

MASTER
MANAGEMENT AND INDUSTRIAL STRATEGY

MASTER'S FINAL WORK
DISSERTATION

**BENEFITS OF ARTIFICIAL INTELLIGENCE IN THE SUPPLY CHAIN
MANAGEMENT**

ANA MARGARIDA RAMOS GONÇALVES

JULY - 2026

MASTER
MANAGEMENT AND INDUSTRIAL STRATEGY

MASTER'S FINAL WORK
DISSERTATION

**BENEFITS OF ARTIFICIAL INTELLIGENCE IN THE SUPPLY CHAIN
MANAGEMENT**

ANA MARGARIDA RAMOS GONÇALVES

SUPERVISION:
PROFESSORA GRAÇA SILVA

JULY - 2026

FOR MY PARENTS,

ACKNOWLEDGEMENTS

First of all, I would like to thank Professora Graça Silva for all the knowledge she has shared and the support she has given me over the years during the elaboration of this dissertation.

I would also like to thank Informa D&B for sharing their database, and to express my gratitude to all the companies that responded to my survey.

I would like to thank Henrique for being my partner and my greatest support at all times, for all his patience over the years and for making me believe that I am capable of achieving my goals. Without you, this would not have been possible – thank you so, so much.

To my parents, for being my pillars of strength and for always believing in me – my special thanks to you.

Thank you to Matilde, my Master's partner and a friend for life. Despite all the difficulties we faced, this journey was made easier with you by my side.

I'd also like to thank all my family and friends for supporting me over the years. You all hold a special place in my heart.

ABSTRACT

Over the last few decades, as organisations search for improvements in efficiency, decision-making, responsiveness, and resilience in ever more complex and uncertain business environments, Artificial Intelligence (AI) has become crucial to Supply Chain Management (SCM). Nonetheless, despite the attention given to AI in SCM, further empirical research is required to understand exactly how companies perceive its adoption and the benefits acquired in specific business contexts.

As such, this study aims to analyse the perceived benefits of AI in SCM from the perspective of Portuguese manufacturing companies. To address this objective, a quantitative research approach was adopted. Data were collected through an online survey administered to manufacturing companies operating in Portugal, resulting in a final sample of 514 complete responses. The data were analysed using descriptive statistics, reliability analysis, Pearson correlation analysis, and one-way ANOVA.

The results indicate that AI-related capabilities and resources are positively associated with supply chain management capabilities. Organisational change and risk management capabilities were found to be particularly important, contributing to higher levels of resilience, responsiveness, and collaboration. The findings further suggest that organisations operating at international and global levels report more advanced AI capabilities, greater perceived benefits, and stronger resilience compared to local and national organisations. Overall, the study demonstrates that successful AI adoption in SCM constitutes not only a technological challenge but also an organisational transformation process dependent on data capabilities, strategic alignment, managerial awareness, risk management, and organisational readiness.

KEYWORDS: Artificial Intelligence; Supply Chain Management; AI barriers; AI Benefits; Supply Chain Capabilities; Portugal.

RESUMO

Nas últimas décadas, à medida que as organizações procuram melhorar a eficiência, a tomada de decisão, a capacidade de resposta e a resiliência em ambientes empresariais cada vez mais complexos e incertos, a Inteligência Artificial (IA) tem assumido um papel crucial na Gestão da Cadeia de Abastecimento. Contudo, apesar da atenção dedicada à aplicação da IA neste domínio, continua a ser necessária investigação empírica adicional que permita compreender de que forma as empresas percecionam a sua adoção e os benefícios daí resultantes em contextos empresariais específicos.

Neste sentido, o presente estudo tem como objetivo analisar os benefícios percecionados da IA na Gestão da Cadeia de Abastecimento, a partir da perspetiva das empresas da indústria transformadora portuguesa. Para responder a este objetivo, foi adotada uma abordagem de investigação quantitativa. Os dados foram recolhidos através de um questionário online dirigido a empresas da indústria transformadora com atividade em Portugal, tendo-se obtido uma amostra final de 514 respostas completas. Os dados foram analisados por meio de estatística descritiva, análise de confiabilidade, análise de correlação de Pearson e análise de variância unidirecional (ANOVA).

Os resultados indicam que as capacidades e os recursos relacionados com a IA estão positivamente associados às capacidades de gestão da cadeia de abastecimento. As capacidades de gestão da mudança organizacional e dos riscos revelaram-se particularmente importantes, contribuindo para níveis mais elevados de resiliência, de capacidade de resposta e de colaboração. Os resultados sugerem igualmente que as organizações com operações de âmbito internacional e global apresentam capacidades de IA mais avançadas, maiores benefícios percecionados e níveis de resiliência mais elevados do que as organizações que operam a nível local e nacional. De um modo geral, o estudo demonstra que a adoção bem-sucedida da IA na Gestão da Cadeia de Abastecimento não constitui apenas um desafio tecnológico, mas também um processo de transformação organizacional, dependente das capacidades relacionadas com os dados, do alinhamento estratégico, da consciencialização da gestão, da gestão dos riscos e da preparação organizacional.

