the world is a complex set of requirements in different jurisdictions. The laws adopted in various countries impose considerable obligations on firms that intend to deploy AI systems, with regulations that vary in their specific requirements. This fragmentation increases compliance costs for organisations (Eisenberg et al., 2025).

Explainability is also an important requirement for the practical deployment of AI systems, motivated by both regulatory compliance and commercial needs. As regulators increasingly require transparency and accountability in AI adoption, the demand for XAI methods continues to grow.

At the same time, supply chain decision-makers and key business stakeholders require trust, confidence, and a clear understanding of how AI-based supplier evaluation models produce their outputs (Giovine et al., 2023). Many companies face a trade-off between model accuracy and interpretability, which has led researchers to integrate explainability methods such as SHAP and LIME as essential components of modern AI frameworks (Baryannis et al., 2019).

Arrieta et al. (2019) introduced a conceptual figure (Figure 9) that clearly illustrates the trade-off between model interpretability and accuracy. Simple models are more explainable but less accurate, while deep neural networks achieve higher accuracy at the cost of interpretability.

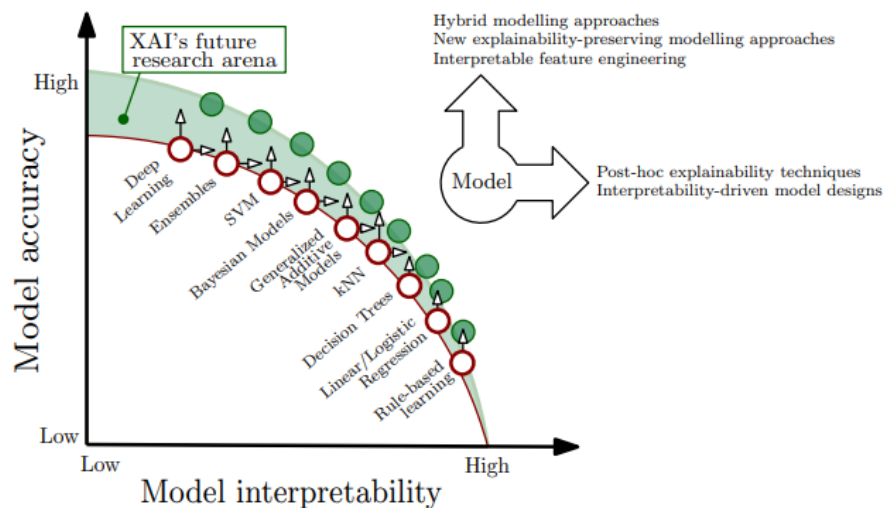


Figure 4-1: Trade-off between model accuracy and interpretability (Source: Arrieta et al., 2019)

4.4 The Benefits and Measurable Impacts from AI Adoption

4.4.1 Accuracy of the Models

In Li et al. (2025), a deep learning model was implemented within the supply chain of Ford Motor Company, resulting in a 50% reduction in prediction error for time-to-survive (TTS) compared to the best-performing alternative models.

In the study by Do et al. (2024), the proposed deep learning model demonstrated high predictive accuracy in forecasting potential supply chain disruptions from suppliers across five Ford manufacturing plants, achieving precision and recall rates above 80%. Luo et al. (2022) report that the accuracy of their ML-based model in predicting the credit score of Chinese NEV supply chain companies reached 96.13%, showing almost perfect classification performance.

4.4.2 Enhanced Visibility

Guida et al. (2023) underscore that the primary advantages of AI adoption include improved visibility and oversight over both internal and external procurement processes, along with procurement risk mitigation achieved through AI's predictive capabilities. In the empirical study by AlMahri et al. (2025), the system achieved deep-tier visibility (Tier-2 and Tier-3), far beyond Tier-1, by using LLM agents in a coordinated pipeline.

4.4.3 Scalability

AI-based approaches offer excellent scalability, allowing companies to assess thousands of suppliers in real time through integration with corporate ERP and SCM systems. This is particularly important in the context of complex automotive supply chains, where traditional methods such as MCDM frameworks lack the speed and automation (Rainy & Chowdhury, 2022).

4.4.4 Managing Incomplete Data

Some machine learning techniques, like the hybrid ANFIS-ANN model, perform especially well in environments with incomplete data, correctly predicting supplier rankings even in cases where some input data is missing (Tavana et al., 2016).

4.4.5 Autonomous Decision-Making and Reduced Operational Workload

One of the key advantages of AI-powered Multi-Agent Systems (MAS) and Distributed Artificial Intelligence (DAI) lies in their capacity for significant autonomy – the ability of agents to operate without human intervention and make decisions. Although the multi-agent system proposed by Zekhnini et al. (2024) is not AI-powered from a technical point of view, it establishes a robust foundational architecture for future autonomous AI-powered MAS systems.

Allal-Cherif et al. (2021) underscore that AI may reduce the operational workload of procurement professionals by automating repetitive tasks such as RFI requests and supplier data collection. As a result, buyers can focus more on strategic and value-creating activities. Kumar et al. (2024) note that tools such as RPA significantly improve operational efficiency; for example, the company achieved a 30% improvement in invoice processing by automating routine tasks with the RPA tool.

4.4.6 Supplier Risk Assessment and ESG Compliance

According to Chiu et al. (2024), AI-powered frameworks can significantly improve the efficiency of supplier risk assessment. They introduced a hybrid framework integrating BERT-based NLP and life cycle assessment (LCA), which allows to automatically scrape and extract supplier-related risk data and conduct green supplier risk assessment.

4.4.7 Cost Savings

According to Kumar et al. (2024), one more important measurable impact for automotive companies from AI implementation is significant procurement cost saving, as optimisation and data insights help improve contract terms.

In terms of supply chain resilience, Kalusivalingam et al. (2022) note that the use of deep reinforcement learning (DRL) not only led to a reduction in logistics costs by 12% but also significantly decreased recovery time after disruptions, with recovery times reduced by 18% and disruption-related costs lowered by 25%. AI implementation led to a reduction in procurement process time and an increase

in procurement visibility, allowing buyers to focus more on strategic tasks such as negotiation. The effect of employing the LSTM forecast feature inside the optimisation model allowed to reduce the purchase and delivery cost by 20% for the Italian automotive manufacturer (Regattieri et al., 2024).

4.4.8 Time Savings

An important measurable impact of AI on the automotive supply chain is the reduction of disruption response time. In the article by AlMahri et al. (2025), traditional disruption response processes are reported to take on average five days, whereas the proposed multi-agentic AI-powered supply resilience framework for the automotive company (Mercedes-Benz) completed the end-to-end cycle – from disruption detection to sourcing alternatives – in under four minutes. AI also accelerates supplier scouting (up to 75% faster) and shortens contract negotiations via automated suggestions and accelerated contract review (Guida et al., 2023; Spreitzenbarth et al., 2024).

4.4.9 Enhanced Supply Chain Resilience

Balan et al. (2025) reported that the application of machine learning and artificial intelligence in supply chain management can decrease demand forecasting errors by 10-20% and improve disruption response times by 20-30%.

In general, artificial intelligence significantly influences the elasticity and performance of the supply chain, providing companies with a technological advantage, improving risk control capabilities, technical service capabilities and reducing operational costs (Wang & Pan, 2024). Hangl et al. (2023) also underscore that one of the main benefits of early AI adoption is getting a competitive edge that leads to lower costs and operational efficiency.

4.5 Strategies for Implementing AI-driven Supplier Evaluation, Selection and Resilience Frameworks in the Automotive Industry.

4.5.1 Phase 1: Organizational Readiness and Strategic Alignment

The WEF report states that the first step is to make sure that AI implementation is aligned with the organisation's overall business goals and, more importantly, its commercial strategy (World Economic Forum, 2023).

Effective change management is another key aspect of successful AI integration. This requires a comprehensive approach that includes upskilling training programmes, clear communication to mitigate employee resistance and fears of job loss, strategies for cultural transformation, and adjustments to organisational structures and processes (Chhatre & Singh, 2024). Burger et al. (2023) also pointed out that AI implementation in procurement should be in close coordination with humans. While AI improves process time and visibility, humans can bring implicit and unique expert knowledge.

According to Solaimani and Swaak (2023), one of the most important elements for the deployment of AI is top management support. This support includes approving new projects, allocating resources, and actively participating in change management. Equally important is the involvement of suppliers in the AI adoption process (van Hoek, 2024). Based on interviews with representatives of automotive companies, Meyer and Henke (2023) also found that successful AI implementation needs staff involvement from the very beginning. It is also important to provide staff with the necessary support and show an open mindset from management.

Furthermore, AI adoption in procurement requires a strong data governance framework for data quality, interoperability, and ethical use. The G7 Toolkit (OECD/UNESCO, 2024) notes that AI systems need trustworthy, well-structured data, clear ownership rules, transparent algorithms, and measures to reduce bias, lack of clarity, transparency and other risks.

4.5.2 Phase 2: Technological and Data Readiness

Technical readiness involves a high-quality data pipeline and infrastructure, starting with a simple on-premises setup during the proof-of-concept stage. It becomes more solid during the productionizing stage, which should be reflected in the modular tech stack (Haefner et al., 2023).

Aldoseri et al. (2024) created a framework to assess an organisation’s data landscape. It has four main components: data quality, accessibility, governance, and volume/variety. Data quality means the accuracy, completeness, and relevance of data used in AI systems. Accessibility refers to the location and storage of data, as well as how easily it can be accessed through APIs, databases, or cloud platforms. Governance includes the policies, roles, and procedures that ensure data reliability, compliance, and security. Finally, the data volume and variety reflect the organisation’s ability to scale its infrastructure to manage large, diverse datasets required for advanced AI applications.

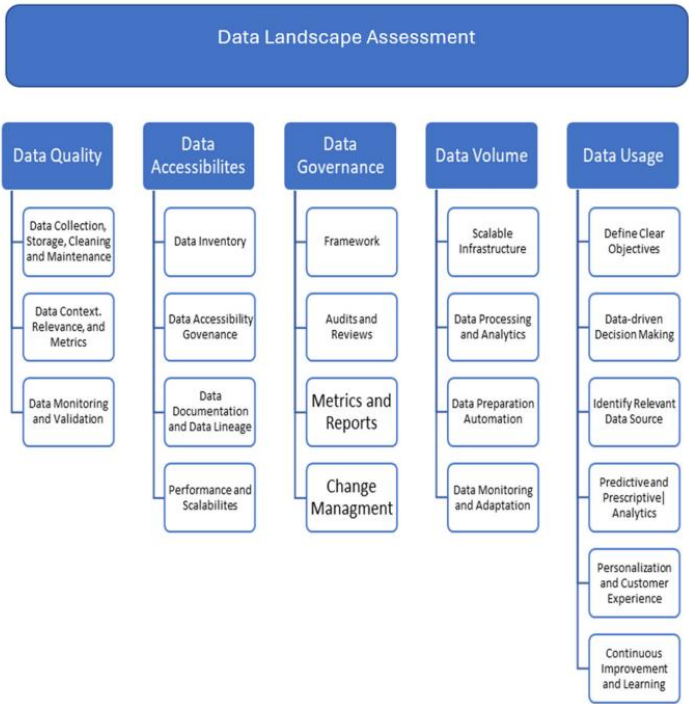


Figure 4-2: Data readiness framework (Source: Aldoseri et al., 2024)

The tech stack for AI adoption must first include data/big data layer, the most foundational layer, where data extracted and cleansed into a single standardised format from heterogeneous sources such as ERP and CRM and prepared to be fed into AI (Kearney, 2024).

Both academic literature (Banh & Strobel, 2023) and consulting reports (BCG, 2024) describe a dedicated model layer (AI/ML layer or model layer) as the foundation of AI-based system architecture. This layer includes pretrained and custom models such as GPT-4 and CodeBERT, tools for model selection, management, orchestration, fine-tuning, and integration, as well as controls for ethical and security compliance. In addition to the model layer, the complete architecture typically includes the infrastructure layer, data layer, the integration and API layer, the application layer and the security and governance layer (Banh & Strobel, 2023; Kearney, 2024; BCG, 2024).

It is important to note that a conceptual technical framework for AI in procurement must also integrate legal oversight, including compliance with regulations like GDPR, and ethical design principles such as fairness, transparency, and accountability, to ensure responsible AI deployment, mitigate risks like bias or privacy violations (Obinna & Kess-Momoh, 2024).

4.5.3 Phase 3: Pilot testing and Gradual Deployment

Shamsuddoha et al. (2025), proposed an AI integration framework that includes pilot testing, gradual deployment of AI systems, and ongoing monitoring and adjustment. The most important step of this particular phase is to focus on prioritised high-value technical features and solutions rather than implementing multiple technical tools at once (McKinsey&Company, 2024). The prioritization is crucial since 95% of GenAI projects fail to advance beyond the pilot stage, according to a recent MIT report (MIT Project NANDA, 2025).

Deloitte (2024) also suggests implementing AI by starting with piloting high-impact use cases and gradually moving from simpler to more complex ones, and simultaneously “continue building the foundation to effectively integrate technology stack, data readiness, and change management.”

According to Spreitzenbarth et al. (2024) research, which is primarily based on interviews with industry practitioners, it is also highly advisable to start small and prioritize key company-level pilot projects.

4.5.4 Phase 4: Scaling AI in the Organisation

In the AI scaling phase, procurement organisations must optimise their technical infrastructure for real-time inference and large-scale data processing. This requires not only robust compute and storage systems but also democratized access to AI tools for non-technical staff. Companies should also transition from narrow models to universal AI platforms, where modules (predictive, analytical, and explainability) can be reused across different business functions (Haefner et al., 2023).

Sjodin et al. (2021) developed a robust framework for scaling AI in the enterprise.

Based on the research, organisations can scale AI by simultaneously developing three interdependent capabilities: data pipeline (integrating and managing data in a secure and scalable way), algorithm development (fine-tuning AI models and tailoring them to meet organisational needs), and AI democratization (making AI accessible across the entire organisation, not just for data scientists). Scalability should also be based on the following innovation principles: agile customer co-creation through customer engagement in the creation of AI-driven business solutions, data-driven delivery operations through real-time AI-powered monitoring and predictive service optimisation, and scalable ecosystem integration through Value Enablement Partnerships with infrastructure providers for accessing scalable infrastructure and technical capabilities, and Value Expansion Partnerships with SMEs, startups, and OEMs for enhanced product value creation.

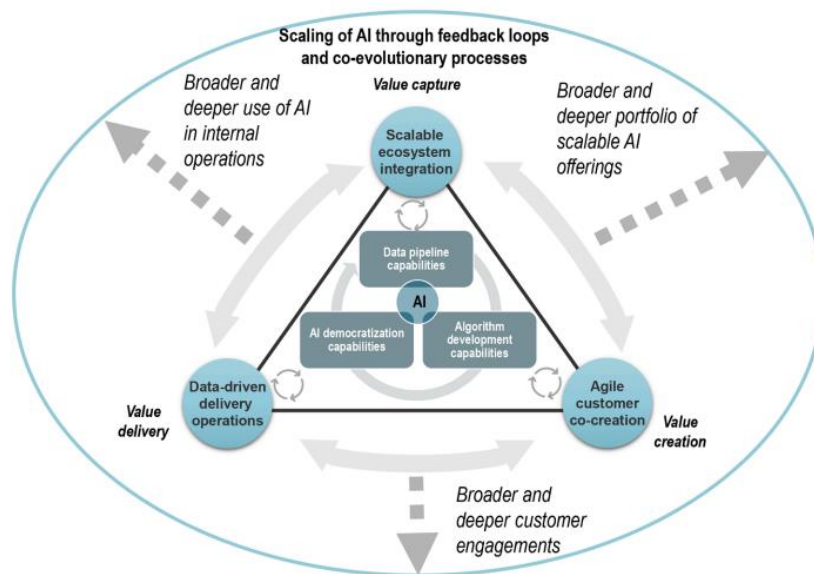


Figure 4-3: AI scalability framework (Source: Sjodin et al., 2021)

4.5.5 Phase 5: Risk Management, Monitoring and Continuous Improvement

For effective surveillance and monitoring of deployed AI systems, it is recommended to establish the following governance bodies: the AI Centre of Excellence, which is responsible for managing issues such as regulatory compliance and AI hallucinations, and the Data Council, which oversees data challenges including data drift (the degradation of model performance due to changes in input data), duplication, discoverability across multiple enterprise data lakes, and the implementation of data governance (Fleck, 2025). This implementation strategy fully aligns with the article by Hadley et al. which introduced the idea of deploying Algorithm Review Boards consisting of data scientists and risk officers as part of responsible AI governance, including review of risks, documentation and approval of algorithms.

It is also crucial to introduce a comprehensive risk management framework. Eisenberg et al. (2025) proposed the unified control framework which combines three key components: an AI risk taxonomy, policy requirements based on current AI regulations and set of controls or actions to address both risks and regulatory requirements. Furthermore, according to Hasija and Esper (2022), it is necessary

to pay attention to the issue of increasing confidence in AI (AI trustworthiness) among employees through post-deployment upskilling, which can be accomplished through data visualization and representation, as well as a clear allocation of responsibility for the outcomes of AI-powered technologies.

4.5.6 Chapter Summary.

This section reports key findings on artificial intelligence application in supplier evaluation, selection, and supply chain resilience in both pre-contract and post-contract phases. It also identifies key applications for supply chain resilience. It covers different types of AI implementation barriers, from data-centric to human-centric and infrastructure-related. It outlines key strategic benefits for AI adoption and measurable impacts as well as a set of recommendations for AI implementation. In general, it can be concluded that in the automotive sector various artificial intelligence tools are employed; however, most tools are still the basic machine learning techniques. The most advanced AI technologies, such as GenAI or MAS systems, still have limited use.

The international automotive sector can derive many measurable benefits from AI adoption that will impact not only operational efficiency and enterprise sustainability but also, importantly for stakeholders and top management, directly affect P&L.

5 CHAPTER 5: DISCUSSION

5.1 Chapter Overview

This discussion chapter synthesizes the thematic findings derived from the systematic literature review. For each research question, the findings were consolidated into conceptual figures that capture the key applications, barriers, benefits, and AI implementation strategies in automotive supplier selection, evaluation, and supply chain resilience. Furthermore, the literature review revealed research gaps, such as a lack of comprehensive work on AI tech stack architectures and enterprise-level implementation roadmaps, limited investigation of generative AI and multi-agent systems, and limited focus of academic literature on supplier classification and ranking.

5.2 Key Applications of AI in the Supplier Selection, Evaluation and Resilience

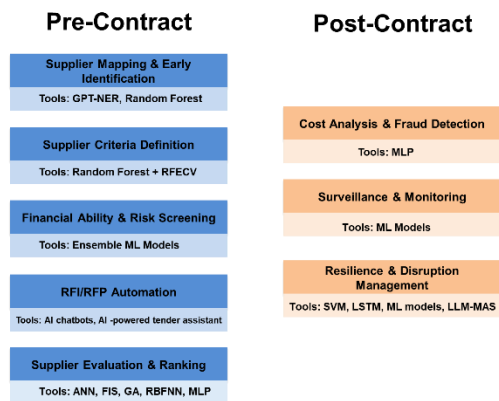


Figure 5-1: AI applications in automotive procurement and supply chain (Source: Author's own work, 2025)

Based on Figure 5-1, it can be concluded that although machine learning models are applied both in the pre-contract stage and the post-contract stage, a clear trend becomes visible: there is a shift from the use of more structural and analytical models in the first stage to predictive and dynamic models like deep learning in the second.

This is because, at the initial stage, it is necessary to collect and structure vital supplier information to build an optimal supplier portfolio. It is also important to

automate routine procurement processes, particularly for non-critical items, and reduce the workload on procurement.

In the second stage, after signing contracts and onboarding suppliers, the focus moves to monitoring, forecasting, and dynamic risk management (both finance-related and supply-related). All of this creates a demand for more advanced AI models, including deep learning techniques.

It is important to note that in most use cases, ML models – specifically classification machine learning models – dominate. These findings are completely in line with the idea of ML cruciality in the supplier selection, highlighted by Gidiagba et al. (2025), since machine learning techniques can learn from new data, process large amounts of data efficiently and find non-linear patterns. The dominance of classification models can also be explained by the fact that, in empirical academic studies on automotive supplier selection and evaluation, most tasks still revolve around classification, ranking, and supplier scoring – most often with a binary output (core vs. non-core, financially healthy vs. financially distressed). From an industrial perspective, ML modules can be easily integrated into legacy IT systems and do not require infrastructure upgrades.

However, according to Ameye et al. (2023), automotive firms perceive some technologies, such as NLP, as significantly more important than machine learning, with machine learning accounting for only 28% of perceived importance compared to 41% for NLP.

The figure also shows that the most promising technology, LLM, is still being used to a limited extent and has not yet been largely reviewed in academic empirical studies, since this technology is still in the early stage of adoption. At the same time, there are already some empirical studies (AlMahri et al., 2024; AlMahri et al., 2025) that apply LLM-powered tools both to increase supply chain visibility and to enhance supply chain resilience.

5.3 Barriers to AI adoption

Barriers/Implementation phases	Organizational readiness and Strategic alignment	Technological and Data readiness	Pilot testing and Gradual deployment	Scaling phase	Risk Management, Monitoring and Continuous Improvement
Data - centric barriers	Low data transparency	<ul style="list-style-type: none"> Poor data quality and data silos Data standardization 			Data governance including data drift, duplication and discoverability
Organizational and Human-Centric Barriers	Change resistance	Low AI literacy	Lack of IT capabilities among providers		AI trustworthiness among employees
Infrastructure - related barriers		<ul style="list-style-type: none"> Insufficient computational resources Cloud Infrastructure 	<ul style="list-style-type: none"> System interoperability Outdated legacy systems 	Cloud infrastructure	
Financial and ROI - related barriers		High upfront cost and initial investments	ROI-related uncertainty	ROI-related uncertainty (36% hesitation in adoption)	Ongoing maintenance costs (data ops, retraining)
Regulatory, Compliance, and Legal Barriers		Compliance with regulatory frameworks (GDPR, EU AI Data act)	Vendor non-compliance with regulations on data privacy and transparency	Explainability gaps (affect stakeholder trust)	<ul style="list-style-type: none"> Explainability and interpretability of AI models Monitoring of compliance with policy requirements and regulations

Figure 5-2: Barriers to AI adoption (Source: Author's own work, 2025)

Figure 5-2 maps out the distribution of barriers across key AI implementation phases, showing that data-centric and human-centric barriers dominate in the first phase. The main barriers at this stage relate to employees' resistance to new technologies, as well as low data transparency across the multi-tier automotive supply chain network, which hinders the development and integration of a high-quality data pipeline.

In the second phase, a greater number of barriers appear. Low data transparency in the automotive sector leads to data silos, making standardisation difficult. If a poor-quality data pipeline also develops, it complicates the deployment and scaling of AI models. This technological unreadiness could also be compounded by low AI literacy among current personnel. Furthermore, there is a need for further investment in infrastructure for model deployment, including additional computational resources and cloud infrastructure. These high upfront costs for infrastructure preparation can discourage key stakeholders, leading to the reallocation of funds to other priorities, which again hinders AI adoption.

At this stage, AI deployment forces companies to pay attention to regulatory compliance barriers. Given the complexity of the automotive supply chain across multiple jurisdictions with different AI regulations, this increases compliance costs for companies.

In the pilot testing and deployment phase, the existing AI skill gaps among employees may be amplified by insufficient AI capabilities among providers. Additionally, the lack of legal oversight by OEMs regarding third-party vendor compliance with data protection regulations can lead to severe legal consequences and penalties. These risks could also be supplemented by stakeholders' uncertainty about the return on investment from AI implementation, as the value remains unclear while substantial costs have already been incurred.

Key infrastructure barriers, as highlighted by Teixeira et al. (2025) and Balan, Kumar, and Raj (2025), continue to include system interoperability and the compatibility of legacy IT systems with AI solutions, only if stakeholders did not commit to their replacement or upgrade in the second phase.

The fourth phase involves providing widespread AI access to staff and encouraging customer participation in AI-driven initiatives. This scaling makes robust cloud-based technical architecture a critical enabler. In this regard, the limited access to cloud infrastructure can be a significant hurdle to AI adoption during the scaling stage, but it can be effectively overcome by building partnerships with major infrastructure providers.

Furthermore, stakeholders and key automotive decision-makers must have trust and confidence in how AI operates and delivers outputs. This requires a high level of explainability and interpretability, particularly for deep learning models used to estimate recovery time from disruptions and detect anomalies.

The last phase requires constant monitoring of deployed AI and ML systems and data-related risks through the establishment of AI governance bodies. Since the models are already in use, ongoing costs arise, associated with both operational processes and system maintenance. Employee trust in embedded AI solutions is also problematic, but it can be effectively addressed through upskilling initiatives and establishing clear accountability for AI-generated outputs.

5.4 Benefits and Measurable Impacts of AI adoption

<i>AI benefits and capabilities</i>	Measurable impacts	Organizational / Strategic Benefits
Model accuracy	<ul style="list-style-type: none"> • 50% reduction in prediction error for TTS • 96% classification accuracy 	<ul style="list-style-type: none"> • More reliable supplier evaluation • Enhanced disruption visibility
Enhanced visibility	<ul style="list-style-type: none"> • Control over both internal and external procurement processes 	
Scalability	<ul style="list-style-type: none"> • Assessment of thousands of suppliers in real time 	<ul style="list-style-type: none"> • Scalable supplier assessment
Cost savings	<ul style="list-style-type: none"> • Procurement cost reduction • 12% reduction in logistics costs 	<ul style="list-style-type: none"> • Significant procurement cost reduction and associated cost savings
Reduced operational workflow	<ul style="list-style-type: none"> • Automation of RFI requests and supplier data collection • 30% improvement in invoice processing 	<ul style="list-style-type: none"> • Operational efficiency gains through automation
Time savings	<ul style="list-style-type: none"> • Disruption response reduced from 5 days → 4 minutes (Mercedes-Benz) • Supplier scouting up to 75% faster • Negotiation time reduced (contract automation) 	<ul style="list-style-type: none"> • Significant time efficiency gains
Supplier Risk Assessment and ESG Compliance	<ul style="list-style-type: none"> • Automated supplier risk assessment with high accuracy (80%) 	<ul style="list-style-type: none"> • ESG compliance of suppliers
Enhanced supply chain resilience	<ul style="list-style-type: none"> • 10-20% reduction in forecasting error • 20-30% improvement in disruption response time 	<ul style="list-style-type: none"> • Stronger supply chain resilience through improved forecasting accuracy and faster disruption response.
Risk prediction & early warnings	<ul style="list-style-type: none"> • Accurate disruption forecasts • Early identification of financial distress 	<ul style="list-style-type: none"> • Enhanced risk mitigation

Figure 5-3: Benefits of AI adoption (Source: Author's own work, 2025)

Figure 5-3 shows the key strategic benefits of AI adoption, along with their measurable tactical impacts. When analysing AI implementation benefits, it is important to split them into two groups: strategic benefits and tactical, measurable impacts. From a procurement perspective, the main strategic benefit is the ability to achieve more accurate, reliable, fast, and scalable supplier evaluation processes. For the automotive industry, this represents a crucial factor, as the multi-tier supplier structure requires rapid and automated systems for evaluating supplier data. AI-powered solutions address this specific need effectively. In terms of measurable impacts, AI tools allow companies to evaluate thousands of suppliers across different tiers in real time, automate RFI requests and tenders, speed up supplier scouting by 75%, assess supplier-related risks with over 80% accuracy, and classify suppliers with almost 100% accuracy.

Improved supply chain resilience is an even more important strategic advantage of applying AI in the automotive industry. This addresses the issue of automotive OEMs' heavy reliance on stable supplies of key components, as illustrated in the Mercedes-Benz case. Any supply failure due to serious disruptions like the semiconductor crisis or COVID-19, or a strategic supplier's refusal to cooperate can result in a complete enterprise shutdown. Therefore, implementing deep learning models is crucial, as they can accurately predict recovery and survival times and improve disruption response time by 20-30%. Additionally, implementing multi-agent systems that monitor risks in real-time and provide early warnings about potential supply chain disruptions down to tier 4 suppliers is also crucial.

The staff of procurement and supply chain departments also benefit from AI implementation. AI can greatly reduce the operational workload and save considerable time that is often spent on highly repetitive and low-value tasks such as invoice processing, contract management, and scouting of non-critical suppliers. This allows procurement staff to focus on building relationships with key strategic partners.

Cost savings is another strategic benefit of implementing AI, particularly for key stakeholders. As shown on Figure, companies truly benefit from AI when its implementation effect begins to show positive impact on the P&L (BCG, 2025). However, it is important to note that cost savings from AI adoption are typically not achieved in a linear way, but rather through insights and optimization of workflow.

The GenAI Staircase to Success

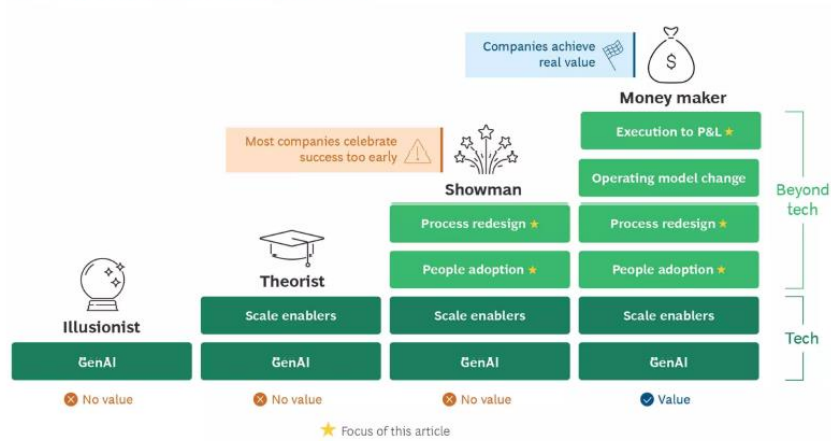


Figure 5-4: The GenAI Staircase to Success (Source: BCG, 2025)

5.5 AI implementation Roadmap

	Key Steps and Actions	Enablers	Functional AI tools	Supportive Tools/Infrastructure Enablers
Organizational readiness and Strategic alignment	<ul style="list-style-type: none"> Align AI with corporate overall commercial strategy (WEF, 2023) <ul style="list-style-type: none"> Build effective change management: training, communication, culture (Chhatre & Singh, 2024) Secure top-management support and supplier engagement (van Hoek, 2024; Meyer & Henke, 2023) Establish data governance and ethical AI use framework (OECD/UNESCO, 2024) 	<ul style="list-style-type: none"> Top management support Supplier involvement Comprehensive change management 		
Technological and Data readiness	<ul style="list-style-type: none"> Assess data quality, accessibility, governance, and volume/variety (Aldoseni et al., 2024) Build modular AI tech stack: Data, Application, API, Security, Infra layers (Jain et al., 2024; BCG, 2024) Ensure compliance with GDPR, AI Act, ethical design principles (Obinna & Kess-Momoh, 2024) 	<ul style="list-style-type: none"> Data standardization and cleansing On premise infrastructure Multi-layer tech stack Legal oversight and compliance with regulations 	Dedicated ML/AI Layer	<ul style="list-style-type: none"> Big Data Layer (ETL, Data cleansing) Application layer Integration & API Layer Security & Compliance Layer Infrastructure & Operations Layer
Pilot testing and Gradual deployment	<ul style="list-style-type: none"> Select high-value use cases for pilot (Mittal et al., 2024) Pilot testing and gradual rollout and ongoing monitoring (Shamsuddoha et al., 2024) Gradual transition from simple to more complex use cases (Rajani and Deng, 2024) 	<ul style="list-style-type: none"> High-quality data pipeline Well - established infrastructure 	<p>Machine Learning (ML)</p> <ul style="list-style-type: none"> Supplier evaluation & risk profiling (ID3, J48, Naive Bayes, k-NN, SVM) KPI-based supplier ranking (MLP) Fraud detection in e-procurement (MLP) Cost breakdown & price pattern analysis <p>Deep Learning (DL)</p> <ul style="list-style-type: none"> Supplier relationship mapping (BERT, NER, GNN) RFI automation (chatbots, NLP) Anomaly detection & disruption forecasting (LSTM Autoencoders) Digital Supply Chain Twins (DL-based cognitive models) 	
Scaling phase	<ul style="list-style-type: none"> Expand infrastructure for real-time inference (Haeffner et al., 2023) Democratize AI tools for non-technical staff (Sjodin et al., 2021) Build ecosystem partnerships (customers and infra providers) Transition to universal AI platforms with reusable modules 	<ul style="list-style-type: none"> Optimized technical infrastructure Ecosystem partnerships with both customers and infra providers Scalable data pipeline 		<ul style="list-style-type: none"> Cloud platforms Explainability frameworks (SHAP, LIME)
Risk Management, Monitoring and Continuous Improvement	<ul style="list-style-type: none"> Implement AI governance framework (IBM, 2024) Monitor data drift, duplication and discoverability Ensure compliance with evolving regulations (EU AI Act, GDPR) Establish AI council 	<ul style="list-style-type: none"> AI Governance Bodies Algorithmic Review Boards 		<ul style="list-style-type: none"> Explainability/interpretability tools ML monitoring platforms

Figure 5-5: AI adoption roadmap (Source: Author's own work, 2025)

Figure 5-5 shows the key recommendations for AI adoption in automotive companies, combined into a unified implementation framework. At each phase, specific steps, enablers, as well as functional and supportive AI/ML tools are outlined. All of these must be incorporated to ensure the successful implementation of this framework within procurement and supply chain.

The initial phase of AI implementation is a strategic step that lays the groundwork for all later adoption initiatives.

At this phase, the key enablers include comprehensive change management, with a focus on procurement and supply chain management workers to overcome reluctance to AI adoption. Top management support and active supplier involvement in the company's AI transformation process are both crucial.

This phase is mostly organisational in nature and does not involve the implementation of functional AI applications or supporting tools and technologies. The next phase is foundational and focuses on data preparation and standardisation and developing a high-quality data pipeline, since AI model effectiveness depends on the quality of training data.

During this stage, companies must also audit or upgrade their current on-premises infrastructure. This allows them to understand whether interoperability issues will arise when implementing the dedicated AI/ML layer and to assess the need for cloud infrastructure, particularly for future deployment and scaling.

Key attention should be given to developing a multi-layered technical architecture. In designing this architecture, additional focus should be placed on the data layer as an important supportive tool.

The third phase, which focuses on pilot testing and gradual deployment, should primarily leverage on-premises infrastructure for pilot projects, with a progressive transition to cloud infrastructure for large-scale rollout. At this phase, the previously established high-quality data pipeline becomes a critical enabler for industrial deployment. The key strategy at this phase is to prioritize high-value use cases, which should first be launched as pilot or proof-of-concept projects, followed by full-scale deployment.

For example, an automotive manufacturer might begin by implementing basic machine learning mechanisms in procurement to classify suppliers across multiple parameters, then introduce more advanced deep learning techniques, such as LSTM Autoencoders, to enhance supply chain resilience during the post-contract phase.

Cloud infrastructure becomes a crucial enabler in the fourth phase due to the widespread access to AI platforms and solutions. Equally important are partnerships with infrastructure providers, as the technical load on systems increases substantially.

At the last stage the key steps involve the implementation of AI governance bodies and risk monitoring frameworks. The supportive tools are ML monitoring platforms and explainability frameworks.

5.6 Research Gaps in Literature

5.6.1 Narrow focus on Supplier Classification

Table 5-1: Mapping literature for the first research question

	AlMahri, 2024	Feng, 2024	Hong 2018	Wu, Jia & Barnes 202	Muniappan & Subramanian 202	Luo 2022	Allat-Cherif et al. 202	Cui, Li & Zhang 2021	Tavana et al. 201	Zekhnini et al. 2025	Wang et al. 2024	Dumitras-cu et al. 2020	Liu, Yu & Kim 2023	Bai & Qiu 2023	Schulze-Horn et al. 2020	Bodendorf et al. 2022	Amellal et al. 2023	Ashraf et al. 2024	Li et al. 2025	Rezki & Mansouri 2024	AlMahri 2025	Regattieri et al. 2024
Pre-Contract																						
Supplier relationship mapping & early identification	X	X	X																			
Supplier Criteria Definition				X																		
Assessment of vendor financial ability (credit/distress)					X	X																
RFI/RFP automation							X	X														
Supplier evaluation, ranking & risk profiling									X	X	X	X	X									
Post-Contract																						
Cost analysis & fraud detection														X	X	X						
AI for supply chain resilience																	X	X	X	X	X	X

Source: Author's own work, 2025

Table 5-1 shows that most empirical studies on supplier evaluation and selection cover pre-contract supplier evaluation, ranking and scoring. Other important stages of pre-contract supplier evaluation, particularly the assessment of vendor financial ability, have received limited attention. While the supply chain resilience part is covered by academic literature, post-contract supplier selection phase remains underexplored.

In addition, many essential stages in supplier management also require further research attention, particularly AI-driven supplier due diligence (crucial in major automotive M&A and JV formation), supplier post-contract risk monitoring, supplier onboarding, and automated contract management through NLP. Moreover, behavioral AI in sourcing, especially the automation of negotiation processes for non-critical items, has received little academic attention.

5.6.2 Limited Review of Regulatory Barriers and Lack of Empirical Studies

Table 5-2: Mapping literature for the second research question

	Klee & Janson 2023	Shrivastav 2021	Doumia et al. 2025	Kumar et al. 2024	Hangl et al. 2022	Zavodna et al. 2024	Guida et al. 2023	Lee et al. 2023	Ghosh 2025	Ahmed et al. 2025	Teixeira et al. 2025	Balan et al. 2025	Ameye et al. 2023	Wang et al. 2025	Zheng & Brintrup 2025	Eisenberg et al. 2025	Giovine et al. 2023	Baryannis et al. 2019
Data-Centric Barriers	X	X	X	X														
Organizational & Human-Centric Barriers					X	X	X											
Infrastructure-Related Barriers					X			X	X	X	X	X						
Financial & ROI-Related Barriers		X											X	X				
Regulatory, Compliance & Legal Barriers															X	X		
Explainability & Trust (XAI) Barriers																	X	X

Source: Author's own work, 2025

As for the second research question, it is evident from the Table 5-2 that researchers focus mainly on technical barriers, particularly infrastructure, data, and explainability issues. However, regulatory and compliance barriers remain almost unstudied, even though AI regulation is actively developing, specifically in countries with the strong automotive sector. Moreover, there are no empirical studies that examine AI implementation barriers using specific cases of automotive manufacturers.

5.6.3 Scalability as a Benefit

Table 5-3: Mapping literature for the third research question

	Li et al. 2025	Do et al. 2024	Luo 2022	Guida et al. 2023	AlMahri et al. 2025	Rainy & Chowdhury 2022	Zekhnini et al. 2024	Allai-Cherif et al. 2024	Kumar et al. 2024	Chiu et al. 2024	Kakusivalingam et al. 2022	Regattieri et al. 2024	Spreitzerbarth et al. 2024	Balan et al. 2025	Wang & Pan 2024	Hangl et al. 2023
Accuracy of the Models	X	X	X													
Enhanced Visibility				X	X											
Scalability						X										
Autonomous Decision-Making & Reduced Workload							X	X	X							
Supplier Risk Assessment & ESG Compliance										X						
Cost Savings									X		X	X				
Time Savings				X	X								X			
Enhanced Supply Chain Resilience											X			X	X	X

Source: Author's own work, 2025

As shown in Table 5-3, the key benefit discussed in academic literature is mainly AI's technical capabilities, specifically its accuracy in both predicting disruptions

and classifying suppliers. However, some important strategic benefits like scalability receive little attention, even though this is one of the most important advantages for the automotive industry, given the number of purchased components and suppliers in this sector.

5.6.4 Pilot Projects, Technical stack and Implementation Roadmap

Table 5-4: Mapping literature for the fourth research question

	Chhatre & Singh, 2024	Burger et al., 2023	Solaimani & Swaak, 2023	van Hoek, 2024	Meyer & Henke, 202	Haefner et al., 2023	Aldoseri et al., 2024	Banh & Strobel, 2023	Obinna & Kess-Momoh, 2024	Shamsuddoha et al	Spreitzenbarth et al., 2024	Sjodin et al., 2021	Hadley et al.	Eisenberg et al., 2025	Hasija & Esper, 2022
Phase 1: Organizational Readiness & Strategic Alignment	X	X	X	X	X										
Phase 2: Technological & Data Readiness						X	X	X	X						
Phase 3: Pilot Testing & Gradual Deployment										X	X				
Phase 4: Scaling AI in the Organization						X						X			
Phase 5: Risk Management, Monitoring & Continuous Improvement													X	X	X

Source: Author's own work, 2025

Based on table 5-4, it becomes obvious that there are no empirical studies in the current academic literature landscape on the implementation and successful deployment of AI pilots and their further scaling in the automotive sector. In general, the phase of deployment and scaling is covered by only a few non-industry-specific conceptual frameworks and qualitative studies.

Moreover, while a few studies and industrial reports briefly address certain layers of technical architecture (Kearney 2024; Samtani et al., 2023), no academic work provides a comprehensive overview of the entire tech stack and its integration into automotive procurement and supply chain systems.

Another significant research gap is the absence of studies that provide a comprehensive, step-by-step AI implementation roadmap. Existing academic literature typically focuses on specific phases of adoption rather than the entire process.

5.6.5 Use of Generative AI and Multi-Agent Systems

The application of generative artificial intelligence and AI-powered multi-agent systems in procurement and supply chain management also remains underexplored. There are a few reviews of the literature (Boone et al., 2023), but there aren't many empirical studies in the automotive sector, since most researchers continue to explore classical machine learning tools. This is partly because generative AI technologies are still in their infancy, and their integration into real-world procurement and supply chain workflows has not yet been systematically examined. However, Generative AI and multi-agent systems are the most important and promising directions, capable of significantly transforming the supplier evaluation and selection process, delivering business value, and contributing to the resilience of the automotive supply chain. Gartner report predicts that AI agents will radically transform procurement processes – from supplier onboarding and selection to contract management – freeing teams to focus on strategic tasks (Gartner, 2025).

5.7 Chapter summary

This chapter discusses the findings of the study in relation to the research questions, using conceptual figures for synthesis. The analysis mapped out the key AI applications across pre-contract and post-contract phases. It also matched key implementation barriers with the most important milestones of AI implementation and pinpointed key enablers and functional and supportive tools.

In addition, the discussion revealed important research gaps, including the narrow focus on machine learning models, limited review of regulatory barriers and scalability benefits, lack of contributions in academic literature on tech stack architecture and implementation roadmaps and the limited attention to generative AI and multi-agent systems.

6 CHAPTER 6: RECOMMENDATION

6.1 Chapter Overview

This chapter includes key recommendations that address the most common bottlenecks during AI implementation phase.

This chapter covers technical and data readiness issues, the importance of effective change management, the necessity of focusing on high-value cases that address the most critical business needs and establishment of AI and data governance.

6.2 Technical Readiness Framework

Before implementing AI, automotive companies must create a Technical Readiness framework. This foundation ensures that AI tools are fully compatible with existing IT systems and are based on high-quality data.

The framework should be developed within 3 to 9 months and completed before any pilot or full-scale AI deployment begins in procurement and supply chain.

Resource requirements include financial investment in data infrastructure audits and interoperability checks. Existing IT legacy systems must be upgraded to ensure compatibility with AI tools. Additional investments are also required to improve data storage capacity, including upgrades in cloud infrastructure, hardware resources, and networking capabilities (Aldoseri et al., 2024).

If this framework is not established prior to deployment, there is a high risk that existing IT systems, data and technical infrastructure will not be incompatible with AI tools. This incompatibility could result in poor integration or complete implementation failure. In this scenario, the risk is evaluated with a probability of 4 and an impact of 4, resulting in an RPN of 16.

The responsibility falls on the Function/Department level, involving IT, supply chain, procurement, legal/compliance, HR departments and top management.

Key KPIs include should include data quality index (completeness, accuracy, consistency, timeliness) and infrastructure readiness.

Table 6-1: Managerial implications and risk analysis for the first recommendation.

No	Managerial Implications	Description
1	Timeline	Medium term (3 - 9 months)
2	Resource requirement	<ul style="list-style-type: none"> Financial: investment in data infrastructure audits, interoperability assessments, upgrades of IT legacy systems Operational/Technological: cloud infrastructure improvements, hardware resources, networking capacity
3	Risk Analysis	<p>High risk. Risk Priority Number (RPN) = Probability (4) × Impact (4) = 16.</p> <ul style="list-style-type: none"> Risks: incompatibility of IT systems and data, poor system integration, or full implementation failure Risk Mitigation: establish technical readiness framework first.
4	Implementation responsibility	Function/Department level: IT, Supply Chain, Procurement, Legal/Compliance, HR departments + Top Management oversight.
5	Success Measurement Mechanism	Data quality index (completeness, accuracy, consistency, timeliness) and infrastructure readiness.

Source: Author's own work, 2025

6.3 Importance of Change Management.

Change management is an important stage, following technical and data readiness, and is essential for the successful adoption of AI in procurement and supply chain. It must encompass not only employees within the relevant departments but also top management and suppliers.

Change management initiatives should begin at the very beginning of any AI implementation project in procurement and should be carried out in the medium term (3-12 months).

Investments in training and upskilling programs as well as communication campaigns are among the most important financial resource requirements.

Change management also requires strong HR support, as many risks come not just from employees' limited understanding of new technologies, but from their fear of job loss. These concerns should be addressed and managed directly by the HR department.

The risk is assessed with a probability of 4 and an impact of 4, resulting in an RPN of 16.

The HR department carries the majority of the responsibility, with top management's support. Key KPIs include employee adaptability in embracing AI technologies, employee sentiment and readiness (how employees feel about AI), and the overall effectiveness of change management, measured through training completion, communication reach, and engagement levels (Lada et al., 2023; Microsoft Corporation, 2024).