PALAVRAS-CHAVE: Inteligência Artificial; Gestão da Cadeia de Abastecimento; Barreiras à Adoção da IA; Benefícios da IA; Capacidades da Cadeia de Abastecimento; Portugal.

DECLARAÇÃO

Durante a realização deste trabalho, a autora utilizou o ChatGPT com o propósito de aperfeiçoar a sintaxe do texto na língua inglesa. Após o uso desta ferramenta, a autora reviu e editou o conteúdo conforme necessário e assume total responsabilidade pelo conteúdo do trabalho.

TABLE OF CONTENTS

ACKNOWLEDGEMENTS	I
ABSTRACT	II
RESUMO	III
TABLE OF CONTENTS	V
TABLE OF TABLES	VI
LIST OF ACRONYMS AND ABBREVIATIONS	VII
1. INTRODUCTION	1
2. LITERATURE REVIEW	3
2.1. Supply Chain Management (SCM) and its importance.....	3
2.2. Artificial Intelligence (AI) in the industry	4
2.3 AI Technologies in Supply Chain Management.....	6
2.3.1 AI and its relevance in SCM.....	6
2.4. Enablers and Benefits of AI in Supply Chain Management	9
2.5. AI and Supply Chain Resilience	11
2.6. Barriers to AI adoption in SCM / Challenges	14
2.7. Ethical, Social, and Human Implications of AI in SCM.....	16
3. METHODOLOGY	19
3.1 Research design.....	19
3.2. Sample and Data Collection.....	20
3.2.1 Survey Development	21
3.2.2 Measurement scales.....	22
4. FINDINGS AND DISCUSSION	23
4.1 Companies Characterisation.....	23
4.2 Respondents Characterisation.....	25
4.3 Reliability Analysis.....	26
4.4 Correlation Analysis	30
4.5 ANOVA Analysis.....	35
5. CONCLUSION	43
REFERENCES	46
APPENDIX	59

TABLE OF FIGURES

Figure 1: Illustration of Industrial Evolution.....	4
Figure 2: Key enabling technologies of Industry 5.0	5
Figure 3: AI technologies in developing resilience in supply chains	12

TABLE OF TABLES

Table I: Companies Characterisation	24
Table II: Role of the surveyed companies in the supply chain.....	25
Table III: Respondents Characterisation	26
Table IV: Cronbach's Alpha.....	27
Table V: AI Adoption in Supply Chain Activities	28
Table VI: Correlation analysis between Competencies and Perceived Benefits.....	32
Table VII: Correlation analysis between Competencies and Strategies and Practices.....	33
Table VIII: Correlation analysis between Competencies and Barriers to AI adoption	34
Table IX: Comparison of means of each variable and SC complexity	35

LIST OF ACRONYMS AND ABBREVIATIONS

AI - Artificial Intelligence.
ANOVA - Analysis of Variance.
B2B - Business to Business.
B2C - Business to Consumer.
CAE - Portuguese Classification of Economic Activities.
CEO - Chief Executive Officer.
COVID-19 - Coronavirus Disease 2019.
CSCMP - Council of Supply Chain Management Professionals.
DL - Deep Learning.
EIB - European Investment Bank.
ERP - Enterprise Resource Planning.
GA - Genetic Algorithm.
GSCM - Green Supply Chain Management.
HRC - Human-Robot Collaboration.
IIoT - Industrial Internet of Things.
IoT - Internet of Things.
IS - Information Systems.
IT - Information Technology.
LLM - Large Language Model.
ML - Machine Learning.
NLP - Natural Language Processing.
OIPT - Organisational Information Processing Theory.
OM - Operations Management.
POS - Point of Sale.
R&D - Research and Development.
RL - Reinforcement Learning.
RQ - Research Question.
SC - Supply Chain.
SCM - Supply Chain Management.
SCR - Supply Chain Resilience.
SKU - Stock Keeping Unit.
SMEs - Small and Medium-sized Enterprises.

1. INTRODUCTION

Over the last few years, there has been an increase in the dynamics and competitiveness of the environments where organisations operate, forcing them to become more adaptable and responsive to change in order to be successful in the long term. In this context, Supply Chain Management (SCM) has gained strategic importance, as companies seek to optimise the flow of materials, information, and operations across their supply chain to improve organisational performance, enhance customer satisfaction, and gain a greater advantage over their competitors (Li et al., 2004).