Table 6-2: Managerial implications and risk analysis for the second recommendation

No	Managerial Implications	Description
1	Timeline	Medium term (3-12 months)
2	Resource requirement	<ul style="list-style-type: none"> Financial: training and upskilling programs, communication campaigns Human Resource: HR support for addressing employee fears and managing organizational change Operational: coordination across departments and suppliers.
3	Risk Analysis	<p>Risk Priority Number (RPN) = Probability (4) × Impact (4) = 16.</p> <p>Risks: resistance to change, lack of understanding of AI technologies, fear of job loss</p> <p>Risk Mitigation: HR involvement, structured communication, and training programs.</p>
4	Implementation responsibility	HR and Top Management
5	Success Measurement Mechanism	Employee adaptability to AI technologies, employee sentiment and readiness (how employees feel about AI), and the overall effectiveness of change management

Source: Author's own work, 2025

6.4 Focus on High-Value Use Cases

When adopting AI in procurement and supply chains, especially during the testing and pilot stage, it is critical to focus on high-value use cases rather than trying to implement everything at once. This approach is necessary because many companies face significant infrastructural and organizational constraints, such as a lack of skilled personnel, poor data quality, and outdated or limited IT infrastructure.

For this reason, once technical readiness is confirmed, companies should pilot the most business-critical AI tools within 3-6 months, selecting simple solutions with clear ROI. For instance, organisations might start with basic ML features for supplier classification and ranking. This approach aligns with Meyer and Henke (2023), who developed ten design principles for implementing AI in automotive procurement and emphasised the identification of key AI use cases as a central principle.

A pilot project budget must be approved by key stakeholders. Additionally, thorough system interoperability verification is essential. From a human resource perspective, successful execution depends on close collaboration between procurement experts and data scientists. The risk is assessed with a probability of 3 and an impact of 4, resulting in an RPN of 12.

The responsibility for implementation lies with the Procurement and Supply Chain teams (use-case definition) as well as with the IT/Data Science teams (model design). To simplify the evaluation of effectiveness during the pilot stage, it is proposed to introduce a single KPI such as overall business impact.

Table 6-3: Managerial implications and risk analysis for the third recommendation

No	Managerial Implications	Description
1	Timeline	Short to medium term (3-6 months)
2	Resource requirement	<ul style="list-style-type: none"> Financial: pilot project budget agreed with key stakeholders Operational/Technological: system interoperability verification, pilot infrastructure Human Resource: collaboration between procurement experts and data scientists
3	Risk Analysis	<p>Risk Priority Number (RPN) = Probability (3) × Impact (4) = 12.</p> <p>Risks: poor data quality, outdated IT systems, lack of skilled personnel.</p> <p>Risk Mitigation: careful selection of high-value use cases, interoperability testing, stakeholder alignment</p>
4	Implementation responsibility	HR and Top Management
5	Success Measurement Mechanism	KPI: overall business impact

Source: Author's own work, 2025

6.5 AI Governance and Compliance

After successful AI implementation and increased maturity of deployed solutions, companies must ensure long-term reliability, accountability, trust and compliance of AI tools.

A robust governance framework is necessary to continuously monitor AI performance and achieve compliance with regulatory standards. In this regard, organizations need to set up AI governance bodies with clearly defined roles and responsibilities, working in two directions: part of the team handles compliance of AI tools with corresponding regulations such as GDPR or EU AI Act and internal data and AI policies. Part of the team handles operational oversight, constantly monitoring the proper functioning of AI systems, as well as monitoring data quality and potential issues such as model drift and data drift.

AI governance should be implemented within 6-18 months, following the deployment and scaling phases.

From a human resource perspective, the participation of the IT/data science department and legal compliance officers is mandatory. Financial costs are primarily associated with ongoing model maintenance, administrative support, and compliance requirements.

Probability is assessed at 3, while impact is rated at 5 (very high, as non-compliance may result in fines or reputational damage), leading to an overall RPN of 15.

As KPIs, organisations can implement the number of non-compliance incidents and model performance stability.

Table 6-4: Managerial implications and risk analysis for the fourth recommendation.

No	Managerial Implications	Description
1	Timeline	Medium to long term (6-18 months)
2	Resource requirement	<ul style="list-style-type: none"> Financial: ongoing model maintenance, administrative support, compliance costs Human Resource: IT/data science teams, legal & compliance officers Operational: AI Governance bodies with defined monitoring and evaluation roles
3	Risk Analysis	<p>High risk of non-compliance or performance issues. Risk Priority Number (RPN) = Probability (3) × Impact (5) = 15.</p> <p>Risks: regulatory non-compliance, data drift, reputational damage</p> <p>Risk Mitigation: AI Council operational oversight, continuous monitoring, regular audits.</p>
4	Implementation responsibility	<p>AI Council (oversight and governance)</p> <p>IT/Data Science teams (monitoring technical performance)</p> <p>Legal & Compliance officers (ensuring regulatory adherence).</p>
5	Success Measurement Mechanism	KPI: number of non-compliance incidents and model performance stability.

Source: Author's own work, 2025

6.6 Chapter Summary

In this chapter, key recommendations for implementing AI in procurement and supply chain were presented. The recommendations include technical and data readiness assessment, effective change management, focus on the most important use cases with clear ROI and establishment of AI governance bodies.

Table 6-5: Summary of recommendations.

No	Risk	Description	Probability (1-5)	Impact (1-5)	Risk Priority Number	Risk Ownership	Risk Disruption Strategy
1	Technical/Data unreadiness	Legacy IT systems and poor data quality may cause AI integration failure if readiness framework not established	4	4	16	IT Manager; Procurement Manager; Top Management; Legal;	Conduct infrastructure audit, upgrade legacy systems, ensure interoperability before deployment
2	Employee Resistance to AI	Fear of job loss and lack of understanding may lower adoption of AI tools	4	4	16	HR Department; Senior Management	Change management program, training, transparent communication, HR-led support
3	Pilot Project Failure	Focusing on too many AI use cases at once may lead to low ROI and potential failure	3	4	12	Procurement Manager; Data Science Manager	Select high-value pilots, align budget with stakeholders
4	Regulatory Non-Compliance	Deployed AI tools may drift or fail to meet regulatory standards, causing fines or reputational damage	3	5	15	AI Governance Council; Legal & Compliance Officers	Establish AI governance framework, continuous monitoring, regular audits

Source: Author's own work, 2025

7 CHAPTER 7: CONCLUSIONS

7.1 Chapter Overview

In this chapter, the study demonstrates how the four research objectives have been met, outlines the research limitations, and proposes further research opportunities.

This chapter is structured as follows. Sections 7.2 to 7.5 revisit the four research objectives, demonstrating how each one has been achieved. Section 7.6 discusses the limitations of the study, while Section 7.7 highlights future research directions.

7.2 Research Objective 1

The first research objective was to identify key AI applications in selecting and evaluating automotive suppliers and improving supply chain resilience. The study mapped a wide range of applications across both pre-contract and post-contract stages, including supplier screening, classification, ranking, surveillance, and monitoring. In addition, the analysis identified key AI applications in automotive supply chain resilience, particularly anomaly detection and recovery predictions.

7.3 Research Objective 2

The second research objective was to identify the key barriers to AI implementation at the enterprise level. The study revealed multiple barriers, including legal and compliance, financial and ROI-related, data-centric, infrastructure, and human-related aspects. Moreover, the analysis distributed these barriers across the specific AI implementation phases identified in this study.

7.4 Research Objective 3

To address the third research objective, this study examined the key benefits and measurable impacts of AI adoption. The main benefits include improved accuracy of supplier selection and evaluation process, cost and time savings, reduced

operational workload, enhanced supply chain resilience, improved risk mitigation and supplier risk assessment. The research also identified specific measurable tactical impacts for each strategic benefit.

7.5 Research Objective 4

The fourth research objective was to recommend strategies for implementing AI-driven supplier evaluation, selection, and resilience frameworks in the automotive industry. After reviewing selected academic and industry sources, the study identified key recommendations and organized them into five main phases. This created a comprehensive AI implementation roadmap for enterprises. Each phase was also aligned with relevant enablers, functional AI tools, and supportive digital technologies.

7.6 Research Limitations

While the review provides valuable insights into the impact of AI on automotive procurement and supply chain management, it is crucial to acknowledge several limitations.

First, the current academic base, particularly empirical studies, is mainly focused on exploring basic machine learning techniques for supplier ranking and scoring. This narrows the scope, making it difficult to cover and analyse in detail both the pre-contract and post-contract phases of supplier selection and evaluation in the automotive industry. Other AI subdomains such as NLP, GenAI as well as important steps of supplier selection and evaluation are also covered but remain fragmented in the academic literature.

Another important limitation is that AI technologies, especially in the field of generative artificial intelligence, are progressing so rapidly that academic literature cannot fully keep pace with these changes. To maintain the relevance of the analysis, reports from consulting and industry organisations were used, but these sources lack scientific rigor.

Furthermore, the analysis of barriers and recommendations was primarily based on cross-industry studies and general AI adoption frameworks, rather than automotive-specific research. While these findings and insights are useful and

applicable to the automotive sector, they may not capture all of the automotive supply chain's unique characteristics such as its complex multi-tier structure.

7.7 Future Research Directions

Given the current landscape of academic work on AI-powered procurement and supply chain resilience in the automotive industry, the focus of future research should be on studying the application of Generative artificial intelligence and multi-agent systems. This particular AI direction is the most promising both in terms of technology development and in terms of close attention from the automotive industry. Moreover, future research should not be limited to traditional OEMs and Tier-1 suppliers but should also extend to Tier-2 and Tier-3 levels. Investigating these deeper layers of the supply chain would provide a more comprehensive understanding of how AI-driven solutions perform in complex, multi-tier supplier automotive networks.

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Appendices

Appendix A approval letter



26 May 2025

Dear Mr Govorukhin ,

Reference: CURES/25323/2025

Project ID: 28843

Title: Investigating the Impact of Artificial Intelligence on Procurement & SCM Strategies. A study of the International Automotive Sector

Thank you for your application to the Cranfield University Research Ethics System (CURES).

We are pleased to inform you your CURES application, reference CURES/25323/2025 has been reviewed. You may now proceed with the research activities you have sought approval for.

If you have any queries, please contact CURES Support.

We wish you every success with your project.

Regards,

CURES Team

Appendix B Data Extraction Forms

1. An integrated framework for sustainable supplier selection and evaluation in supply chains

01	Author of the article	Luthra, S., Govindan, K., Kannan, D., Mangla, S. K., & Garg, C. P.
02	Title of the article	An integrated framework for sustainable supplier selection and evaluation in supply chains
03	Document name	Luthra et al., 2017
04	Journal title	Journal of Cleaner Production
05	Date of publication	2017
06	Volume	140
07	Number	-
08	Page numbers	1686 - 1698
09	Paper Type	Empirical study
10	Geographical Location	India
11	Context/Industry	Automotive industry
12	Sample size	Case study with 22 evaluation criteria, 5 alternative suppliers
13	Data collection method	
14	Method of data analysis	AHP plus MCDM
15	Study Characteristics	AHP - VIKOR model for sustainable supplier evaluation and selectio
16	Key findings related to research questions	Used in the research background part as a rationale for transitioning to machine learning
17	Abstract	This study applies a hybrid AHP - VIKOR framework for sustainable supplier selection in supply chains, based on the example for Indian Automotive sector
18	Key words	Supplier Selection; AHP - VIKOR
19	Organization Field	Supply Chain Management, Automotive Industry; AHP - MCDM
20	Quality Appraisal Score	2.5/3.0

2. Supplier selection using fuzzy AHP and TOPSIS: A case study in the Indian automotive industry

01	Author of the article	Jain, V., Sangaiah, A. K., Sakhuja, S., Thoduka, N., & Aggarwal, R.
02	Title of the article	Supplier selection using fuzzy AHP and TOPSIS: A case study in the Indian automotive industry
03	Document name	Jain et al., 2018
04	Journal title	Neural Computing and Applications
05	Date of publication	2018
06	Volume	29
07	Number	2
08	Page numbers	555 - 564
09	Paper Type	Empirical study
10	Geographical Location	India
11	Context/Industry	Automotive industry
12	Sample size	Case study with 8 evaluation criteria, 3 suppliers
13	Data collection method	Expert interviews and pairwise comparisons
14	Method of data analysis	Fuzzy AHP plus TOPSIS
15	Study Characteristics	Hybrid fuzzy AHP - TOPSIS model for supplier evaluation in automotive sector
16	Key findings related to research questions	Used in the research background part as a rationale for transitioning to machine learning
17	Abstract	The paper proposes a hybrid fuzzy AHP - TOPSIS approach for supplier selection in the Indian automotive industry.
18	Key words	Supplier Selection; AHP - Topsis
19	Organization Field	Supply Chain Management, Automotive Industry; AHP - MCDM
20	Quality Appraisal Score	2.5/3.0

3. Performance Evaluation for a Sustainable Supply Chain Management System in the Automotive Industry Using Artificial Intelligence

01	Author of the article	Oana Dumitrascu, Manuel Dumitrascu, Dan Dobrota
02	Title of the article	Performance Evaluation for a Sustainable Supply Chain Management System in the Automotive Industry Using Artificial Intelligence
03	Document name	Dumitrascu et al.
04	Journal title	Processes
05	Date of publication	30 October 2020
06	Volume	8
07	Number	11
08	Page numbers	1 - 20
09	Paper Type	Empirical study
10	Geographical Location	Romania
11	Context/Industry	Automotive Industry, Supply Chain Management
12	Sample size	50 respondents from 12 international automotive companies
13	Data collection method	Interview method
14	Method of data analysis	Data mining, Multilayer Perceptron Algorithm
15	Study Characteristics	This study provides a machine learning-based model for supply chain performance evaluation within the automotive industry. The model identifies the most relevant KPIs based on specific problems encountered in each SCM subsystem.
16	Key findings related to research questions	RQ1: The AI model improves supplier selection and evaluation by identifying the most relevant KPIs for each specific problem within the supply chain. Using a MLP neural network the model links supplier related issues such as delivery delays, quality noncompliance, or long lead times to key performance indicators. This allows companies to make data - driven decisions
17	Abstract	The paper presents a performance evaluation model that links problems in the automotive supply chain management system to KPIs using artificial intelligence. By applying MLP, the model identifies the most relevant KPIs for each subsystem of the supply chain
18	Key words	Performance evaluation, artificial intelligence, neural networks, data mining
19	Organization Field	Supply Chain Management, Automotive Industry
20	Quality Appraisal Score	2.5/3.0

4. A hybrid intelligent fuzzy predictive model with simulation for supplier evaluation and selection

01	Author of the article	Tavana, M., Fallahpour, A., Di Caprio, D., & Santos-Arteaga, F. J.
02	Title of the article	A hybrid intelligent fuzzy predictive model with simulation for supplier evaluation and selection
03	Document name	Tavana et al. (2016)
04	Journal title	Expert Systems With Applications
05	Date of publication	2016
06	Volume	61
07	Number	
08	Page numbers	129-144
09	Paper Type	Empirical study
10	Geographical Location	Not specified
11	Context/Industry	Automotive industry
12	Sample size	Dataset (31 suppliers, 8 products)
13	Data collection method	Case study using the improved GHD dataset: historical and current operational data of suppliers across five criteria, combined with expert evaluations aggregated through AHP.
14	Method of data analysis	Artificial Neural Network (ANN), Adaptive Neuro Fuzzy Inference System (ANFIS)
15	Study Characteristics	The study proposes a hybrid ANFIS-ANN model to define supplier ranking
16	Key findings related to research questions	<p>RQ1: The ANFIS-ANN model is applied to identify critical criteria (price, quality, delivery, technology) and ANN (MLP) to predict supplier ranking. It excels in situations when data is incomplete or missing.</p> <p>RQ3: The ANFIS-ANN model excels in incomplete data environment, maintaining high prediction accuracy in supplier ranking even when part of the input information is missing.</p>
17	Abstract	A hybrid ANFIS-ANN model for supplier ranking and evaluation in the automotive sector is proposed in this study. Based on the most important criteria identified by ANFIS, ANN forecasts supplier performance.
18	Key words	Supplier selection, ANN, ANFIS, MLP
19	Organization Field	Artificial Intelligence, Supply Chain Management
20	Quality Appraisal Score	2.5

5. A multi-agent based big data analytics system for viable supplier selection

01	Author of the article	Kamar Zekhnini, Abba Chaouni Benabdellah, Anass Cherrafi
02	Title of the article	A multi-agent based big data analytics system for viable supplier selection
03	Document name	Zekhnini et al. (2024)
04	Journal title	Journal of Intelligent Manufacturing
05	Date of publication	24 October 2023
06	Volume	35
07	Number	
08	Page numbers	3753-3773
09	Paper Type	Methodological, Framework
10	Geographical Location	Not specified
11	Context/Industry	Supplier Selection
12	Sample size	None
13	Data collection method	Literature review (144 papers) plus expert panel (7 specialists)
14	Method of data analysis	Conceptual architecture design using MAS and FIS
15	Study Characteristics	A study proposes a layered architecture combining MAS plus Big Data plus FIS for supplier evaluation. Emphasis on digitalization, resilience, sustainability.
16	Key findings related to research questions	RQ3. One of the key advantages of AI-powered Multi-Agent Systems (MAS) and Distributed Artificial Intelligence (DAI) lies in their capacity for significant autonomy – the ability of agents to operate without human intervention and make decisions.
17	Abstract	This study proposes a multi-agent system integrated with big data analytics layer to evaluate and select viable suppliers based on digitalization, resilience, and sustainability
18	Key words	Supplier selection, Multi-agent system, Big Data Analytics, Viability, VUCA
19	Organization Field	Supplier Selection
20	Quality Appraisal Score	2.5/3

6. Enhancing Supply Chain Safety and Security: A Novel AI-Assisted Supplier Selection Method

01	Author of the article	Jozsef Pap, Csaba Mako, Adrian Horvath, Zoltan Baracscai, Tamas Zelles, Judit Bilinovics-Sipos, Sandor Remsei
02	Title of the article	Enhancing Supply Chain Safety and Security: A Novel AI-Assisted Supplier Selection Method
03	Document name	Pap et al., 2024
04	Journal title	Decision Making: Applications in Management and Engineering
05	Date of publication	16 July 2024
06	Volume	8
07	Number	1
08	Page numbers	22-41
09	Paper Type	Empirical study
10	Geographical Location	Japan
11	Context/Industry	Warehousing Service/Providers outsourcing
12	Sample size	3 suppliers (RfQ case), 7 stakeholders, 5 expert interviewees
13	Data collection method	Expert interviews, RfQ documents, system data
14	Method of data analysis	ID3 decision tree, rule-based reasoning, entropy/information gain
15	Study Characteristics	Expert system for supplier selection based on AI (ID3); tested in real logistics project in Japan
16	Key findings related to research questions	<p>RQ1. Supplier evaluation model for logistics providers, based on a wide range of parameters aggregated into key categories (such as TCO and reliability). Suppliers are classified into three levels (Recommended, Acceptable with Risk, Not Recommended) using the ID3 algorithm, followed by a rule-based mechanism for decision support. Great system for supplier pre-contract screening with multiple criteria</p> <p>RQ3. Reduced lead time for supplier evaluation In the case study, the supplier selection process was reduced from 6 to 3 months.</p>
17	Abstract	The article presents AI-assisted supplier selection model based on expert systems and ID3 algorithm, applied to warehousing service provider selection. The model was tested in a real case in Japan and proved to outperform traditional scorecard methods.
18	Key words	Artificial Intelligence; Supplier Selection; Strategic Sourcing
19	Organization Field	Supplier Evaluation
20	Quality Appraisal Score	2.5/3.0

7. Revolutionizing Sourcing with AI: Harnessing Technology for Unprecedented Efficiency and Savings

01	Author of the article	Praveen Kumar, Divya Choubey, Olamide Raimat Amosu, Yewande Mariam Ogunsuji, Bibitayo Ebunlomo Abikoye, Stanley Chidozie Umeorah
02	Title of the article	Revolutionizing Sourcing with AI: Harnessing Technology for Unprecedented Efficiency and Savings
03	Document name	Kumar et al. (2024)
04	Journal title	World Journal of Advanced Research and Reviews
05	Date of publication	August 2024
06	Volume	23
07	Number	02
08	Page numbers	925-938
09	Paper Type	Industry article
10	Geographical Location	USA
11	Context/Industry	Manufacturing (Ford Motor Company), Retail (Walmart), Healthcare (Mayo Clinic)
12	Sample size	Case studies of 3 organizations (Ford, Walmart, Mayo Clinic); 10 expert interviews
13	Data collection method	Case studies (sourcing strategies, AI tools, procurement records, supplier metrics), semi-structured interviews with 10 experts
14	Method of data analysis	Qualitative (thematic analysis of interviews), Quantitative
15	Study Characteristics	The study applies a mixed-method approach combining qualitative and quantitative analysis. Case studies include Ford (manufacturing), Walmart (retail), and Mayo Clinic (healthcare).
16	Key findings related to research questions	<p>RQ1: Machine Learning (ML): Example: Ford used ML to predict supplier performance, reducing supplier-related issues by 15%. Natural Language Processing (NLP): Ford applied NLP to analyze contracts, identifying risks like ambiguous terms Robotic Process Automation (RPA): Ford's RPA tools reduced administrative workload by 30%, allowing procurement teams to focus on strategic supplier assessments.</p> <p>RQ2: Data Quality: Ford faced issues with inconsistent data formats across systems, which hindered AI performance. Low-quality data can result in flawed supplier evaluations or sourcing decisions. Integration with Existing Systems: Ford struggled to integrate AI with its existing systems due to varied data formats. Lack of skilled personnel Ford noted that scaling AI across departments was resource-intensive and required a phased approach.</p> <p>RQ3: Reduction in Supplier Issues: Ford reduced supplier-related issues by 15%. Procurement Cost Savings: Impact: Procurement costs decreased by 12%. Improved Operational Efficiency: Impact: RPA reduced administrative workload by 30%, speeding up processes like invoice and order management.</p>

17	Abstract	This paper explores how AI technologies such as machine learning, NLP, and predictive analytics are revolutionizing sourcing processes in various segments including automotive
18	Key words	Artificial Intelligence, Sourcing, Efficiency, Supply Chain Optimization
19	Organization Field	Procurement and Supplier Selection
20	Quality Appraisal Score	2.5/3.0

8. Forecasting Automotive Supply Chain Disruption with Heterogeneous Time Series

01	Author of the article	Bach Viet Do, Xingyu Li, Chaoye Pan, Oleg Gusikhin
02	Title of the article	Forecasting Automotive Supply Chain Disruption with Heterogeneous Time Series
03	Document name	Do et al., 2024
04	Journal title	ANY INFORMS JOURNAL
05	Date of publication	2024
06	Volume	
07	Number	
08	Page numbers	
09	Paper Type	Empirical study
10	Geographical Location	USA
11	Context/Industry	Automotive
12	Sample size	Over five hundred thousand time series
13	Data collection method	Dataset collected from Ford's supply chain operations
14	Method of data analysis	Attention Sequence to Sequence Deep Learning architecture, Neural Network Embeddings, Survival Analysis model, SHAP framework
15	Study Characteristics	The study uses a large dataset of multivariate time series to forecast first-tier supply chain disruptions. It proposes a methodology that integrates Attention Sequence to Sequence Deep Learning architecture, using Neural Network Embeddings with a Survival Analysis model.
16	Key findings related to research questions	<p>RQ1: AI application for supply chain resilience, using a Heterogeneous Seq2Surv model combining Attention Sequence-to-Sequence Deep Learning, Neural Network Embeddings, and Survival Analysis to forecast first-tier supply chain disruptions at Ford. The SHAP framework enhances interpretability of the model.</p> <p>RQ3: The proposed deep learning model shows high predictive accuracy in forecasting potential supply chain disruptions from suppliers across five Ford manufacturing plants, achieving precision and recall rates above 80%</p>
17	Abstract	The study explores how artificial intelligence can help prevent supply chain disruptions at Ford. Using data from suppliers and manufacturing plants, the authors show that a deep learning model can predict delivery failures. Tested across five Ford plants in North America, the model with over 80% accuracy
18	Key words	Supply Chain Disruption; Supply Chain Resilience; Supply Chain Deep Learning; Survival Analysis; Sequence-to-Sequence
19	Organization Field	Supply Chain Management, Machine Learning
20	Quality Appraisal Score	2.5

9. Enhancing the sustainability and robustness of critical material supply in electrical vehicle market: an AI-powered supplier selection approach

01	Author of the article	Zhu-Jun Wang, Zhen-Song Chen, Qin Su, Wai-Sang Chi, Witold Pedrycz, ·Mirosław J. Skibniewski
02	Title of the article	Enhancing the sustainability and robustness of critical material supply in electrical vehicle market: an AI-powered supplier selection approach
03	Document name	Zhao et al., 2024
04	Journal title	Annals of Operations Research
05	Date of publication	2024
06	Volume	342
07	Number	1
08	Page numbers	921 - 958
09	Paper Type	Empirical study
10	Geographical Location	China
11	Context/Industry	Electric vehicle supply chains; selection of critical raw material suppliers (Li, Co, Ni, Mn)
12	Sample size	
13	Data collection method	Secondary data from company websites and reports, complemented by expert input
14	Method of data analysis	Qualitative thematic/content analysis with expert validation
15	Study Characteristics	The study develops an AI - driven framework that aggregates expert judgments (via SPGM) and applies knapsack optimization to select sustainable suppliers of critical EV materials, balancing environmental, social, and economic criteria under budget constraints.
16	Key findings related to research questions	RQ1: SPGM-GA hybrid model is applied to aggregate experts' opinions into sustainability scores and generate an optimal supplier portfolio, selecting the most sustainable and cost-efficient supplier for each critical battery commodity within budget constraints.
17	Abstract	This study proposes an AI-supported decision-making framework for selecting sustainable suppliers of critical materials (Li, Co, Ni, Mn) in the electric vehicle (EV) industry. The framework integrates expert-based evaluation with multi-objective optimization under uncertainty and budget constraints.
18	Key words	Supplier Selection
19	Organization Field	Supplier Selection; Artificial Intelligence
20	Quality Appraisal Score	3.0/3.0

10. End-to-end supply chain resilience management using deep learning, survival analysis, and explainable artificial intelligence

01	Author of the article	Xingyu Li, Vasiliy Krivtsov, Chaoye Pan, Aydin Nassehi, Robert X. Gao, Dmitry Ivanov
02	Title of the article	End-to-end supply chain resilience management using deep learning, survival analysis, and explainable artificial intelligence
03	Document name	Li et al., 2025
04	Journal title	INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH
05	Date of publication	2025
06	Volume	63
07	Number	
08	Page numbers	1174-1202
09	Paper Type	Empirical study
10	Geographical Location	United States, United Kingdom, Germany
11	Context/Industry	Automotive
12	Sample size	10 000 different parts, 271 018 training instances
13	Data collection method	Internal operational data (inventory levels, supplier delays, order history) collected from the automotive company
14	Method of data analysis	Deep Learning, Survival Analysis, Explainable AI
15	Study Characteristics	Real-world automotive industry case study focusing on unknown-unknown risks. The seq2disr deep learning model predicted Time-to-Survive (TTS) with 80% accuracy.
16	Key findings related to research questions	<p>RO1:</p> <ul style="list-style-type: none"> • SCREM introduces a deep learning-based framework for resilience prediction (TTS). • Operates entirely on internal ERP data (inventory, delays, usage). • Applied in a real automotive setting with 10000 parts. <p>RO3:</p> <ul style="list-style-type: none"> • Achieves 50% error reduction over baseline models. • Predicts time-to-survive (TTS) within 20 days on a 180-day horizon.
17	Abstract	This study introduces an end-to-end Supply Chain Resilience Management (SCREM) framework leveraging deep learning, survival analysis, and explainable AI to enhance supply chain (SC) resilience against disruptions, particularly those with unknown-unknown uncertainties. The framework uses company's data to detect anomalies, assess risks, and identify mitigation strategies without extensive supplier data or complex SC modelling.
18	Key words	Supply chain resilience, supply chain risk management, survival analysis
19	Organization Field	Supply Chain Management, Artificial Intelligence
20	Quality Appraisal Score	3.0/3.0

11. Integrating machine learning and deep learning for enhanced supplier risk prediction

01	Author of the article	Nisrine Rezki, Mohamed Mansouri
02	Title of the article	Integrating machine learning and deep learning for enhanced supplier risk prediction
03	Document name	Rezki & Mansouri, 2024
04	Journal title	Acta Logistica - International Scientific Journal about Logistics
05	Date of publication	2024
06	Volume	11
07	Number	3
08	Page numbers	387 - 396
09	Paper Type	Empirical study
10	Geographical Location	Morocco
11	Context/Industry	Automotive and parts manufacturing
12	Sample size	20000 supplier-related quality incidents across 7 years, 429 suppliers, 20 manufacturing sites
13	Data collection method	ERP data from an automotive company
14	Method of data analysis	Machine learning models
15	Study Characteristics	Predictive analytics case study in the automotive supply chain; classification - regression framework addressing supplier-related quality issues
16	Key findings related to research questions	RQ1: Combined classification - regression ML model based on ERP data from a wiring harness manufacturer. The system predicts supplier-related quality issues by identifying which suppliers are most likely to deliver non-conforming parts, estimating the potential number of incidents, and, most importantly, forecasting the total cost of failures
17	Abstract	Rezki and Mansouri (2024) conduct a predictive analytics study within the automotive supply chain utilizing ERP data from a wiring harness manufacturer. They use machine learning models to predict quality problems with suppliers, failures types and associated costs.
18	Key words	Supplier evaluation, Supply Chain Resilience
19	Organization Field	Supply Chain Risk Management; Supply Chain Resilience
20	Quality Appraisal Score	2.5/3.0

12. Hybrid intelligence in procurement: Disillusionment with AI's superiority?

01	Author of the article	Markus Burger, Anna-Maria Nitsche, Julia Arlinghaus
02	Title of the article	Hybrid intelligence in procurement: Disillusionment with AI's superiority?
03	Document name	Computers in Industry 150 (2023) 103946
04	Journal title	Computers in Industry
05	Date of publication	2023
06	Volume	150
07	Number	
08	Page numbers	103946
09	Paper Type	Case study/Empirical study
10	Geographical Location	Germany
11	Context/Industry	Retail, Engineering
12	Sample size	4 in-depth case studies
13	Data collection method	
14	Method of data analysis	
15	Study Characteristics	Qualitative case study examining the interplay between human and artificial intelligence in procurement processes
16	Key findings related to research questions	RQ4: AI implementation in procurement should be in close coordination with humans, since despite improvements in process time and visibility, humans can bring implicit and unique expert knowledge. Human experts play an important role as mediators.
17	Abstract	This paper examines the limits of artificial intelligence and the capabilities of so-called hybrid intelligence. The study offers four case studies on the integration of human and artificial intelligence in procurement, including demand planning, supplier selection, order management, and procurement analytics.
18	Key words	Hybrid intelligence, Artificial intelligence, Procurement
19	Organization Field	Supply Chain Management, Procurement, Artificial Intelligence
20	Quality Appraisal Score	2.5/3.0

13. Artificial intelligence for supplier scouting: an information processing theory approach

01	Author of the article	Michela Guida, Federico Caniato, Antonella Moretto and Stefano Ronchi
02	Title of the article	Artificial intelligence for supplier scouting: an information processing theory approach
03	Document name	Guida et al., 2023
04	Journal title	International Journal of Physical Distribution & Logistics Management
05	Date of publication	2023
06	Volume	Not specified in the text
07	Number	1-38
08	Page numbers	1-38
09	Paper Type	Empirical
10	Geographical Location	Italy
11	Context/Industry	Not specified
12	Sample size	12 cases of IT and information providers offering AI-based scouting solutions
13	Data collection method	The study employed a triangulated data collection approach, combining semi-structured interviews as the primary method with secondary data analysis
14	Method of data analysis	Data were analyzed using within- and cross-case analysis with Gioia coding, guided by Information Processing Theory (IPT).
15	Study Characteristics	Exploratory research using information processing theory (IPT) as theoretical lens, focusing on information processing needs (IPNs) and capabilities (IPCs)
16	Key findings related to research questions	RQ2: <ol style="list-style-type: none"> 1. Low maturity of AI technology for supplier scouting 2. Skills of the personnel in the purchasing department are lacking 3. Cultural barriers and change management issue 4. Low degree of comfort about sharing sensitive information between buyers and suppliers by means of the procurement platform.
17	Abstract	The goal of this paper is to study the role of AI in supporting the supplier scouting process. Twelve cases of IT and information providers offering AI-based scouting solutions were studied. The unit of analysis was the AI-based scouting solution, specifically the relationship between the provider and the buyer.
18	Key words	Supplier scouting, Sourcing, Artificial intelligence, Information processing theory
19	Organization Field	Supply Chain Management
20	Quality Appraisal Score	3

14. Criteria system construction for sustainable supplier selection: A product-category-oriented intelligent model

01	Author of the article	Chong Wu, Yiqun Jia, David Barnes
02	Title of the article	Criteria system construction for sustainable supplier selection: A product-category-oriented intelligent model
03	Document name	Wu et al., 2023
04	Journal title	Applied Soft Computing
05	Date of publication	2023
06	Volume	145
07	Number	
08	Page numbers	110586
09	Paper Type	Empirical study
10	Geographical Location	China
11	Context/Industry	Machinery/Forklift company
12	Sample size	6 suppliers, 300 vendor-product records
13	Data collection method	A combination of Delphi method and expert evaluation was used.
14	Method of data analysis	Random Forest algorithm, Recursive Feature Elimination Cross-Validation (RFECV), machine learning
15	Study Characteristics	Product-category-oriented intelligent model for sustainable supplier selection criteria system construction
16	Key findings related to research questions	<p>RQ1: Random Forest algorithm and RFECV for constructing supplier selection criteria.</p> <p>RQ3: The study shows significant improvements through AI application in supplier evaluation. The proposed Random Forest - based model achieved an 86.68% accuracy rate in identifying an optimal sustainable supplier selection criteria system.</p>
17	Abstract	This paper proposes an intelligent method to identify the most important supplier evaluation criteria, tailored to specific product categories. Using Random Forest plus RFECV, the model selects an optimal subset of criteria.
18	Key words	Criteria system construction, Sustainable supplier selection, Product category, Machine learning, Random Forest algorithm
19	Organization Field	Supply Chain Management, Sustainability
20	Quality Appraisal Score	2.5/3.0

15. The role of artificial intelligence in the procurement process: State of the art and research agenda

01	Author of the article	Guida, M.; Caniato, F.; Moretto, A.; Ronchi, S.
02	Title of the article	The role of artificial intelligence in the procurement process: State of the art and research agenda
03	Document name	Guida et al., 2023
04	Journal title	Journal of Purchasing and Supply Management
05	Date of publication	2023
06	Volume	29
07	Number	1
08	Page numbers	
09	Paper Type	Exploratory study
10	Geographical Location	Not explicitly specified
11	Context/Industry	General procurement context across industries, with application in automotive, FMCG, manufacturing
12	Sample size	85 papers reviewed; 33 AI platform providers; 13 procurement managers in focus group
13	Data collection method	Systematic literature review (Scopus) Mapping of AI-based procurement platforms Focus group with procurement managers
14	Method of data analysis	
15	Study Characteristics	The study applies a multi-method approach combining three sources: a systematic literature review (85 articles), an analysis of 33 AI-enabled procurement platforms, and qualitative data from a focus group of 13 procurement professionals.
16	Key findings related to research questions	RQ1: <ul style="list-style-type: none"> Spend analysis and purchasing category management Risk management solutions Supplier scouting Automated negotiations Automation of non-value-added activities RQ3: The primary advantages of AI adoption include improved visibility and oversight over both internal and external procurement processes, along with procurement risk mitigation achieved through AI's predictive capabilities.
17	Abstract	The study maps AI applications across procurement processes by combining a systematic literature review, vendor platform analysis, and focus group feedback. It identifies how AI is currently used, identifies benefits, challenges and future research directions.
18	Key words	Procurement, Supplier Scouting
19	Organization Field	Procurement and Supply Chain
20	Quality Appraisal Score	3.0/3.0

16. A systematic review of machine learning applications in sustainable supplier selection

01	Author of the article	Joachim O. Gidiagba, Lagouge K. Tartibu, Modestus O. Okwu
02	Title of the article	A systematic review of machine learning applications in sustainable supplier selection
03	Document name	Gidiagba et al., 2025
04	Journal title	Decision Analytics Journal
05	Date of publication	2025
06	Volume	14
07	Number	Not specified
08	Page numbers	1-21
09	Paper Type	Systematic literature review
10	Geographical Location	Not specified
11	Context/Industry	Supply chain management; sustainable supplier selection across industries
12	Sample size	50 research papers (25 from Scopus, 12 from Web of Science, 13 from Google Scholar)
13	Data collection method	Systematic literature review using PRISMA (2010-2024)
14	Method of data analysis	Qualitative synthesis; comparative analysis of machine learning vs. traditional methods across supplier selection stages
15	Study Characteristics	Reviews machine learning applications in sustainable supplier selection from 2010-2024, focusing on trends, techniques, challenges, and future directions.
16	Key findings related to research questions	Conclusions: Machine learning techniques can learn from new data, process large amount of data efficiently and find non-linear patterns.
17	Abstract	The article provides a comprehensive overview of machine learning models in supplier selection and evaluation across various industries
18	Key words	Sustainable supplier selection, Machine learning
19	Organization Field	Supplier Selection; Machine Learning
20	Quality Appraisal Score	2.5/3.0

17. Viable industrial supplier performance evaluation using fuzzy inference system: a case of the automotive industry

01	Author of the article	Kamar Zekhnini, Abla Chaouni Benabdellah, Anass Cherrafi, Imane Bouhaddou, Surajit Bag
02	Title of the article	Viable industrial supplier performance evaluation using fuzzy inference system: a case of the automotive industry
03	Document name	Zekhnini et al., 2025
04	Journal title	Journal of Business & Industrial Marketing
05	Date of publication	2025
06	Volume	40
07	Number	
08	Page numbers	941-962
09	Paper Type	Empirical study
10	Geographical Location	Not specified
11	Context/Industry	Automotive industry
12	Sample size	One case study firm with multiple supplier evaluations
13	Data collection method	Real-world case study in automotive industry using fuzzy set theory and fuzzy inference system (FIS)
14	Method of data analysis	Fuzzy inference system (FIS)
15	Study Characteristics	Decision-making framework for industrial supplier evaluation and selection using viability as a new criterion in VUCA environment
16	Key findings related to research questions	RQ1: FIS-based model for supplier selection in the automotive industry, where standard selection criteria are supplemented by VUCA selection criteria: resilience, sustainability, and digitalization. The evaluation is performed using 17 sub-criteria that divided into four main categories, resulting in an aggregated supplier score for each supplier.
17	Abstract	This paper aims to present a decision-making system using a fuzzy inference system (FIS) for industrial supplier evaluation and selection, considering a new criterion: viability.
18	Key words	Supplier selection
19	Organization Field	Supply Chain Management; AI
20	Quality Appraisal Score	2.5/3.0

18. Improving Lead Time Forecasting and Anomaly Detection for Automotive Spare Parts with A Combined CNN-LSTM Approach

01	Author of the article	Asmae Amellal, Issam Amellal, Hamid Seghioeur, Mohammed Rida Ech-Charrat
02	Title of the article	Improving Lead Time Forecasting and Anomaly Detection for Automotive Spare Parts with A Combined CNN-LSTM Approach
03	Document name	Amellal et al., 2023
04	Journal title	Operations and Supply Chain Management
05	Date of publication	2023
06	Volume	16
07	Number	
08	Page numbers	265-278
09	Paper Type	Empirical study
10	Geographical Location	Morocco
11	Context/Industry	Automotive
12	Sample size	Data from a major automotive distributor in Morocco's ERP system, more than 50 000 inputs
13	Data collection method	Legal ERP system of a major automotive distributor in Morocco
14	Method of data analysis	CNN (Convolutional Neural Network), LSTM (Long Short Term Memory), Bidirectional LSTM, LSTM autoencoder, One-Class Support Vector Machine (OCSVM)
15	Study Characteristics	Framework development combining CNN-BiLSTM for lead time forecasting and LSTM autoencoder with OCSVM for anomaly detection
16	Key findings related to research questions	<p>RQ1: The study focuses on a specific AI application in the automotive industry: a combined CNN-LSTM approach for lead time forecasting and LSTM - OCSVM approach for anomaly detection in spare parts supply chains.</p> <p>RQ3: The study shows significant benefits from implementing the AI-driven framework for lead time management in automotive spare parts distribution. The combined CNN-LSTM approach provides more accurate lead time forecasting compared to traditional methods. The anomaly detection component using LSTM autoencoder with OCSVM helps identify unreliable data, improving overall data quality for decision-making.</p>
17	Abstract	This paper presents a solution to a challenge faced in the supply chain management of a spare parts distributor in Morocco. The problem is a lack of accurate lead time information, leading to difficulties in meeting customer demand. The proposed solution is a framework using an LSTM model for lead time forecasting and anomaly detection. The framework uses CNN -BiLSTM model for forecasting and an LSTM autoencoder with One-Class Support Vector Machine for anomaly detection.
18	Key words	Anomaly detection, forecasting, long-term short memory, one class support vector machine
19	Organization Field	Supply Chain Management, Supply Chain Resilience
20	Quality Appraisal Score	2.5/3.0

19. Modeling Supply Chain Interaction and Disruption: Insights from Real-world Data and Complex Adaptive System

01	Author of the article	Jiawei Feng, Mengsi Cai, Fangze Dai, Tianci Bu, Xiaoyu Zhang, Huijun Zheng, Xin Lu
02	Title of the article	Modeling Supply Chain Interaction and Disruption: Insights from Real-world Data and Complex Adaptive System
03	Document name	Feng et al., 2024
04	Journal title	
05	Date of publication	2024
06	Volume	N/A
07	Number	N/A
08	Page numbers	1 - 24
09	Paper Type	Empirical
10	Geographical Location	China
11	Context/Industry	Automotive Industry
12	Sample size	7784 firms and 8576 connections
13	Data collection method	Open domain databases, internet data,
14	Method of data analysis	Knowledge graph, NER , fuzzy matching
15	Study Characteristics	Empirical study based on data from the Chinese automotive industry (2000 - 2020) from open sources and CSMAR/Wind databases; a network of 7,784 firms and 8,576 connections was constructed; GPT-NER, transfer learning, fuzzy matching, and LLM+KG were used to extract and supplement connections
16	Key findings related to research questions	RQ1: Authors used GPT-NER technology for firm entity recognition and for mapping the Chinese automotive SoC supply chain network
17	Abstract	
18	Key words	Supply Chain Visibility
19	Organization Field	Supply Chain Management
20	Quality Appraisal Score	2.0/3.0

20. How artificial intelligence can redefine the purchasing function

01	Author of the article	Oihab Allal-Cherif, Virginia Simon-Moya, Antonio Carlos Cuenca Ballester
02	Title of the article	How artificial intelligence can redefine the purchasing function
03	Document name	Allal-Cherif et al., 2021
04	Journal title	Journal of Business Research
05	Date of publication	2022
06	Volume	124
07	Number	
08	Page numbers	69 - 76
09	Paper Type	Research paper
10	Geographical Location	Spain
11	Context/Industry	Procurement and Supply Chain Management
12	Sample size	Not specified
13	Data collection method	Qualitative: Multiple case study analyzing documentary data of five AI-based purchasing technologies (Synertrade, Silex, SAP Ariba, Jaggner, Ideapoke)
14	Method of data analysis	Exploratory approach analyzing applications, advantages, limitations, and impacts of AI technologies in purchasing
15	Study Characteristics	The study investigates the applications of artificial intelligence in automating the purchasing function
16	Key findings related to research questions	RQ1: Process Automation: AI automates and optimizes purchasing repetitive tasks (expenditure analysis, contract management, supplier communication via chatbots, supplier matching, RFI requests) RQ3: AI may reduce the operational workload of procurement professionals by automating repetitive tasks. As a result, buyers can focus more on strategic and value-creating activities.
17	Abstract	This study explores how AI transforms the purchasing function through automation, predictive buying and decision aids and supplier relationship management. Using a qualitative multiple case study of five AI-based platforms, it analyzes AI's applications, benefits and limitations.
18	Key words	AI Automation
19	Organization Field	Supply Chain Management
20	Quality Appraisal Score	2.5/3.0

21. Disruption detection for a cognitive digital supply chain twin using hybrid deep learning

01	Author of the article	Mahmoud Ashraf, Amr Eltawil, Islam Ali
02	Title of the article	Disruption detection for a cognitive digital supply chain twin using hybrid deep learning
03	Document name	Ashraf et al., 2024
04	Journal title	International Journal of Sustainable Development & World Ecology
05	Date of publication	2024
06	Volume	24
07	Number	
08	Page numbers	1-31
09	Paper Type	Empirical
10	Geographical Location	Egypt
11	Context/Industry	Supply Chain Management
12	Sample size	Not applicable (simulation-based), simulated dataset
13	Data collection method	
14	Method of data analysis	Hybrid deep learning pipeline: 1. Deep autoencoder for feature extraction One-Class SVM for disruption detection 2. LSTM classifier for disrupted echelon identification 3. LSTM regressor for Time-to-Recovery (TTR) prediction.
15	Study Characteristics	Development of a CDSCT (Cognitive Digital Supply Chain Twin) to detect disruptions in real time, identify disruption, and predict time-to-recovery, using deep learning and machine learning unsupervised models
16	Key findings related to research questions	RQ1: <ul style="list-style-type: none"> Deep autoencoder plus One-Class SVM used to detect supply chain disruptions. LSTM classifier identifies which echelon is disrupted (including supplier level). LSTM regressor predicts Time-to-Recovery (TTR) after disruption. Relevant for evaluating supplier resilience in downstream automotive chains. RQ3: End-to-end visibility: The system detects disruptions in real time and immediately identifies the specific echelon affected (supplier, manufacturer, distributor).
17	Abstract	This study introduces a hybrid deep learning-based Cognitive Digital Supply Chain Twin (CDSCT) framework for real-time disruption detection, disrupted echelon identification, and Time-to-Recovery (TTR) prediction in a three-echelon make-to-order supply chain.
18	Key words	Digital Twin, Cognitive Digital Supply Chain Twin, Supply Chain Resilience
19	Organization Field	Supply Chain Management, Supply Chain Resilience
20	Quality Appraisal Score	2.5/3.

22. Automatic Procurement Fraud Detection with Machine Learning

01	Author of the article	Jin Bai, Tong Qiu
02	Title of the article	Automatic Procurement Fraud Detection with Machine Learning
03	Document name	Bai & Qiu, 2023
04	Journal title	arXiv
05	Date of publication	2023
06	Volume	Not applicable
07	Number	
08	Page numbers	1-12
09	Paper Type	Empirical study
10	Geographical Location	China
11	Context/Industry	Supply Chain Management, Logistics
12	Sample size	50,000 procurement records from SF Express (25,000 positive + 25,000 negative cases)
13	Data collection method	
14	Method of data analysis	Internal SAP procurement data (2015 - 2017), manually labeled, extracted via Arbutus Analyzer
15	Study Characteristics	The study applies supervised machine learning, specifically a multilayer perceptron (MLP), to detect and classify procurement fraud using a structured dataset of 50000 procurement records from SF Express (China). The research includes both binary classification (fraud vs. no fraud) and multiclass classification (fraud types), achieving 84.5% and 98% accuracy respectively.
16	Key findings related to research questions	<p>RQ1: The paper demonstrates how AI can be used to:</p> <ul style="list-style-type: none"> Identify fraud patterns linked to specific suppliers Classify fraud types <p>RQ3: The model achieved near-perfect accuracy (98%) in classifying fraud types.</p>
17	Abstract	This study explores the application of machine learning, specifically multilayer perceptron (MLP) networks, to detect and classify procurement fraud in large-scale enterprise data. Using a dataset from SF Express (2015 - 2017), the model achieves 84.5% accuracy in fraud detection and 98% in fraud type classification.
18	Key words	Fraud detection, e - procurement
19	Organization Field	Artificial intelligence (AI), Fraud detection
20	Quality Appraisal Score	2.0

23. Revolutionizing Supply Chains: Unleashing the Power of AI-Driven Intelligent Automation and Real-Time Information Flow

01	Author of the article	Mohammad Shamsuddoha, Eijaz Ahmed Khan, Md Maruf Hossan Chowdhury, Tasnuba Nasir
02	Title of the article	Revolutionizing Supply Chains: Unleashing the Power of AI-Driven Intelligent Automation and Real-Time Information Flow
03	Document name	Shamsuddoha et al., 2025
04	Journal title	Information
05	Date of publication	2025
06	Volume	16
07	Number	26
08	Page numbers	1-19
09	Paper Type	SLR
10	Geographical Location	Not specified
11	Context/Industry	Supply Chain Management; Cross-Industry
12	Sample size	383 peer-reviewed articles (2017-2024)
13	Data collection method	Systematic literature review
14	Method of data analysis	Thematic analysis of 383 articles using Web of Science, Google Scholar, Scopus; Boolean operators for keyword searches
15	Study Characteristics	The study reviews AI - driven automation intelligent automation in supply chains, analyzing 383 articles to propose a strategic framework for AI- adoption. Real-world case studies (Amazon, Walmart, Siemens)
16	Key findings related to research questions	RQ4: Authors proposed an AI integration framework that includes pilot testing, gradual deployment of AI systems, and ongoing monitoring and adjustment.
17	Abstract	Artificial intelligence (AI) and smart automation are revolutionizing the global supply chain ecosystem, providing potential for resilience, innovation, efficacy, and profitability. This paper examines how AI, ML, and RPA enhance forecasting, logistics, and real-time decision-making.
18	Key words	Artificial Intelligence, Supply Chain Management
19	Organization Field	Artificial intelligence
20	Quality Appraisal Score	3.0/3.0

24. Developing a conceptual technical framework for ethical AI in procurement with emphasis on legal oversight

01	Author of the article	Amaka Justina Obinna, Azeez Jason Kess-Momoh
02	Title of the article	Developing a conceptual technical framework for ethical AI in procurement with emphasis on legal oversight
03	Document name	Obinna, Kess-Momoh, 2024
04	Journal title	GSC Advanced Research and Reviews
05	Date of publication	2024
06	Volume	19
07	Number	01
08	Page numbers	146-160
09	Paper Type	Conceptual / Framework Paper
10	Geographical Location	Not specified
11	Context/Industry	Procurement / AI Ethics & Compliance
12	Sample size	Not applicable
13	Data collection method	Systematic literature review plus case studies
14	Method of data analysis	Thematic synthesis of literature
15	Study Characteristics	The article develops a conceptual technical framework integrating ethical principles and legal oversight in AI-enhanced procurement. Case studies from 4 firms illustrate implementation and lessons learned.
16	Key findings related to research questions	RQ 4: The article directly addresses RQ4 by proposing a conceptual technical framework for the ethical implementation of AI in procurement, with a strong emphasis on legal oversight. It outlines strategies for integrating legal requirements, mitigating risks (bias, privacy), ensuring transparency, and engaging stakeholders.
17	Abstract	This article presents a conceptual technical framework for ethical AI deployment in procurement, emphasizing legal oversight. It outlines strategies to ensure compliance with data protection laws, mitigate algorithmic bias, promote transparency, and engage stakeholders.
18	Key words	Artificial Intelligence, Legal Compliance
19	Organization Field	Artificial intelligence (AI), Legal compliance
20	Quality Appraisal Score	2.5/3.0

25. Implementing and scaling artificial intelligence: A review, framework, and research agenda

01	Author of the article	Naomi Haefner, Vinit Parida, Oliver Gassmann, Joakim Wincent
02	Title of the article	Implementing and scaling artificial intelligence: A review, framework, and research agenda
03	Document name	Haefner et al., 2023
04	Journal title	Technological Forecasting & Social Change
05	Date of publication	2023
06	Volume	197
07	Number	122878
08	Page numbers	Naomi Haefner, Vinit Parida, Oliver Gassmann, Joakim Wincent
09	Paper Type	Framework Paper
10	Geographical Location	Not specified
11	Context/Industry	Not specified
12	Sample size	Cross - industry
13	Data collection method	Case-based data from TWIML AI podcast expert interview
14	Method of data analysis	Thematic analysis
15	Study Characteristics	The article presents a three-phase socio-technical framework for implementing and scaling AI in organisations (Proving Concept, Productionizing, and Platformizing) based on case data from 22 firms, including automotive industry. It highlights key technical and social components required for AI scalability
16	Key findings related to research questions	RQ4: In the AI scaling phase, procurement organisations must optimize their technical infrastructure for real-time inference and large-scale data processing. This requires not only robust compute and storage systems, but also democratized access to AI tools for non-technical staff. Companies should also transition from narrow models to universal AI platforms, where modules (predictive, analytical, explainability) can be reused across different business functions
17	Abstract	The article presents a three-phase socio-technical framework for implementing and scaling AI in organisations (Proving Concept, Productionizing, and Platformizing) based on case data from 22 firms, including automotive industry. It highlights key technical and social components required for AI scalability
18	Key words	Artificial Intelligence, AI Scaling strategy
19	Organization Field	Artificial intelligence, Scaling AI in the organization
20	Quality Appraisal Score	3.0/3.0

26. How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops

01	Author of the article	David Sjodin, Vinit Parida, Maximilian Palmie, Joakim Wincent
02	Title of the article	How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops
03	Document name	Sjodin et al., 2021
04	Journal title	Journal of Business Research
05	Date of publication	2021
06	Volume	134
07	Number	122878
08	Page numbers	574-587
09	Paper Type	Empirical Qualitative Case Study
10	Geographical Location	Sweden
11	Context/Industry	B2B Industrial Manufacturing Firms (Digital Servitization)
12	Sample size	6 industrial firms
13	Data collection method	42 in-depth interviews
14	Method of data analysis	Thematic analysis
15	Study Characteristics	This is a qualitative multiple case study based on six leading Swedish industrial manufacturers engaged in digital servitization. The researchers conducted 42 in-depth interviews with key stakeholders. The study focuses on how firms develop AI capabilities and scalable AI implementation.
16	Key findings related to research questions	RQ 4: AI Scaling phase Organizations can scale AI by simultaneously developing three interdependent capabilities: data pipeline (integrating and managing data in a secure and scalable way), algorithm development (fine-tuning AI models and tailoring them to meet organizational needs), and AI democratization (making AI accessible across the entire organization, not just for data scientists). Scalability should also be based on the following innovation principles: agile customer co-creation through customer engagement in the creation of AI-driven business solutions, data-driven delivery operations through real-time AI-powered monitoring and predictive service optimization, and scalable ecosystem integration through Value Enablement Partnerships with infrastructure providers for accessing scalable infrastructure and technical capabilities, and Value Expansion Partnerships with SMEs, startups, and OEMs for enhanced product value creation.
17	Abstract	The study explores how manufacturing firms can scale AI by developing three interdependent capabilities: data pipelines, algorithm development, and AI democratization. It identifies three principles for business model innovation: agile co-creation, data-driven delivery, and scalable ecosystem integration. A co-evolutionary framework is also proposed.
18	Key words	Artificial Intelligence, AI Scaling strategy
19	Organization Field	Artificial intelligence, Scaling AI in the organization
20	Quality Appraisal Score	3.0

27. Investigating Relevant Data in Automotive Procurement Departments: External Shocks as Transparency Creator for Data Deficits in Decision-Making

01	Author of the article	Sven Klee, Andreas Janson
02	Title of the article	Investigating Relevant Data in Automotive Procurement Departments: External Shocks as Transparency Creator for Data Deficits in Decision-Making
03	Document name	Klee & Janson, 2023
04	Journal title	Information Systems Frontiers
05	Date of publication	2023
06	Volume	-
07	Number	-
08	Page numbers	-
09	Paper Type	Empirical Qualitative Study
10	Geographical Location	Germany (experts from automotive and consulting firms)
11	Context/Industry	Automotive Procurement and Supply Chain
12	Sample size	23 experts from 20 organisations
13	Data collection method	Semi-structured interviews
14	Method of data analysis	Thematic analysis
15	Study Characteristics	The study explores what procurement-relevant data is needed for decision-making in the automotive sector. It focuses on availability, usability, and infrastructure challenges, using expert interviews with OEMs, consultants, and IT/data specialists.
16	Key findings related to research questions	RQ2: Limited data transparency Most OEMs have limited or no access to sub-tier supplier data (2nd/3rd tier), logistics provider data, and external market data, which significantly impairs decision-making in times of disruption.
17	Abstract	This study investigates which data sets are needed for procurement decision-making in the automotive industry, especially under external shocks like COVID-19. Based on 23 expert interviews, it identifies six data categories and highlights data usability challenges.
18	Key words	Procurement, Data Analytics, Supply Chain Transparency
19	Organization Field	Procurement
20	Quality Appraisal Score	2.5

28. Barriers Related to AI Implementation in Supply Chain Management

01	Author of the article	Monika Shrivastav
02	Title of the article	Barriers Related to AI Implementation in Supply Chain Management
03	Document name	Shrivastav, 2022
04	Journal title	Journal of Global Information Management
05	Date of publication	2022
06	Volume	30
07	Number	8
08	Page numbers	1-19
09	Paper Type	Review Article
10	Geographical Location	USA
11	Context/Industry	-
12	Sample size	-
13	Data collection method	Structured literature review combined with professional/industry experience
14	Method of data analysis	Thematic analysis
15	Study Characteristics	The study explores what procurement-relevant data is needed for decision-making in the automotive sector. It focuses on availability, usability, and infrastructure challenges, using expert interviews with OEMs, consultants, and IT/data specialists.
16	Key findings related to research questions	RQ 2: The article analyzes all major types of barriers to AI implementation across the supply chain, including technology barriers, change management barriers, talent barriers, geopolitical barriers, organizational barriers, top management barriers, and AI-specific barriers such as scaling and explainability
17	Abstract	This article provides a structured review of the barriers hindering AI implementation in supply chain management. It categorizes ten types of barriers, including organizational, technological, and AI-specific challenges
18	Key words	Barriers; AI implementation
19	Organization Field	Supply Chain Management
20	Quality Appraisal Score	2.5

29. Machine learning and deep learning applications in the automotive manufacturing industry: A systematic literature review and industry insights

01	Author of the article	Soufiane Douimia, Abdelghani Bekrar, Abdessamad Ait El Cadi, Yassin El Hillali, David Fillon
02	Title of the article	Machine learning and deep learning applications in the automotive manufacturing industry: A systematic literature review and industry insights
03	Document name	Douimia et al., 2025
04	Journal title	Robotics and Computer-Integrated Manufacturing
05	Date of publication	2025
06	Volume	96
07	Number	103034
08	Page numbers	1-19
09	Paper Type	Systematic Literature Review (SLR)
10	Geographical Location	France
11	Context/Industry	Automotive
12	Sample size	257 peer-reviewed articles (from 2786 initially screened)
13	Data collection method	PRISMA protocol
14	Method of data analysis	Thematic mapping, bibliometric keyword clustering
15	Study Characteristics	SLR that includes 5 domains (equipment optimization, quality improvement, supply chain, production efficiency, energy management).
16	Key findings related to research questions	<p>RQ1: ML/DL used in 5 domains:</p> <ul style="list-style-type: none"> • Equipment optimization • Quality improvement • Supply chain • Production efficiency • Energy management <p>RQ2:</p> <ul style="list-style-type: none"> • Data quality and interoperability issues • Lack of standardization • Latency and infrastructure constraints in edge/cloud setups
17	Abstract	
18	Key words	Barriers; AI implementation
19	Organization Field	Supply Chain Management
20	Quality Appraisal Score	2.5

30. Barriers, Drivers, and Social Considerations for AI Adoption in Supply Chain Management: A Tertiary Study

01	Author of the article	Johannes Hangl, Viktoria Joy Behrens, Simon Krause
02	Title of the article	Barriers, Drivers, and Social Considerations for AI Adoption in Supply Chain Management: A Tertiary Study
03	Document name	Hangl et al., 2022
04	Journal title	Logistics
05	Date of publication	2022
06	Volume	6
07	Number	3
08	Page numbers	1-22
09	Paper Type	Tertiary Study (Systematic Literature Review of 44 SLRs)
10	Geographical Location	Not specified
11	Context/Industry	Supply Chain Management
12	Sample size	44 SLRs (covering 7089 primary studies)
13	Data collection method	Collection of SLRs
14	Method of data analysis	Thematic analysis using MAXQDA
15	Study Characteristics	A tertiary SLR that synthesizes insights from 44 systematic literature reviews on AI in SCM
16	Key findings related to research questions	RQ2: Article provided a comprehensive review of various barriers towards implementation of AI: Change Management, Technical Limitation Human Acceptance and understanding of AI technology.
17	Abstract	This article is a tertiary study that synthesizes 44 systematic literature reviews on the adoption of AI in supply chain management. It identifies key barriers (such as change management, technical limitations, and human resistance), drivers (like cost reduction and efficiency improvement), and social considerations
18	Key words	Barriers; Drivers; AI implementation
19	Organization Field	Supply Chain Management
20	Quality Appraisal Score	2.5

31. Barriers to the implementation of artificial intelligence in small and medium sized enterprises: Pilot study

01	Author of the article	Lucie Sara Zavodna, Margarethe Uberwimmer, Elisabeth Frankus
02	Title of the article	Barriers to the implementation of artificial intelligence in small and medium sized enterprises: Pilot study
03	Document name	Zavodna et al., 2024
04	Journal title	Journal of Economics and Management
05	Date of publication	2024
06	Volume	46
07	Number	
08	Page numbers	331-352
09	Paper Type	Empirical Qualitative Pilot Study
10	Geographical Location	Czech Republic and Austria
11	Context/Industry	Small and Medium-Sized Enterprises (SMEs) across different sectors
12	Sample size	22 interviews
13	Data collection method	Expert interviews
14	Method of data analysis	Semi-structured expert interviews, qualitative research approach
15	Study Characteristics	The paper investigates key barriers to AI implementation in SMEs in Central Europe via qualitative interviews with experts.
16	Key findings related to research questions	RQ2: <ul style="list-style-type: none"> • Lack of trust including trust toward data sources, data collection processes, and data management • Lack of knowledge includes low AI literacy, resistance to change, insufficient expert availability. • Lack of infrastructure; weak technical and legal infrastructure, few local knowledge hubs • Lack of resources
17	Abstract	This pilot study explores the key barriers hindering AI adoption in SMEs in the Czech Republic and Austria. Based on 22 expert interviews, four main obstacles were identified: lack of trust, lack of knowledge, insufficient infrastructure, and limited resources.
18	Key words	Barriers; AI implementation
19	Organization Field	Supply Chain Management
20	Quality Appraisal Score	2.5/3.0

32. When does AI pay off? AI-adoption intensity, complementary investments, and R&D strategy

01	Author of the article	Yong Suk Lee, Taekyun Kim, Sukwoong Choi, Wonjoon Kim
02	Title of the article	When does AI pay off? AI-adoption intensity, complementary investments, and R&D strategy
03	Document name	Lee et al., 2022
04	Journal title	Technovation
05	Date of publication	2022
06	Volume	117
07	Number	102590
08	Page numbers	Not specified
09	Paper Type	Empirical quantitative study
10	Geographical Location	South Korea
11	Context/Industry	High-tech ventures
12	Sample size	160 high-tech ventures
13	Data collection method	Structured survey
14	Method of data analysis	Descriptive statistics, Ordered Logit Regression, Ordinary Least Squares
15	Study Characteristics	This study investigates how AI adoption intensity affects the performance of high-tech ventures in South Korea.
16	Key findings related to research questions	RQ2: Companies with access to large amounts of data, equipped with extensive datasets and powerful computing infrastructure are able to derive greater benefits from AI adoption.
17	Abstract	This study investigates how AI-adoption intensity influences firm performance in high-tech ventures. Using survey from 160 Korean firms, the authors find that AI adoption leads to significant revenue growth only at higher levels of adoption.
18	Key words	AI adoption
19	Organization Field	Supply Chain Management; Artificial Intelligence
20	Quality Appraisal Score	2.5/3

33. Developing artificial intelligence (AI) capabilities for data-driven business model innovation: Roles of organizational adaptability and leadership

01	Author of the article	Swapan Ghosh
02	Title of the article	Developing artificial intelligence (AI) capabilities for data-driven business model innovation: Roles of organizational adaptability and leadership
03	Document name	Ghosh, 2025
04	Journal title	Journal of Engineering and Technology Management
05	Date of publication	2025
06	Volume	75
07	Number	14
08	Page numbers	1-16
09	Paper Type	Empirical Study
10	Geographical Location	United States
11	Context/Industry	B2B companies
12	Sample size	25 interviews from 5 firms
13	Data collection method	Semi-structured interviews with 25 informants
14	Method of data analysis	Thematic analysis
15	Study Characteristics	The paper explores how industrial firms develop and deploy AI capabilities to ensure Data-Driven Business Model (DDBM) innovation
16	Key findings related to research questions	RQ2 The article explores several barriers towards implementation of AI including cloud infrastructure, data limitations and lack of skilled personnel
17	Abstract	This study explores how industrial firms build AI capabilities (data, technology, and infrastructure) to drive data-driven business model innovation.
18	Key words	AI deployment, Data-Driven Business Model Innovation, AI Capabilities
19	Organization Field	Supply Chain Management
20	Quality Appraisal Score	2.5

34. Methodological Approach to Assessing the Current State of Organizations for AI-Based Digital Transformation

01	Author of the article	Abdulaziz Aldoseri, Khalifa N. Al-Khalifa, Abdel Magid Hamouda
02	Title of the article	Methodological Approach to Assessing the Current State of Organizations for AI-Based Digital Transformation
03	Document name	Aldoseri et al., 2024
04	Journal title	Applied System Innovation
05	Date of publication	2024
06	Volume	7
07	Number	14
08	Page numbers	1-33
09	Paper Type	Framework Paper
10	Geographical Location	Qatar
11	Context/Industry	General application of AI
12	Sample size	Not applicable
13	Data collection method	Structured literature review
14	Method of data analysis	Thematic analysis of literature plus synthesis of practitioner experience
15	Study Characteristics	The paper develops a structured framework for assessing organizational readiness for AI-based digital transformation. The framework includes four key pillars: (1) Current Processes, (2) Existing Systems, (3) Data Landscape, and (4) AI Capabilities
16	Key findings related to research questions	RQ2: Paper provides framework for assessing an organization's data landscape. It has four key components: data quality, data accessibility, data governance, and data volume and variety. Data quality refers to the accuracy, completeness, and relevance of data used in AI systems. Data accessibility evaluates where and how data are stored, and the extent to which they can be accessed via APIs, databases, or cloud platforms. Data governance focuses on the policies, roles, and procedures that ensure data reliability, compliance, and security. Finally, data volume and variety reflect the organization's ability to scale infrastructure to handle large, diverse datasets required for advanced AI applications.
17	Abstract	This study develops a comprehensive methodology to assess organizational readiness for AI-based digital transformation.
18	Key words	AI adoption; Framework; Data readiness
19	Organization Field	Supply Chain Management; AI adoption
20	Quality Appraisal Score	3.0

35. Deep learning framework for interpretable supply chain forecasting using SOM ANN and SHAP

01	Author of the article	Khandakar Rabbi Ahmed, Md Eahia Ansari, Md. Naimul Ahsan, Arafat Roha, Md Borhan Uddin & Mir Araf Hossain Rivin
02	Title of the article	Deep learning framework for interpretable supply chain forecasting using SOM ANN and SHAP
03	Document name	Ahmed et al., 2025.
04	Journal title	Scientific Reports (Nature Portfolio)
05	Date of publication	2025
06	Volume	15
07	Number	14
08	Page numbers	26355
09	Paper Type	Empirical
10	Geographical Location	Not specified
11	Context/Industry	Supply chain
12	Sample size	2 datasets
13	Data collection method	Secondary/public datasets from Kaggle, no primary data
14	Method of data analysis	Thematic analysis of literature plus synthesis of practitioner experience
15	Study Characteristics	The study proposes an interpretable hybrid deep learning pipeline combining Principal Component Analysis (PCA), Self-Organizing Maps (SOM), and a Genetic Algorithm–optimized Backpropagation Neural Network (GA-BPNN).
16	Key findings related to research questions	RQ2: The significant computational resources needed for deep learning models present a challenge for SMEs without the infrastructure needed to support these technologies.
17	Abstract	This study introduces a deep learning approach that combines PCA, SOM, and a GA-optimized neural network to predict delivery times and identify late deliveries in supply chains. The method is tested on two real datasets, showing higher accuracy than traditional machine learning models.
18	Key words	Supply Chain; Predictive Analytics; SOM; ANN; SHAP
19	Organization Field	Supply Chain Management
20	Quality Appraisal Score	3.0

36. Intelligent Supply Chain Management: A Systematic Literature Review on Artificial Intelligence Contributions

01	Author of the article	Antonio R. Teixeira, Jose Vasconcelos Ferreira, Ana Luisa Ramos
02	Title of the article	Intelligent Supply Chain Management: A Systematic Literature Review on Artificial Intelligence Contributions
03	Document name	Teixeira et al., 2025
04	Journal title	Information
05	Date of publication	2025
06	Volume	16
07	Number	399
08	Page numbers	1-40
09	Paper Type	Systematic Literature Review
10	Geographical Location	Global scope
11	Context/Industry	General application of Artificial Intelligence in Supply Chain Management
12	Sample size	66 peer-reviewed articles
13	Data collection method	Systematic literature review using PRISMA (2020) framework
14	Method of data analysis	Bibliometric analysis, Content analysis
15	Study Characteristics	The paper systematically reviews 66 studies on AI in SCM
16	Key findings related to research questions	RQ2: Teixeira et al. (2025) identify several barriers to AI implementation in supply chain management, including data governance issues, ethical concerns, scalability challenges. An important barrier mentioned by the authors is the difficulty of embedding AI into existing infrastructures, caused by system interoperability constraints and the rigidity of legacy IT systems.
17	Abstract	This study reviews 66 recent articles on AI in supply chain management, focusing on resilience, optimization, sustainability, and adoption challenges.
18	Key words	Artificial intelligence; Supply chain management; Resilience;
19	Organization Field	Supply Chain Management; Artificial Intelligence
20	Quality Appraisal Score	2.5/3.0

37. Machine learning and artificial intelligence methods and applications for post-crisis supply chain resiliency and recovery

01	Author of the article	G. Sakthi Balan, V. Santhosh Kumar, S. Aravind Raj
02	Title of the article	Machine learning and artificial intelligence methods and applications for post-crisis supply chain resiliency and recovery
03	Document name	Balan et al., 2025
04	Journal title	Supply Chain Analytics
05	Date of publication	2025
06	Volume	10
07	Number	100121
08	Page numbers	Review article
09	Paper Type	Systematic Literature Review
10	Geographical Location	Global context
11	Context/Industry	Multi-industry focus
12	Sample size	
13	Data collection method	Systematic literature review
14	Method of data analysis	Thematic analysis, bibliometric mapping, case study synthesis
15	Study Characteristics	This is a comprehensive review examining how AI and ML methods can enhance supply chain resilience and recovery after crises such as natural disasters, pandemics, and wars.
16	Key findings related to research questions	<p>RQ2: IT legacy systems as a barrier Legacy systems often fail to process data in real time, adapt to rapidly changing conditions, and ensure compatibility with modern data format; therefore, for the deployment of ML/AI during crises, existing legacy systems should be either updated or replaced with newer, more adaptable systems.</p> <p>RQ3: The application of machine learning and artificial intelligence in supply chain management can decrease demand forecasting errors by 10 - 20% and improve disruption response times by 20 - 30%.</p>
17	Abstract	This study reviews 66 recent articles on AI in supply chain management, focusing on resilience, optimization, sustainability, and adoption challenges.
18	Key words	Artificial intelligence; supply chain management; resilience;
19	Organization Field	Supply Chain Management; Machine Learning
20	Quality Appraisal Score	2.5/3.0

38. Explainable Artificial Intelligence (XAI): Concepts, Taxonomies, Opportunities and Challenges toward Responsible AI

01	Author of the article	Alejandro Barredo Arrieta, Natalia Diaz-Rodriguez, Javier Del Ser, Adrien Bennetot, Siham Tabik, Alberto Barbado, Salvador Garcia, Sergio Gil-Lopez, Daniel Molina, Richard Benjamins, Raja Chatila, Francisco Herrera
02	Title of the article	Explainable Artificial Intelligence (XAI): Concepts, Taxonomies, Opportunities and Challenges toward Responsible AI
03	Document name	Arrieta et al., 2019
04	Journal title	Information Fusion (preprint on arXiv)
05	Date of publication	December 30, 2019
06	Volume	N/A
07	Number	N/A
08	Page numbers	N/A
09	Paper Type	Literature review
10	Geographical Location	Global
11	Context/Industry	Artificial Intelligence
12	Sample size	
13	Data collection method	Systematic literature review and conceptual synthesis of XAI methods
14	Method of data analysis	Comparative taxonomy development, classification of approaches
15	Study Characteristics	Study provides one of the most comprehensive early surveys of XAI.
16	Key findings related to research questions	The trade-off between model interpretability and accuracy is shown. Simple models are more explainable but less accurate, while deep neural networks achieve higher accuracy at the cost of interpretability.
17	Abstract	The paper reviews the field of explainable artificial intelligence (XAI). The authors outline the main goals of explainability and present a taxonomy of methods for both classical machine learning and deep learning. In the end, they propose the concept of Responsible AI.
18	Key words	Explainable AI, Interpretability, Transparency,
19	Organization Field	Artificial Intelligence
20	Quality Appraisal Score	2.5/3.0

39. Developing design principles for the implementation of AI in PSM: An investigation with expert interviews

01	Author of the article	Dennis Meyer; Michael Henke
02	Title of the article	Developing design principles for the implementation of AI in PSM: An investigation with expert interviews
03	Document name	Meyer & Henke., 2023
04	Journal title	Journal of Purchasing & Supply Management
05	Date of publication	2023
06	Volume	29
07	Number	N/A
08	Page numbers	
09	Paper Type	Qualitative study
10	Geographical Location	Not specified
11	Context/Industry	Purchasing & Supply Management (PSM)
12	Sample size	17 interviews
13	Data collection method	Interviews
14	Method of data analysis	Qualitative content analysis
15	Study Characteristics	The authors identified 40 requirements for the successful implementation of AI in PSM by combining a survey of the literature with 17 expert interviews. They then developed ten design principles and connected various AI use cases to various PSM processes
16	Key findings related to research questions	RQ1: Five areas for implementation including spend analysis, lead time prediction, AI-based price forecasting RQ4: AI implementation in procurement requires actively involving staff from the very beginning, providing them with the necessary support, and demonstrating an open mindset from the management. Ten design principles have been developed including the identification of key AI use cases
17	Abstract	A qualitative study based on 17 expert interviews with representatives of large companies. The analysis resulted in 40 implementation requirements and 10 design principles for AI in PSM.
18	Key words	AI Compliance
19	Organization Field	Artificial Intelligence, Private procurement
20	Quality Appraisal Score	3.0/3.0

40. Artificial Intelligence in Purchasing: Facilitating Mechanism Design-based Negotiations

01	Author of the article	Ines Schulze-Horn; Sabrina Hueren; Paul Scheffler; Holger Schiele
02	Title of the article	Artificial Intelligence in Purchasing: Facilitating Mechanism Design-based Negotiations
03	Document name	Schulze-Horn et al., 2020
04	Journal title	Applied Artificial Intelligence
05	Date of publication	2020
06	Volume	34
07	Number	8
08	Page numbers	618 - 642
09	Paper Type	Qualitative study
10	Geographical Location	Europe
11	Context/Industry	Purchasing & Supply Management (PSM)
12	Sample size	20 experts
13	Data collection method	World Cafe
14	Method of data analysis	Analysis of discussion outputs
15	Study Characteristics	World Cafe study at a European automotive OEM with 20 experts (purchasing and AI). Discussions covered four themes: AI in purchasing, AI in mechanism design-based negotiations, implementation of AI, and future skills.
16	Key findings related to research questions	RQ1: AI can systematically analyze suppliers' cost breakdowns to uncover hidden cost drivers.
17	Abstract	This exploratory study investigates whether AI can facilitate mechanism design-based negotiations in purchasing. Using a World Café method with 20 experts from purchasing at a European automotive OEM, the study identified potential applications such as negotiation simulations, behavior analysis, and automated design generation.
18	Key words	AI, Purchasing Management
19	Organization Field	Artificial Intelligence, Procurement
20	Quality Appraisal Score	3.0/3.0

41. Artificial neural networks for intelligent cost estimation - a contribution to strategic cost management in the manufacturing supply chain

01	Author of the article	Frank Bodendorf; Philipp Merkl; Jorg Franke
02	Title of the article	Artificial neural networks for intelligent cost estimation - a contribution to strategic cost management in the manufacturing supply chain
03	Document name	Bodendorf et al., 2022
04	Journal title	International Journal of Production Research
05	Date of publication	2022
06	Volume	60
07	Number	21
08	Page numbers	6637 - 6658
09	Paper Type	Empirical case study
10	Geographical Location	Germany
11	Context/Industry	Automotive manufacturing
12	Sample size	767 datasets
13	Data collection method	Archival data from Teamcenter PCM and text mining
14	Method of data analysis	CRISP-DM, Feature engineering, Wrapper-based feature selection
15	Study Characteristics	The study uses archival cost data from a German automotive OEM to explore AI-based cost estimation. A dataset of 767 records was analysed to compare neural networks with other models such as k-NN, LSSVM, and linear regression.
16	Key findings related to research questions	RQ1: AI can be applied for early cost estimation of materials, specifically to generate forecasted cost estimates for supplied aluminium parts, for the German manufacturer.
17	Abstract	This paper looks into how AI can be used to estimate costs in the automotive supply chain. The study compares neural networks to k-NN, LSSVM, and linear regression using 767 cost records from a German OEM. The results show that neural networks offered both competitive accuracy and better cost management transparency.
18	Key words	AI, Cost Estimation, ANN, Automotive
19	Organization Field	Artificial Intelligence, Cost Management
20	Quality Appraisal Score	3.0/3.0

42. Critical Success Factors in a multi-stage adoption of Artificial Intelligence: A Necessary Condition Analysis

01	Author of the article	Sam Solaimani; Lucas Swaak
02	Title of the article	Critical Success Factors in a multi-stage adoption of Artificial Intelligence: A Necessary Condition Analysis
03	Document name	Solaimani & Swaak, 2023
04	Journal title	Journal of Engineering and Technology Management
05	Date of publication	2023
06	Volume	69
07	Number	-
08	Page numbers	101760
09	Paper Type	Quantitative empirical study
10	Geographical Location	Germany
11	Context/Industry	AI; AI adoption
12	Sample size	60 responses
13	Data collection method	Cross-sectional organizational survey
14	Method of data analysis	NCA/CFA
15	Study Characteristics	The study identifies seven critical success factors (CSFs) for AI adoption using the Technology-Organization-Environment (TOE) framework. Factors include outsourcing certainty, perceived ease of use, performance expectancy, technical competencies/resources, trading partner leverage, top management support, and organizational compatibility.
16	Key findings related to research questions	RQ4: One of the most important elements for the effective deployment of AI is top management support, which includes approving new projects, allocating resources, and actively participating in change management.
17	Abstract	This paper identifies key success factors for AI adoption using Necessary Condition Analysis. Based on a survey of 60 respondents from different industries, the study identifies performance expectancy, top management support, technical competencies/resources, organizational compatibility, trading partner leverage as key success factors.
18	Key words	Artificial Intelligence; Technology adoption
19	Organization Field	Artificial Intelligence
20	Quality Appraisal Score	2.5/3.0

43. Insight from industry - early lessons learned about AI adoption in core procurement processes, directions for managers and researchers

01	Author of the article	Remko van Hoek
02	Title of the article	Insight from industry - early lessons learned about AI adoption in core procurement processes, directions for managers and researchers
03	Document name	van Hoek, 2024
04	Journal title	Supply Chain Management: An International Journal
05	Date of publication	2024
06	Volume	29
07	Number	4
08	Page numbers	794 - 803
09	Paper Type	Empirical
10	Geographical Location	Global
11	Context/Industry	Procurement
12	Sample size	97 responses from procurement managers
13	Data collection method	Survey, workshop discussions
14	Method of data analysis	Descriptive statistics, comparative analysis
15	Study Characteristics	The paper explores AI use in procurement processes. It assesses current adoption levels, benefits, barriers, as well as organizational/supplier/data readiness for AI in sourcing, ordering, and supplier relationship management.
16	Key findings related to research questions	RQ4: Essential part of the AI adoption is the engagement of suppliers in the AI adoption process.
17	Abstract	This is the empirical study on the actual application of AI in core procurement processes (sourcing, ordering, SRM). The aim is to show adoption levels, benefits, barriers, and readiness factors for AI use.
18	Key words	Artificial Intelligence; AI Adoption
19	Organization Field	Artificial Intelligence
20	Quality Appraisal Score	2.5/3.0

44. Is it necessary for the supply chain to implement artificial intelligence-driven sales services at both the front-end and back-end stage

01	Author of the article	Yuyan Wang; Junhong Gao; T.C.E. Cheng; Mingzhou Jin; Xiaohang Yue; Huajie Wang
02	Title of the article	Is it necessary for the supply chain to implement artificial intelligence-driven sales services at both the front-end and back-end stage
03	Document name	Wang et al., 2025
04	Journal title	Journal title Transportation Research Part E: Logistics and Transportation Review
05	Date of publication	2025
06	Volume	194
07	Number	-
08	Page numbers	103923
09	Paper Type	Empical
10	Geographical Location	Global
11	Context/Industry	Supply Chain Management; Automotive industry included
12	Sample size	-
13	Data collection method	Survey, workshop discussions
14	Method of data analysis	Stackelberg model
15	Study Characteristics	The study examines AI implementation in sales services at both the manufacturer and retailer tiers, differentiating between front-end and back-end applications. It examines four possible adoption scenarios: none, only the manufacturer, only the retailer, and both. Using a Stackelberg game framework, the paper examines the impacts on wholesale and retail pricing, demand, and profitability.
16	Key findings related to research questions	RQ2: Essential part of the AI adoption is the engagement of suppliers in the AI adoption process.
17	Abstract	The research investigates the implementation of AI in supply chain sales services at both the front-end (store) and back-end (maker) through a Stackelberg game model. The findings indicate that AI typically lowers prices; nevertheless, its impact on demand is nonlinear. In general, AI is rarely profitable for retailers
18	Key words	Artificial Intelligence; AI Adoption
19	Organization Field	Artificial Intelligence
20	Quality Appraisal Score	2.5/3.0

45. A machine learning approach for enhancing supply chain visibility with graph-based learning

01	Author of the article	Ge Zheng; Alexandra Brintrup
02	Title of the article	A machine learning approach for enhancing supply chain visibility with graph-based learning
03	Document name	Zheng & Brintrup, 2025
04	Journal title	Supply Chain Analytics
05	Date of publication	2025
06	Volume	2
07	Number	1
08	Page numbers	100035
09	Paper Type	Empirical study
10	Geographical Location	Global
11	Context/Industry	Supply Chain Management; Automotive industry
12	Sample size	41693 companies, 2353 customers, 927 product categories, 5 certification types, 79 countries
13	Data collection method	Data from MarkLines automotive
14	Method of data analysis	Graph Convolutional Networks (GCNs), Federated Learning (FL), Link prediction (ROC-AUC, AP)
15	Study Characteristics	The paper looks at the problem of limited supply chain visibility caused by data confidentiality. The authors propose a method that combines federated learning and graph neural networks to predict missing links in supply chain graphs. Each country trains a local model on its own subgraph and shares only the model parameters, not the raw data. Experiments were done using the MarkLines database.
16	Key findings related to research questions	RQ2: Data privacy limitations Data privacy and security are key concerns for AI implementation in multi-tier supply chain networks, as regulatory frameworks such as the GDPR impose strict requirements on data sharing and necessitate the protection of sensitive information.
17	Abstract	
18	Key words	Artificial Intelligence; Supply Chain Visibility
19	Organization Field	Artificial Intelligence; Supply Chain Management
20	Quality Appraisal Score	2.5/3.0

46. AI liability in Europe: How does it complement risk regulation and deal with the problem of human oversight?

01	Author of the article	Beatriz Botero Arcila
02	Title of the article	AI liability in Europe: How does it complement risk regulation and deal with the problem of human oversight?
03	Document name	Botero Arcila, 2024
04	Journal title	Computer Law & Security Review
05	Date of publication	2024
06	Volume	54
07	Number	1
08	Page numbers	1 - 18
09	Paper Type	Legal paper
10	Geographical Location	EU
11	Context/Industry	AI governance and regulatory compliance
12	Sample size	N/A
13	Data collection method	-
14	Method of data analysis	Comparative analysis
15	Study Characteristics	The article is a conceptual and legal analysis of the European regulatory framework in the field of artificial intelligence. The author examines how the proposals for the AI Responsibility Directive (AILD) and the revised Product Responsibility Directive (PLD) complement the risk-based approach of the AI Act. The focus is on the issue of human oversight, as future claims for damages will depend on whether the oversight was effective.
16	Key findings related to research questions	RQ2: Data privacy limitations The article provides comprehensive overview of risk classification of AI - powered systems according to EU AI act
17	Abstract	The article analyzes how the AILD and PLD directives complement the AI Act's risk-based approach, identifying gaps in regulation and emphasizing the importance of effective human oversight.
18	Key words	Legal Compliance, EU Act
19	Organization Field	Artificial Intelligence; Legal Compliance
20	Quality Appraisal Score	2.5/3.0

47. Determining factors related to artificial intelligence (AI) adoption among Malaysia's small and medium-sized businesses

01	Author of the article	Suddin Lada; Brahim Chekima; Mohd. Rahimie Abdul Karim; Noor Fzlinda Fabeil; Mat Salleh Ayub; Sharifah Milda Amirul; Rudy Ansar; Mohamed Bouteraa; Lim Ming Fook; Hafizah Omar Zaki
02	Title of the article	Determining factors related to artificial intelligence (AI) adoption among Malaysia's small and medium-sized businesses
03	Document name	Lada et al., 2023
04	Journal title	Journal of Open Innovation: Technology, Market, and Complexity
05	Date of publication	2023
06	Volume	9
07	Number	100144
08	Page numbers	N/A
09	Paper Type	Quantitative empirical study
10	Geographical Location	Malaysia
11	Context/Industry	Small and Medium-sized Enterprises (SMEs) across various industries
12	Sample size	196 responses from managers
13	Data collection method	Survey questionnaire
14	Method of data analysis	PLS-LSM
15	Study Characteristics	The article studies the factors of AI adoption in small and medium-sized enterprises in Malaysia. The sample consists of 196 SME owners/managers from various industries. The data were collected through a questionnaire, and the analysis was conducted using the PLS-SEM method. The results show that only top management commitment and organizational readiness are significant.
16	Key findings related to research questions	Recommendation: Employee adaptability could be introduced as an important KPI for change management
17	Abstract	The study analyzes the factors influencing the adoption of AI in small and medium-sized enterprises in Malaysia. Based on a survey of 196 owners/managers and a PLS-SEM analysis, it was found that top management commitment and organizational readiness are the decisive factors, while competitive pressure, employee adaptability, and external support do not have a significant impact.
18	Key words	Legal Compliance Framework
19	Organization Field	Artificial Intelligence; Legal Compliance
20	Quality Appraisal Score	2.5/3.0

48. Enhancing Supply Chain Visibility with Knowledge Graphs and Large Language Models

01	Author of the article	Sara AlMahri; Liming Xu; Alexandra Brintrup
02	Title of the article	Enhancing Supply Chain Visibility with Knowledge Graphs and Large Language Models
03	Document name	AlMahri, Xu & Brintrup., 2024
04	Journal title	Preprint (under review, arXiv)
05	Date of publication	2024
06	Volume	N/A
07	Number	N/A
08	Page numbers	1-31
09	Paper Type	Empirical case study
10	Geographical Location	Not specified
11	Context/Industry	Automotive industry
12	Sample size	Dataset from Wikipedia (1277 sentences)
13	Data collection method	Data collected from publicly available Wikipedia pages
14	Method of data analysis	NER, RE powered by GPT-4
15	Study Characteristics	The article describes a framework based on Knowledge Graphs and LLM (GPT-4) that allows you to automatically extract supply chain data from open sources and build a knowledge graph. NER was used to find entities in the text, while RE established the relationships between them. Extended visibility beyond Tier-1, identification of alternative suppliers has been achieved with the application of this technology.
16	Key findings related to research questions	RQ1: A GPT-powered framework that incorporates NER and RE tools to automatically extract entities and relations between suppliers. The framework is a solid basis for identifying strategic suppliers and alternatives, and it offers visibility down to the third-tier supply chain level.
17	Abstract	The authors propose a new method for improving supply chain visibility using knowledge graphs and large language models. The approach is based on zero-shot entity and relationship extraction using GPT from open sources and allows for enhanced visibility beyond tier-2 of the automotive supply chain (EV industry)
18	Key words	Supply Chain Visibility
19	Organization Field	Artificial Intelligence; Supply Chain Management
20	Quality Appraisal Score	3.0/3.0

49. A Majority Voting Mechanism-Based Ensemble Learning Approach for Financial Distress Prediction in Indian Automobile Industry

01	Author of the article	Manoranjitham Muniappan; Nithya Darisini Paruvachi Subramanian
02	Title of the article	A Majority Voting Mechanism-Based Ensemble Learning Approach for Financial Distress Prediction in Indian Automobile Industry
03	Document name	Muniappan & Subramanian., 2025
04	Journal title	Journal of Risk and Financial Management
05	Date of publication	2025
06	Volume	18
07	Number	4
08	Page numbers	1 - 31
09	Paper Type	Empirical study
10	Geographical Location	India
11	Context/Industry	Automotive industry
12	Sample size	100 automobile companies between 2013 and 2019
13	Data collection method	The corporate database from CMIE
14	Method of data analysis	
15	Study Characteristics	The study is devoted to predicting financial distress in the Indian automotive industry. The sample data included 100 companies. For the analysis, 23 financial coefficients were used, covering profitability, liquidity and activity. The authors applied 11 basic classifiers and tested 2047 of their ensemble combinations using Hard Voting mechanism. The best combination gave an accuracy of almost 100% in predicting financial distress of the automotive company.
16	Key findings related to research questions	RQ1: Ensemble of classification models has been applied to predict the financial distress of Indian automobile manufacturers. The study employed eleven machine learning classifiers combined through a hard voting mechanism, classifying firms as either healthy or distressed based on 23 financial ratios. The ensemble achieved nearly 100% classification accuracy.
17	Abstract	The article focuses on predicting financial distress in Indian automobile companies using machine learning and ensemble methods. The authors tested 2047 classifier combinations with a hard majority voting mechanism.
18	Key words	Financial Due Diligence, Financial Assessment
19	Organization Field	Machine Learning; Supply Chain Management
20	Quality Appraisal Score	2.5/3.0

50. Construction of Artificial Intelligence Application Model for Supply Chain Financial Risk Assessment

01	Author of the article	Shutong Luo; Min Xing; Jialu Zhao
02	Title of the article	Construction of Artificial Intelligence Application Model for Supply Chain Financial Risk Assessment
03	Document name	Luo, Xing, & Zhao., 2022
04	Journal title	Scientific Programming
05	Date of publication	2022
06	Volume	N/A
07	Number	N/A
08	Page numbers	1-8
09	Paper Type	Quantitative study
10	Geographical Location	China
11	Context/Industry	New Energy Vehicle (NEV) industry
12	Sample size	320 samples, 60 vendors
13	Data collection method	Secondary data from financial statements and supply chain
14	Method of data analysis	Thematic analysis
15	Study Characteristics	An ML-driven framework for classifying the financial credit risk of suppliers in the Chinese NEV industry. The model integrates multiple ML classifiers as well as key financial and non – financial indicators
16	Key findings related to research questions	<p>RQ1: An ML-driven framework for classifying the financial credit risk of suppliers in the Chinese NEV industry. The model integrates multiple ML classifiers as well as key financial and non – financial indicators, such as debt-paying ability, profitability, and overall supply chain situation.</p> <p>RQ3: The accuracy of their ML-based model in predicting the credit score reached 96.13%</p>
17	Abstract	The study focuses on the trustworthiness in AI in supply chain management based on the analysis of vendor materials and interviews with organizational leaders
18	Key words	Supply Chain Finance
19	Organization Field	Machine Learning, Supply Chain Management
20	Quality Appraisal Score	2.5/3.0

51. In artificial intelligence (AI) we trust: A qualitative investigation of AI technology acceptance

01	Author of the article	Abhinav Hasija; Terry L. Esper
02	Title of the article	In artificial intelligence (AI) we trust: A qualitative investigation of AI technology acceptance
03	Document name	Hasija & Esper., 2022
04	Journal title	Journal of Business Logistics
05	Date of publication	2022
06	Volume	43
07	Number	3
08	Page numbers	388 - 412
09	Paper Type	Qualitative study
10	Geographical Location	Not specified
11	Context/Industry	Supply Chain Management
12	Sample size	27 AI vendors
13	Data collection method	Interviews and data collection
14	Method of data analysis	Thematic analysis
15	Study Characteristics	The study explores the issue of AI trustworthiness Priming phase (pre-deployment): upskilling (bilingual employees), twinning (data/feature engineering, experimenting), soothing (ethics & job loss concerns). Reinforcing phase (deployment/post-deployment): continuous upskilling, integrating), visualizing (data representation), clarifying (defined ownership and accountability for AI outcomes).
16	Key findings related to research questions	RQ4: According to the study, it is critical to pay attention to the issue of increasing confidence in AI (AI trustworthiness) through post-deployment upskilling, which can be accomplished through data visualization and representation, as well as a clear allocation of responsibility for the outcomes of AI-powered technologies.
17	Abstract	The study focuses on the trustworthiness in AI in supply chain management based on the analysis of vendor materials and interviews with organizational leaders
18	Key words	AI Adoption Framework
19	Organization Field	Artificial Intelligence, Supply Chain Management
20	Quality Appraisal Score	2.5/3.0

52. How uncertainty shapes herding in the corporate use of artificial intelligence technology

01	Author of the article	Nicolas Ameye; Jacques Bughin; Nicolas van Zeebroeck
02	Title of the article	How uncertainty shapes herding in the corporate use of artificial intelligence technology
03	Document name	Ameve et al., 2023
04	Journal title	Technovation
05	Date of publication	2023
06	Volume	127
07	Number	N/A
08	Page numbers	N/A
09	Paper Type	Quantitative empirical study
10	Geographical Location	Global
11	Context/Industry	Corporate sector
12	Sample size	3073 firms
13	Data collection method	Online survey conducted by TNS for McKinsey & Company
14	Method of data analysis	Thematic analysis
15	Study Characteristics	The study integrates the TOE framework with microeconomic diffusion theory, introducing herding and stock/order effects under uncertainty. Two types of uncertainty are tested: use-case and ROI.
16	Key findings related to research questions	RQ4: ROI-related uncertainty is among highest implementation obstacles and accounts for approximately 36% of the hesitation to adopt AI
17	Abstract	Based on a global survey of 3073 firms, the authors extend the TOE framework with industry stock effects and two uncertainty dimensions. They find that epidemic (herding) effects dominate stock/order effects
18	Key words	AI Uncertainty
19	Organization Field	Artificial Intelligence, Supply Chain Management
20	Quality Appraisal Score	2.5/3.0

53. The Unified Control Framework: Establishing a Common Foundation for Enterprise AI Governance, Risk Management and Regulatory Compliance

01	Author of the article	Ian W. Eisenberg; Lucia Gamboa; Eli Sherman
02	Title of the article	The Unified Control Framework: Establishing a Common Foundation for Enterprise AI Governance, Risk Management and Regulatory Compliance
03	Document name	Eisenberg, Gamboa & Sherman (2025)
04	Journal title	arXiv preprint
05	Date of publication	March 2025
06	Volume	N/A
07	Number	N/A
08	Page numbers	1 - 31
09	Paper Type	Conceptual framework
10	Geographical Location	Global
11	Context/Industry	Enterprise AI governance, risk management & regulatory compliance
12	Sample size	N/A
13	Data collection method	Synthesis of existing risk frameworks
14	Method of data analysis	MECE-based taxonomy building; semantic clustering
15	Study Characteristics	The article suggests the Unified Control Framework (UCF) for risk management and compliance with AI regulation. It is based on an analysis of existing frameworks (NIST AI RMF, IBM Risk Atlas, MIT Repository) and interviews with experts.
16	Key findings related to research questions	RQ2: The laws adopted in various countries impose considerable obligations on organisations that intend to deploy AI systems, with regulations that vary in their specific requirements. This fragmentation increases compliance costs for organisations.
17	Abstract	The article introduces the Unified Control Framework (UCF) for risk management and regulatory compliance. The framework integrates a risk taxonomy, a library of regulatory requirements, and a set of 42 control measures.
18	Key words	AI governance; Risk management
19	Organization Field	Artificial Intelligence, AI Governance
20	Quality Appraisal Score	2.5/3.0

54. Predicting supply chain risks using machine learning: The trade-off between performance and interpretability

01	Author of the article	George Baryannis, Samir Dani, Grigoris Antoniou
02	Title of the article	Predicting supply chain risks using machine learning: The trade-off between performance and interpretability
03	Document name	Baryannis et al., 2019
04	Journal title	Future Generation Computer Systems
05	Date of publication	2019
06	Volume	101
07	Number	N/A
08	Page numbers	993-1004
09	Paper Type	Empirical
10	Geographical Location	Europe
11	Context/Industry	Aerospace
12	Sample size	500,000 product deliveries dataset
13	Data collection method	Dataset from suppliers data
14	Method of data analysis	
15	Study Characteristics	ML-based risk prediction framework in supply chains, aerospace SC case (500 000 product deliveries). SVM and decision trees for binary classification of delays are applied. The compromise between accuracy and interpretability is shown.
16	Key findings related to research questions	RQ2: Many organisations face a trade-off between model accuracy and interpretability, which has led researchers to integrate explainability methods such as SHAP and LIME as essential components of modern AI frameworks
17	Abstract	The article offers a framework for predicting risks in supply chains using ML. The example of the aviation chain shows the trade-off between high accuracy (SVM) and interpretability (decision trees), as well as the impact of data imbalance.
18	Key words	AI governance; Risk management
19	Organization Field	Artificial Intelligence, Interpretability
20	Quality Appraisal Score	2.5/3.0

55. Enhancing Supply Chain Resilience through AI: Leveraging Deep Reinforcement Learning and Predictive Analytics

01	Author of the article	Aravind Kumar Kalusivalingam; Amit Sharma; Neha Patel; Vikram Singh
02	Title of the article	Enhancing Supply Chain Resilience through AI: Leveraging Deep Reinforcement Learning and Predictive Analytics
03	Document name	Kalusivalingam et al., 2022
04	Journal title	Not specified
05	Date of publication	2022
06	Volume	N/A
07	Number	N/A
08	Page numbers	1-23
09	Paper Type	Empirical paper
10	Geographical Location	Global
11	Context/Industry	Supply chain resilience
12	Sample size	Historical data from multinational company, spanning 5 years
13	Data collection method	Secondary internal operational data
14	Method of data analysis	DRL; predictive models
15	Study Characteristics	The paper presents a combined approach using deep reinforcement learning and predictive analytics to make supply chains more resilient. The authors used simulations and five years of a company's operational data. The main measures were service level, logistics costs, recovery time, and forecast accuracy.
16	Key findings related to research questions	RQ2: Use of deep reinforcement learning (DRL) not only allowed to achieve a reduction in logistics costs by 12%, but also significantly decreased recovery time after disruptions, with recovery times reduced by 18% and disruption-related costs lowered by 25%.
17	Abstract	The study shows that combining deep reinforcement learning with predictive analytics can improve supply chain resilience. It helps raise service levels, cut costs, speed up recovery after disruptions, and make forecasts more accurate.
18	Key words	Supply Chain Resilience; Reinforcement Learning
19	Organization Field	Artificial Intelligence, Supply Chain Resilience
20	Quality Appraisal Score	2.5/3.0

56. Artificial intelligence and machine learning in purchasing and supply management: A mixed-methods review of the state-of-the-art in literature and practice

01	Author of the article	Spreitzenbarth, J. M., Bode, C., & Stuckenschmidt, H.
02	Title of the article	Artificial intelligence and machine learning in purchasing and supply management: A mixed-methods review of the state-of-the-art in literature and practice
03	Document name	Spreitzenbarth et al., 2024
04	Journal title	Journal of Purchasing & Supply Management
05	Date of publication	2024
06	Volume	30
07	Number	2
08	Page numbers	100896
09	Paper Type	Mixed-methods review (SLR plus interviews)
10	Geographical Location	Germany (empirical part), global (literature scope)
11	Context/Industry	Procurement & Supply Management
12	Sample size	25 experts, 349 articles
13	Data collection method	SLR plus semi-structured interviews
14	Method of data analysis	Bibliometric plus qualitative content analysis
15	Study Characteristics	Mixed-method state-of-the-art review
16	Key findings related to research questions	RQ2: Use of AI speeds up supplier scouting by more than 75% RQ4: Companies should prioritize their pilot project during deployment stage
17	Abstract	The study shows that combining deep reinforcement learning with predictive analytics can improve supply chain resilience. It helps raise service levels, cut costs, speed up recovery after disruptions, and make forecasts more accurate.
18	Key words	Artificial intelligence; Supply Chain and Procurement Management
19	Organization Field	Procurement; Supply Chain Management
20	Quality Appraisal Score	3.0/3.0

57. Automating Supply Chain Disruption Monitoring via an Agentic AI Approach

01	Author of the article	Sara AlMahri, Liming Xu, Alexandra Brintrup
02	Title of the article	Automating Supply Chain Disruption Monitoring via an Agentic AI Approach
03	Document name	AlMahri et al., 2025
04	Journal title	SSRN Preprint
05	Date of publication	2025
06	Volume	N/A
07	Number	N/A
08	Page numbers	1-44
09	Paper Type	Empirical case study
10	Geographical Location	Global focus; case study: Germany
11	Context/Industry	Automotive industry
12	Sample size	Knowledge graph with Tier-1 to Tier-4 suppliers
13	Data collection method	News article ingestion by LLM
14	Method of data analysis	Multi-agent LLM framework
15	Study Characteristics	The research introduces the fully autonomous LLM-driven multi-agent system for the monitoring and alleviation of supply chain disruptions. The framework has seven agents: monitoring disruptions, querying knowledge graphs, searching for products, assessing risks, visualizing data, managing the supply chain, and finding alternative sources. Showed on the Mercedes-Benz case that the system tracked Tier-2/3 disruption
16	Key findings related to research questions	RQ2: Researchers have developed an advanced LLM-powered MAS supply chain disruption monitoring system for the automotive industry using the example of Mercedes-Benz (catalyst supplies). The system works as a set of independent multi-agents that monitor newsfeeds, find and classify disruptions according to the risk level, visualize the supply chain network, and offer risk mitigation strategies, including the search for alternative suppliers RQ3: Disruption visibility beyond Tier-1
17	Abstract	The paper introduces the first fully autonomous LLM-powered multi-agent system for supply chain disruption monitoring and mitigation, with seven agents, fully autonomous and independent. Significantly reduces time to react to the disruption
18	Key words	Artificial intelligence; Supply Chain Resilience; Supply Chain Risk monitoring
19	Organization Field	Procurement; Supply Chain Management; Risk Monitoring
20	Quality Appraisal Score	3.0/3.0

58. AI and Procurement

01	Author of the article	Ruomeng Cui; Meng Li; Shichen Zhang
02	Title of the article	AI and Procurement
03	Document name	Cui et al., 2021
04	Journal title	Manufacturing & Service Operations Management
05	Date of publication	August 2021
06	Volume	N/A
07	Number	N/A
08	Page numbers	N/A
09	Paper Type	Empirical case study
10	Geographical Location	China
11	Context/Industry	Automotive industry; B2B procurement
12	Sample size	3960 suppliers
13	Data collection method	Chatbots and direct inquiries
14	Method of data analysis	Multi-agent LLM framework
15	Study Characteristics	The study is a field experiment on the Alibaba 1688 platform in China in the automotive segment. The impact of customer type (male, female, chatbot) and recommendation signal (no, human, AI) on supplier discounts was tested by the authors.
16	Key findings related to research questions	RQ2: Chatbots are used to automate buyer inquiries for non-critical automotive items such as car accessories on the Chinese B2B e-commerce platform. They also evaluated the impact of AI-based supplier recommendations on initial price quotes.
17	Abstract	The study is a field experiment on the Alibaba 1688 platform in China in the automotive segment.
18	Key words	Artificial intelligence; Procurement; AI-based negotiations
19	Organization Field	Procurement; Supply Chain Management
20	Quality Appraisal Score	2.5/3.0

59. Identification of Core Suppliers Based on E-Invoice Data Using Supervised Machine Learning

01	Author of the article	Jung-sik Hong; Hyeongyu Yeo; Nam-Wook Cho; Taeuk Ahn
02	Title of the article	Identification of Core Suppliers Based on E-Invoice Data Using Supervised Machine Learning
03	Document name	Hong et al., 2018
04	Journal title	Journal of Risk and Financial Management
05	Date of publication	2018
06	Volume	11
07	Number	4
08	Page numbers	1-13
09	Paper Type	Empirical case study
10	Geographical Location	South Korea
11	Context/Industry	Automotive industry
12	Sample size	125 suppliers; 3378 e-invoices
13	Data collection method	Extraction of transactional e-invoice data
14	Method of data analysis	Supervised ML (Random Forest, 200,000 trees)
15	Study Characteristics	The study proposes the supplier segmentation approach based on e-invoice data from Korean automotive manufacturer using Random Forest technique
16	Key findings related to research questions	RQ1: Authors segmented core suppliers using corporate e-invoice data from a Korean auto parts manufacturer using the Random Forest algorithm. The percentage of critical items, transaction frequency/cycle, total cost of purchase, and partnership duration were the main criteria used to categorize core versus non-core suppliers.
17	Abstract	The study proposes the supplier segmentation approach based on e-invoice data from Korean automotive manufacturer using Random Forest technique. 125 suppliers; 3,378 e-invoices
18	Key words	Artificial intelligence; Procurement; Supplier Segmentation
19	Organization Field	Procurement; Supply Chain Management
20	Quality Appraisal Score	2.5/3.0

60. Balancing Data Acquisition Benefits and Ordering Costs for Predictive Supplier Selection and Order Allocation

01	Author of the article	Alberto Regattieri, Matteo Gabellini, Francesca Calabrese, Lorenzo Civolani, Francesco Gabriele Galizia
02	Title of the article	Balancing Data Acquisition Benefits and Ordering Costs for Predictive Supplier Selection and Order Allocation
03	Document name	Regattieri et al., 2024
04	Journal title	Applied Sciences
05	Date of publication	2024
06	Volume	14
07	Number	10
08	Page numbers	-
09	Paper Type	Empirical study
10	Geographical Location	Italy
11	Context/Industry	Automotive industry
12	Sample size	8 critical components, 2 suppliers
13	Data collection method	Operational data from automotive manufacturer
14	Method of data analysis	LSTM - MILP
15	Study Characteristics	Case study on dual-sourcing strategy for an Italian car manufacturer; compares cost outcomes across predictive-optimization model; evaluates trade-off between cost of placing orders and benefit of acquiring supplier data.
16	Key findings related to research questions	RQ1: Deep learning is used through the LSTM model, which, according to historical order data, predicts the punctuality of suppliers of the Italian automaker and serves as the basis for an optimization model for the distribution of orders. RQ3: Cost savings more than 20% (logistics and procurement)
17	Abstract	
18	Key words	Artificial intelligence; Supply Chain Resilience
19	Organization Field	Supply Chain Management; Supply Chain Resilience
20	Quality Appraisal Score	2.5/3.0

61. Drivers of Artificial Intelligence and Their Effects on Supply Chain Resilience and Performance: An Empirical Analysis on an Emerging Market

01	Author of the article	Mengmeng Wang, Xiaoming Pan
02	Title of the article	Drivers of Artificial Intelligence and Their Effects on Supply Chain Resilience and Performance: An Empirical Analysis on an Emerging Market
03	Document name	Wang & Pan., 2022
04	Journal title	Sustainability
05	Date of publication	2022
06	Volume	14
07	Number	24
08	Page numbers	1-16
09	Paper Type	Empirical study
10	Geographical Location	China
11	Context/Industry	Supply Chain Management
12	Sample size	318 firms
13	Data collection method	Survey questionnaire plus pre-testing with managers
14	Method of data analysis	PLS-SEM
15	Study Characteristics	The article is an empirical study based on 318 Chinese companies. The TOE framework and resource theory are used. The drivers of AI adoption have been explored: technological advantages, collaboration in the supply chain, and external uncertainty.
16	Key findings related to research questions	RQ3: Artificial intelligence significantly influences elasticity and performance of the supply chain, providing companies with a technology advantage, improving risk control capabilities, technical service capabilities and reducing operational costs
17	Abstract	The article is an empirical study based on 318 Chinese companies. The TOE framework and resource theory are used. The drivers of AI adoption have been explored: technological advantages, collaboration in the supply chain, and external uncertainty.
18	Key words	Artificial intelligence; Supply Chain Resilience
19	Organization Field	Supply Chain Management; Supply Chain Resilience
20	Quality Appraisal Score	2.5/3.0

62. Drivers, barriers and social considerations for AI adoption in SCM

01	Author of the article	Johannes Hangl, Stefan Krause и Volker J. Behrens
02	Title of the article	Drivers, barriers and social considerations for AI adoption in SCM
03	Document name	Hangl et al., 2023
04	Journal title	Technology in Society
05	Date of publication	June 2023
06	Volume	74
07	Number	
08	Page numbers	102299
09	Paper Type	Empirical qualitative research
10	Geographical Location	Global
11	Context/Industry	Supply Chain Management
12	Sample size	12 experts
13	Data collection method	Semi-structured interviews
14	Method of data analysis	
15	Study Characteristics	The article is an empirical qualitative study across SMEs and large SCM enterprises. The study identifies drivers, barriers, and social considerations for AI adoption in SCM. It produces a list of 14 recommended implementation steps.
16	Key findings related to research questions	RQ3: Authors underscore that one of the main benefits of early AI adoption is getting a competitive edge that leads to lower costs and operational efficiency.
17	Abstract	
18	Key words	Artificial intelligence; Supply Chain Resilience
19	Organization Field	Supply Chain Management; Supply Chain Resilience
20	Quality Appraisal Score	2.5/3.0

63. AI and Organizational Change: Dynamics and Management Strategies

01	Author of the article	Rohan Chhatre; Seema Singh
02	Title of the article	AI and Organizational Change: Dynamics and Management Strategies
03	Document name	Chhatre & Singh, 2024
04	Journal title	SSRN
05	Date of publication	May 2024
06	Volume	N/A
07	Number	N/A
08	Page numbers	1-23
09	Paper Type	Conceptual paper
10	Geographical Location	Global
11	Context/Industry	Cross-industry
12	Sample size	-
13	Data collection method	Secondary sources: academic and practitioner literature
14	Method of data analysis	Qualitative synthesis
15	Study Characteristics	Conceptual framework. Examples from different companies (Siemens, Accenture, Microsoft). The topic is how AI is changing work, culture, and management.
16	Key findings related to research questions	RQ4: Another critical component of successful AI integration is effective change management. This requires a comprehensive approach, including upskilling training programs, effective communication to mitigate resistance and fear of losing a job, cultural transformation strategies and adjustments to organizational structures and processes
17	Abstract	The article explores how the introduction of artificial intelligence causes organizational changes, affecting the structure, processes and corporate culture. The authors rely on classical theories of change management and apply them to AI integration.
18	Key words	Artificial intelligence; AI Adoption; Organizational Change;
19	Organization Field	Supply Chain Management; AI adoption
20	Quality Appraisal Score	2.5/3.0

64. Generative artificial intelligence

01	Author of the article	Leonardo Banh, Gero Strobel
02	Title of the article	Generative artificial intelligence
03	Document name	Banh & Strobel, 2023
04	Journal title	Electronic Markets
05	Date of publication	2023
06	Volume	33
07	Number	63
08	Page numbers	1-17
09	Paper Type	Conceptual paper/Technical paper
10	Geographical Location	Not specified
11	Context/Industry	Artificial Intelligence
12	Sample size	N/A
13	Data collection method	Synthesis of academic and industry literature
14	Method of data analysis	Qualitative synthesis
15	Study Characteristics	The article is conceptual, provides the overview of GAI fundamentals, shows how it differs from ML/DL. The model layer, connection layer, and application layer architecture of GAI systems is described. Five primary challenges (bias, transparency, hallucinations, misuse, and societal impact) are highlighted
16	Key findings related to research questions	RQ4: A separate model layer (AI/ML layer or model layer) as the foundation of AI-based system architecture must be included in tech stack. This layer includes pretrained and custom models, tools for model selection and management, orchestration, fine-tuning, and integration, as well as mechanisms for control and compliance with ethical and security constraints.
17	Abstract	The article explains the basics of generative AI, its differences from traditional AI, and key models. The fields of application and the main challenges are observed
18	Key words	Artificial intelligence; AI Tech Architecture
19	Organization Field	Supply Chain Management; AI adoption
20	Quality Appraisal Score	3.0/3.0

65. Generative AI: Opportunities, challenges, and research directions for supply chain resilience

01	Author of the article	Tonya Boone, Behnam Fahimnia, Ram Ganeshan, David M. Herold, Nada R. Sanders
02	Title of the article	Generative AI: Opportunities, challenges, and research directions for supply chain resilience
03	Document name	Boone et al., 2025
04	Journal title	Transportation Research Part E
05	Date of publication	2025
06	Volume	199
07	Number	N/A
08	Page numbers	104135
09	Paper Type	Conceptual paper/ Review article
10	Geographical Location	Not specified
11	Context/Industry	Supply Chain Management and Procurement
12	Sample size	N/A
13	Data collection method	N/A
14	Method of data analysis	N/A
15	Study Characteristics	The article is a review of GenAI applications in supply chain resilience across demand and inventory planning, geopolitical risks, procurement and sourcing.
16	Key findings related to research questions	RQ4: A separate model layer (AI/ML layer or model layer) as the foundation of AI-based system architecture must be included in tech stack. This layer includes pretrained and custom models (), tools for model selection and management, orchestration, fine-tuning, and integration, as well as mechanisms for control and compliance with ethical and security constraints.
17	Abstract	The paper examines potential research topics and GenAI applications in key supply chain domains while also addressing challenges such as misinformation, security risks, and governance
18	Key words	Artificial intelligence; AI Tech Architecture
19	Organization Field	Supply Chain Management; AI adoption
20	Quality Appraisal Score	3.0/3.0

66. Investigating Algorithm Review Boards for Organizational Responsible Artificial Intelligence Governance

01	Author of the article	Emily Hadley; Alan Blatecky; Megan Comfort
02	Title of the article	Investigating Algorithm Review Boards for Organizational Responsible Artificial Intelligence Governance
03	Document name	Hadley et al., 2024
04	Journal title	arXiv preprint
05	Date of publication	2024
06	Volume	N/A
07	Number	N/A
08	Page numbers	104135
09	Paper Type	Qualitative empirical study
10	Geographical Location	Not specified
11	Context/Industry	Responsible AI governance
12	Sample size	17 technical practitioners
13	Data collection method	Semi-structured interviews
14	Method of data analysis	N/A
15	Study Characteristics	The paper introduces the concept of Responsible AI and Algorithm Review Boards
16	Key findings related to research questions	RQ4: Algorithm Review Boards consisting of data scientists and risk officers as part of responsible AI governance, including review of risks, documentation and approval of algorithms.
17	Abstract	A study based on 17 interviews shows that Algorithm Review Boards are becoming a key internal management tool for responsible AI
18	Key words	Artificial intelligence; Responsible AI
19	Organization Field	Responsible AI
20	Quality Appraisal Score	3.0/3.0

67. Developing a smart green supplier risk assessment system integrating natural language processing and life cycle assessment based on AHP framework: An empirical study

01	Author of the article	Ming-Chuan Chiu; Pei-Yi Tai; Chih-Yuan Chu
02	Title of the article	Developing a smart green supplier risk assessment system integrating natural language processing and life cycle assessment based on AHP framework: An empirical study
03	Document name	Chiu et al., 2024
04	Journal title	Resources, Conservation & Recycling
05	Date of publication	2024
06	Volume	207
07	Number	N/A
08	Page numbers	107671
09	Paper Type	Empirical study
10	Geographical Location	China
11	Context/Industry	Electronics
12	Sample size	News scraped in total - 4748, 3 suppliers
13	Data collection method	Web scraping
14	Method of data analysis	BERT, LCA, NLP
15	Study Characteristics	The paper introduces the BERT- LCA - NLP approach to automatically extract data and classify suppliers risks
16	Key findings related to research questions	RQ4: AI-powered frameworks can significantly improve the efficiency of supplier risk assessment. They introduced a hybrid framework integrating BERT-based NLP and life cycle assessment (LCA), which allows to automatically scrape and extract supplier-related risk data and conduct green supplier risk assessment.
17	Abstract	The paper proposes a smart green supplier risk assessment system integrating NLP and life cycle assessment within an AHP framework. Using an electronics case study with three suppliers, the model achieved 81.7% classification accuracy
18	Key words	Artificial intelligence; NLP; Supplier Risk Assessment
19	Organization Field	Artificial Intelligence; Supplier Risk Assessment
20	Quality Appraisal Score	2.5/3.0

68. Supplier Evaluation in Supply Chain Environment Based on Radial Basis Function Neural Network

01	Author of the article	Shilin Liu; Guangbin Yu; Youngchul Kim
02	Title of the article	Supplier Evaluation in Supply Chain Environment Based on Radial Basis Function Neural Network
03	Document name	Liu et al., 2024
04	Journal title	International Journal of Information Technology and Web Engineering
05	Date of publication	2024
06	Volume	19
07	Number	1
08	Page numbers	1-18
09	Paper Type	Empirical case study
10	Geographical Location	China
11	Context/Industry	Automotive sector
12	Sample size	8 potential suppliers
13	Data collection method	Radial Basis Function Neural Network
14	Method of data analysis	BERT, LCA, NLP
15	Study Characteristics	Builds a 20-indicator supplier evaluation model for GAC Toyota
16	Key findings related to research questions	RQ4: Supplier evaluation and ranking model to eight auto parts suppliers of the Chinese joint venture GAC Toyota, using a radial basis function neural network (RBFNN) that integrated 20 key selection criteria into a single supplier score.
17	Abstract	The study applies a radial basis function neural network to evaluate and rank eight GAC Toyota auto parts suppliers, 20 selection criteria combined into a single supplier score
18	Key words	Artificial intelligence; Supplier Evaluation
19	Organization Field	Artificial Intelligence; Supplier Evaluation
20	Quality Appraisal Score	2.5/3.0

69. The Role of Artificial Intelligence in Vendor Performance Evaluation within Digital Retail Supply Chains: A Review of Strategic Decision-Making Models

01	Author of the article	Tahmina Akter Rainy; Abdur Razzak Chowdhury
02	Title of the article	The Role of Artificial Intelligence in Vendor Performance Evaluation within Digital Retail Supply Chains: A Review of Strategic Decision-Making Models
03	Document name	Rainy & Chowdhury, 2022
04	Journal title	American Journal of Scholarly Research and Innovation
05	Date of publication	2022
06	Volume	01
07	Number	01
08	Page numbers	220-248
09	Paper Type	Literature review
10	Geographical Location	Global
11	Context/Industry	Digital Retail Supply Chains
12	Sample size	86 documents
13	Data collection method	Systematic search
14	Method of data analysis	
15	Study Characteristics	Explores AI models for vendor evaluation and strategic sourcing in retail
16	Key findings related to research questions	RQ3: It can be inferred that AI-based approaches offer great scalability, allowing companies to assess thousands of suppliers in real time through integration with corporate ERP and SCM systems. This is particularly important in the context of complex automotive supply chains, where traditional methods such as MCDM frameworks lack the speed and automation
17	Abstract	Review of 86 sources examining how AI enhances supplier evaluation in digital retail.
18	Key words	Artificial intelligence; Retail Supply Chain
19	Organization Field	Artificial Intelligence; Supplier Evaluation
20	Quality Appraisal Score	2.5/3.0

70. A Survey of Data Quality Measurement and Monitoring Tools

01	Author of the article	Lisa Ehrlinger; Elisa Ruzs; Wolfram Wob
02	Title of the article	A Survey of Data Quality Measurement and Monitoring Tools
03	Document name	Ehrlinger et al., 2019
04	Journal title	arXiv preprint
05	Date of publication	2019
06	Volume	N/A
07	Number	N/A
08	Page numbers	1-30
09	Paper Type	Literature review
10	Geographical Location	Austria
11	Context/Industry	General data management / Data Quality
12	Sample size	86 documents
13	Data collection method	Systematic search
14	Method of data analysis	667 identified tools
15	Study Characteristics	Provides comprehensive overview of data quality measurement and monitoring tools
16	Key findings related to research questions	Recommendation: Study provides the detailed overview of data quality measurement and monitoring tools, including data quality characteristics
17	Abstract	Survey of 667 data quality tools; 13 evaluated on profiling, measurement, and monitoring functions
18	Key words	Data Quality; Measurement
19	Organization Field	Data Management
20	Quality Appraisal Score	2.5/3.0

71. Capturing Real-World Value in Automotive AI

01	Author of the article	BCG, 2025
02	Title of the article	Capturing Real-World Value in Automotive AI
03	Document name	BCG, 2025
04	Journal title	BCG
05	Date of publication	2025
06	Volume	N/A
07	Number	N/A
08	Page numbers	N/A
09	Paper Type	Industry report
10	Geographical Location	Global
11	Context/Industry	Automotive Industry
12	Sample size	350 projects
13	Data collection method	Industry and case-based insights
14	Method of data analysis	
15	Study Characteristics	The article explains how car companies can get real value from using AI and GenAI. It is based on insights from more than 350 projects. It proposes so called Gen AI stairway which includes the following elements: people adoption, process redesign, execution to P&L
16	Key findings related to research questions	RQ1: BCG helped BMW to introduce AI – powered tender assistant to streamline RFPs as well as tendering processes
17	Abstract	The article explains how car companies can get real value from using AI and GenAI. It is based on insights from more than 350 projects. It proposes so called Gen AI stairway which includes the following elements: people adoption, process redesign, execution to P&L
18	Key words	Automotive AI, AI adoption
19	Organization Field	Artificial Intelligence, Supply Chain Management
20	Quality Appraisal Score	2.5/3.0

72. Adopting AI Responsibly: Guidelines for Procurement of AI Solutions by the Private Sector

01	Author of the article	World Economic Forum; in collaboration with GEP
02	Title of the article	Adopting AI Responsibly: Guidelines for Procurement of AI Solutions by the Private Sector
03	Document name	World Economic Forum, 2023
04	Journal title	Insight Report (World Economic Forum publication)
05	Date of publication	June 2023
06	Volume	N/A
07	Number	N/A
08	Page numbers	1 - 32
09	Paper Type	Structured report
10	Geographical Location	Global
11	Context/Industry	Private sector procurement and AI adoption
12	Sample size	
13	Data collection method	Workshops, interviews, consultations
14	Method of data analysis	Synthesis
15	Study Characteristics	The report provides practical guidance on evaluating AI solutions ethics and compliance, aligning them with business goals, and assessing their potential impact.
16	Key findings related to research questions	RQ4: AI implementation in procurement and supply chain should be aligned with the organization's overall business goals and its commercial strategy
17	Abstract	The report offers a structured toolkit for responsible procurement of AI solutions, including alignment with business and commercial strategy, data management, ethics and sustainability.
18	Key words	AI Compliance
19	Organization Field	Artificial Intelligence, Private procurement
20	Quality Appraisal Score	3.0/3.0

73. A practical approach to building an enterprise AI tech stack

01	Author of the article	Kearney, 2024
02	Title of the article	A practical approach to building an enterprise AI tech stack
03	Document name	Kearney, 2024
04	Journal title	Kearney Insight Article
05	Date of publication	2024
06	Volume	N/A
07	Number	N/A
08	Page numbers	1 - 7
09	Paper Type	Industry report
10	Geographical Location	Global
11	Context/Industry	General implementation framework
12	Sample size	Not applicable
13	Data collection method	Expert analysis based on industry experience and market observation
14	Method of data analysis	
15	Study Characteristics	The article proposes a practical, phased approach for building an enterprise AI technology stack. It identifies three interlinked archetypes: software-embedded AI, custom AI, and AI platforms
16	Key findings related to research questions	RQ4: The article recommends structuring the enterprise AI technology stack around five interdependent layers: <ul style="list-style-type: none"> • Infrastructure inc. computing resources, data storage, and networking • Data Management Layer including data cleaning, standardization, and governance • Model Development Layer • Operations & Governance • User Experience Layer
17	Abstract	The report presents a practical framework for building an enterprise AI tech stack, structured into five layers: infrastructure, data management, model development, operations & governance, and user experience. It outlines three archetypes: software-embedded AI, AI platforms, and custom AI and proposes a phased implementation roadmap.
18	Key words	Artificial intelligence adoption; Tech stack
19	Organization Field	AI
20	Quality Appraisal Score	2.5

74. G7 Toolkit for Artificial Intelligence in the Public Sector

01	Author of the article	OECD Directorate for Public Governance & UNESCO, prepared for the 2024 Italian G7 Presidency and the G7 Digital and Technology Working Group
02	Title of the article	G7 Toolkit for Artificial Intelligence in the Public Sector
03	Document name	OECD, 2024
04	Journal title	Not applicable
05	Date of publication	2024
06	Volume	N/A
07	Number	N/A
08	Page numbers	1-90
09	Paper Type	Government report
10	Geographical Location	
11	Context/Industry	Public sector governance, AI policy
12	Sample size	Questionnaire to G7 members (21 questions) + case studies/examples from G7
13	Data collection method	Structured questionnaire to G7 members
14	Method of data analysis	
15	Study Characteristics	The report provides a structured, practical guide for policymakers and public sector leaders in G7 countries to implement AI in a safe, secure, and trustworthy way.
16	Key findings related to research questions	RQ4: Successful AI adoption in procurement requires a robust data governance framework that ensures data quality, interoperability, and ethical use. Effective AI systems depend on trustworthy, well-structured data, clear ownership and access rules, algorithmic transparency, and safeguards to mitigate risks such as bias, opacity, or misuse.
17	Abstract	The report provides a practical guide for G7 governments to develop, deploy, and use AI in the public sector safely, securely, and ethically. It combines national strategies, governance frameworks, safeguards, and best practices
18	Key words	Artificial intelligence governance
19	Organization Field	AI Governance, AI Policy
20	Quality Appraisal Score	2.5

75. Revolutionizing procurement: Leveraging data and AI for strategic advantage

01	Author of the article	McKinsey & Company, 2024
02	Title of the article	Revolutionizing procurement: Leveraging data and AI for strategic advantage
03	Document name	McKinsey & Company, 2024
04	Journal title	McKinsey & Company
05	Date of publication	2024
06	Volume	N/A
07	Number	N/A
08	Page numbers	1-6
09	Paper Type	Industry Report
10	Geographical Location	Global
11	Context/Industry	Procurement and Supply Chain Management
12	Sample size	examples from Sanofi, Teva Pharmaceuticals, WEF Lighthouse members
13	Data collection method	Expert insights, industry case examples
14	Method of data analysis	
15	Study Characteristics	McKinsey industry report on AI- and data-driven procurement transformation. Covers five key application areas (spend/demand optimization, commodity risk, supplier performance, supply risk, sustainability) with case examples from Sanofi and Teva. Highlights main barriers (data quality, business case, adoption) and success factors.
16	Key findings related to research questions	RQ4: Focus on a prioritized set of high-value technical features and solutions rather than attempting to implement multiple tools at once
17	Abstract	
18	Key words	Procurement, Artificial Intelligence
19	Organization Field	AI Governance, AI Policy
20	Quality Appraisal Score	2.5/3.0

76. Executive Perspectives - Data and Digital Platforms: The Future of the AI-Driven Tech and People Stack

01	Author of the article	BCG, 2024
02	Title of the article	Executive Perspectives - Data and Digital Platforms: The Future of the AI-Driven Tech and People Stack
03	Document name	BCG, 2024
04	Journal title	Boston Consulting Group
05	Date of publication	2024
06	Volume	N/A
07	Number	N/A
08	Page numbers	1-23
09	Paper Type	Executive consulting report
10	Geographical Location	Global
11	Context/Industry	Cross-industry
12	Sample size	Over 1000 BCG client cases
13	Data collection method	BCG client cases, case studies
14	Method of data analysis	
15	Study Characteristics	The study provides a detailed tech-stack architecture but with the dedicated ML layer. Business application layer as well as data layer are also included
16	Key findings related to research questions	RQ4: The key part of any AI tech stack is a dedicated ML/AI layer.
17	Abstract	This BCG Executive Perspectives report explores how organizations can harness value from AI by modernizing data and digital platforms.
18	Key words	Artificial Intelligence; AI technical architecture
19	Organization Field	AI Tech stack, AI Adoption
20	Quality Appraisal Score	2.5/3.0

77. EU AI Act in Automotive Industry

01	Author of the article	Capgemini
02	Title of the article	EU AI Act in Automotive Industry
03	Document name	Capgemini, 2024
04	Journal title	Capgemini, 2024
05	Date of publication	2024
06	Volume	N/A
07	Number	N/A
08	Page numbers	1-18
09	Paper Type	Consulting report; Policy/Compliance guidance
10	Geographical Location	European Union
11	Context/Industry	Automotive industry
12	Sample size	N/A
13	Data collection method	N/A
14	Method of data analysis	
15	Study Characteristics	The Capgemini report is a practical guide for the automotive industry on compliance with the requirements of the EU AI Act and AI projects risk classification
16	Key findings related to research questions	RQ4: Capgemini report outlines a case in which General Motors procured supply chain analytics solutions powered by artificial intelligence from third-party vendors. From a compliance and legal perspective, such deployments are assessed as “systematic risk” due to the potential non-alignment of many vendors with EU regulations on data privacy, transparency, and accountability
17	Abstract	The Capgemini report shows how the EU AI Act affects the automotive industry: classification of AI cases by risk, company responsibilities, penalties, and practical steps to comply.
18	Key words	EU AI Act; Automotive; AI Compliance
19	Organization Field	AI Compliance
20	Quality Appraisal Score	2.5/3.0

78. Navigating AI transformations: The playbook for measuring Copilot implementation and impact with Viva

01	Author of the article	Microsoft Corporation
02	Title of the article	Navigating AI transformations: The playbook for measuring Copilot implementation and impact with Viva
03	Document name	Microsoft 365 Copilot Implementation Measurement Playbook
04	Journal title	Microsoft internal report / Corporate playbook
05	Date of publication	2024
06	Volume	Volume I
07	Number	N/A
08	Page numbers	1-37
09	Paper Type	Corporate Playbook
10	Geographical Location	European Union
11	Context/Industry	General management/AI Management
12	Sample size	N/A
13	Data collection method	N/A
14	Method of data analysis	N/A
15	Study Characteristics	The Microsoft Playbook provides a structured framework for measuring Microsoft 365 Copilot implementation. It introduces a three-part strategy (Readiness, Adoption, Impact) supported by Viva Insights, Glint, and Pulse.
16	Key findings related to research questions	RQ4: Key KPIs include employee adaptability in embracing AI technologies, employee sentiment and readiness (how employees feel about AI), and the overall effectiveness of change management, measured through training completion, communication reach, and engagement levels
17	Abstract	The Microsoft Playbook provides a structured framework for measuring Microsoft 365 Copilot implementation. It introduces a three-part strategy (Readiness, Adoption, Impact) supported by Viva Insights, Glint, and Pulse. It also introduces KPI system for effective change management implementation
18	Key words	AI Implementation; AI KPIs
19	Organization Field	AI Implementation
20	Quality Appraisal Score	2.5/3.0

79. Porsche, Audi and Volkswagen use Artificial Intelligence to minimise sustainability risks

01	Author of the article	Dr. Ing. h.c. F. Porsche Aktiengesellschaft (Corporate Communications)
02	Title of the article	Porsche, Audi and Volkswagen use Artificial Intelligence to minimise sustainability risks
03	Document name	Porsche AG., 2021
04	Journal title	Porsche corporate press - release
05	Date of publication	2021
06	Volume	N/A
07	Number	N/A
08	Page numbers	1-2
09	Paper Type	Press Release
10	Geographical Location	Germany
11	Context/Industry	Automotive industry
12	Sample size	N/A
13	Data collection method	N/A
14	Method of data analysis	N/A
15	Study Characteristics	Press release about a pilot project by Porsche, Audi, and Volkswagen with Prewave. The system monitors 4,000 suppliers in more than 150 countries and 50 languages. It flags risks like environmental issues, human rights problems, or corruption
16	Key findings related to research questions	RQ4: Key KPIs include employee adaptability in embracing AI technologies, employee sentiment and readiness (how employees feel about AI), and the overall effectiveness of change management, measured through training completion, communication reach, and engagement levels
17	Abstract	Press release about a pilot project by Porsche, Audi, and Volkswagen with Prewave. The system monitors 4,000 suppliers in more than 150 countries and 50 languages. It flags risks like environmental issues, human rights problems, or corruption
18	Key words	AI Implementation; AI KPIs
19	Organization Field	AI Implementation
20	Quality Appraisal Score	2.5/3.0

80. Predicts 2025: Procurement Addresses Data Challenges and Embraces Rapid Change

01	Author of the article	Gartner, 2025
02	Title of the article	Predicts 2025: Procurement Addresses Data Challenges and Embraces Rapid Change
03	Document name	Gartner, 2025
04	Journal title	Gartner report
05	Date of publication	January, 2025
06	Volume	N/A
07	Number	N/A
08	Page numbers	1-17
09	Paper Type	Industry report
10	Geographical Location	Not specified
11	Context/Industry	Supply Chain and Procurement
12	Sample size	N/A
13	Data collection method	Synthesis of Gartner surveys & market analysis
14	Method of data analysis	Descriptive analytics
15	Study Characteristics	The Gartner report presents five predictions for procurement: data quality challenges, failure from weak data and analytics governance, adoption of AI agents, gig-based talent, and centralization of supplier risk management.
16	Key findings related to research questions	Gartner predicts that AI agents will radically transform procurement processes – from supplier onboarding and selection to contract management – freeing teams to focus on strategic tasks
17	Abstract	The report predicts key trends in procurement until 2028: data manipulation, widespread use of AI agents, new employment models, and vendor risk management
18	Key words	Procurement; Generative AI; AI agent
19	Organization Field	Artificial Intelligence
20	Quality Appraisal Score	2.5/3.0

81. The GenAI divide: State of AI in business 2025

01	Author of the article	MIT Project NANDA
02	Title of the article	The GenAI divide: State of AI in business 2025
03	Document name	MIT Project NANDA, 2025
04	Journal title	MIT Project
05	Date of publication	July, 2025
06	Volume	N/A
07	Number	N/A
08	Page numbers	1-26
09	Paper Type	Industry report
10	Geographical Location	Global
11	Context/Industry	Cross-industry
12	Sample size	300 AI initiatives reviewed; 52 structured interviews; 153 survey responses
13	Data collection method	
14	Method of data analysis	Descriptive analytics
15	Study Characteristics	According to a report, only 5% of enterprise Gen AI pilots succeed, while 95% of them fail to move beyond pilot phase
16	Key findings related to research questions	RQ4: According to a recent MIT report, 95% of GenAI projects fail to advance beyond the pilot stage.
17	Abstract	The MIT Project NANDA (State of AI in Business 2025) report describes the "GenAI gap": 95% of AI pilots do not bring measurable ROI, only 5% achieve success. The greatest effect is achieved in back-office functions (procurement, finance, risk management), not in sales or marketing
18	Key words	Generative AI; AI Pilots
19	Organization Field	Artificial Intelligence
20	Quality Appraisal Score	2.5/3.0

82. Guiding hands: Inside the councils steering AI projects at Microsoft

01	Author of the article	Alex Fleck
02	Title of the article	Guiding hands: Inside the councils steering AI projects at Microsoft
03	Document name	Fleck, 2025
04	Journal title	Microsoft Inside Track
05	Date of publication	May 1, 2025
06	Volume	N/A
07	Number	N/A
08	Page numbers	N/A
09	Paper Type	Web article
10	Geographical Location	Not specified
11	Context/Industry	Enterprise IT
12	Sample size	N/A
13	Data collection method	N/A
14	Method of data analysis	N/A
15	Study Characteristics	Describes Microsoft Digital's governance structure for AI via three bodies: AI Center of Excellence, Data Council, and Responsible AI Council
16	Key findings related to research questions	RQ4: According to a recent MIT report, 95% of GenAI projects fail to advance beyond the pilot stage.
17	Abstract	The article outlines how Microsoft Digital builds AI adoption through an AI CoE, a Data Council, and a Responsible AI Council.
18	Key words	AI Monitoring; AI Governance
19	Organization Field	Artificial Intelligence; AI Monitoring
20	Quality Appraisal Score	2.5/3.0

83. Transforming Digital Procurement With Generative AI

01	Author of the article	Deloitte
02	Title of the article	Transforming Digital Procurement With Generative AI
03	Document name	Deloitte, 2024
04	Journal title	Deloitte Business
05	Date of publication	January 4, 2024
06	Volume	N/A
07	Number	N/A
08	Page numbers	N/A
09	Paper Type	Web article
10	Geographical Location	Not specified
11	Context/Industry	Procurement; Supply Chain;
12	Sample size	N/A
13	Data collection method	N/A
14	Method of data analysis	N/A
15	Study Characteristics	The article explores how Generative AI can transform procurement processes through three main use cases: contract review, category strategy generation, and guided buying
16	Key findings related to research questions	RQ4: Implementing AI by starting with piloting high-impact use cases and gradually moving from simpler to more complex ones, and simultaneously “continue building the foundation to effectively integrate technology stack, data readiness, and change management.”
17	Abstract	
18	Key words	Generative AI; Digital Procurement; Contract Review
19	Organization Field	Artificial Intelligence; Digital Procurement; Supply Chain Management
20	Quality Appraisal Score	2.5/3.0

84. Unleashing the power of generative AI in procurement

01	Author of the article	KPMG
02	Title of the article	Unleashing the power of generative AI in procurement
03	Document name	KPMG, 2024
04	Journal title	Deloitte Business
05	Date of publication	January 4, 2024
06	Volume	N/A
07	Number	N/A
08	Page numbers	N/A
09	Paper Type	Industry report
10	Geographical Location	Not specified
11	Context/Industry	Procurement
12	Sample size	400 executives
13	Data collection method	N/A
14	Method of data analysis	N/A
15	Study Characteristics	The article explores how Generative AI can transform procurement processes through three main use cases: contract review, category strategy generation, and guided buying
16	Key findings related to research questions	RQ4: 50-80% of procurement tasks will be automated or eliminated by AI via enhanced productivity or self-service.
17	Abstract	The KPMG report explores how generative AI can transform procurement across the source-to-pay cycle. It highlights applications such as automated category strategies, RFx development, contract review, supplier risk insights
18	Key words	Generative AI; Procurement; Source-to-Pay
19	Organization Field	Artificial Intelligence; GenAI
20	Quality Appraisal Score	2.5/3.0