The digitalisation of business operations and the emergence of Industry 4.0 and 5.0 technologies have transformed supply chain activities (Ivanov et al., 2018; Maddikunta et al., 2021). Among these technologies, Artificial Intelligence (AI) has emerged as one of the most transformative innovations affecting organisations and supply chain management (Dubey et al., 2019; Grover et al., 2020; Wamba et al., 2021). Artificial Intelligence can be understood as the development of intelligent systems and computer programs capable of performing tasks that require forms of reasoning, learning, and problem-solving (McCarthy, 2007).

The integration of AI into SCM has become relevant particularly by supporting key supply chain activities, such as forecasting, inventory management, predictive maintenance, logistics optimisation, quality control, and supplier-related decisions (Ennajeh & Najar, 2023; Gupta et al., 2021; Min, 2009). It has also been associated with several organisational benefits, including improved forecasting accuracy, cost reduction, increased operational efficiency, enhanced customer satisfaction, and greater supply chain resilience (Hendriksen, 2023; Osman et al., 2022; Shahzadi et al., 2024). During periods of disruption and uncertainty, AI-based systems have additionally demonstrated their ability to improve supply chain visibility and increase its adaptability and responsiveness (Modgil et al., 2021).

Despite the potential benefits of AI adoption, organisations also face multiple barriers. As studied by Hangl et al. (2022) and Shahzadi et al. (2024), when implementing AI technologies, companies are not always ready at the financial, technical, and organisational levels, lacking high-quality data, cybersecurity readiness or even human expertise, leading to resistance to change. Moreover, ethical and organisational concerns must also be taken into account when adopting AI for decision-making processes, as companies must ensure not only human supervision but also transparency, trust, and governance in the use of such technologies (Hangl et al., 2023; Ivanov & Dolgui, 2020).

Although there has been growing academic interest in AI and SCM, further empirical research is still needed to understand how organisations perceive AI adoption and its benefits in specific business contexts. Although research highlights the potential of AI to improve forecasting, efficiency, decision-making, resilience, and other supply chain characteristics, managers' perceptions of these benefits may vary according to their own organisations' supply chain characteristics. Understanding managerial perceptions is of utmost importance, as it correlates directly to their decisions on technology adoption, based on their expectations of returns and possible implementation challenges. This is particularly relevant in the context of Portuguese manufacturing companies, where the adoption of AI in supply chain activities may still be in its early stages.

Therefore, this study aims to analyse the perceived benefits of Artificial Intelligence in Supply Chain Management from the perspective of Portuguese manufacturing companies. Specifically, it examines how managers perceive the adoption of AI within organisations, the extent to which AI is being adopted in supply chain activities, and how AI capabilities and perceived benefits are associated with supply chain resilience. Based on these objectives, the study seeks to answer the following research questions:

- RQ1: *How do managers in Portuguese manufacturing companies perceive the adoption of Artificial Intelligence within their organisations?*
- RQ2: *How are Artificial Intelligence capabilities associated with supply chain resilience in Portuguese manufacturing companies?*

To address these questions, a quantitative research approach was adopted, based on the collection and analysis of survey data from manufacturing companies operating in Portugal, including several dimensions associated with AI adoption in SCM, such as AI capabilities and organisational resources, perceived AI benefits, SCM practices, and barriers to AI adoption.

This dissertation is structured into five chapters. Following this introduction, the second chapter presents a review of the literature covering the topics of supply chain management, Artificial Intelligence and its technologies in supply chain management, the benefits and barriers associated with the adoption of AI, including enhancements to supply chain resilience, as well as the ethical, social and human implications of integrating AI in SCM. Thereafter, the third chapter describes the research methodology adopted in the study. The fourth chapter presents and analyses the empirical findings obtained from the survey data, and, finally, the fifth chapter discusses the main conclusions, implications, limitations, and suggestions for future research.

2. LITERATURE REVIEW

2.1. Supply Chain Management (SCM) and its importance

The Council of Supply Chain Management Professionals (CSCMP) defines supply chain management as "the planning and management of all activities involved in sourcing and procurement, conversion, and all logistics management activities [...] it also includes coordination and collaboration with channel partners" (CSCMP, n.d.). However, the strategic value of managing supply chains predates the term itself. Ford's vertically integrated manufacturing, Toyota's Lean Production, and Haier's supply chain reengineering each showed, in different ways, how coordinating the chain could become a source of advantage; more recently, firms such as Nike have built their networks around global outsourcing and tight inventory control (Wei & Xiang, 2013).

Supply Chain Management concerns the flow of materials, information, and operations from raw material suppliers to end customers, with the aim of lowering costs and reducing the uncertainty and risk that surround such flows (Mentzer et al., 2001). When properly applied, it leads to tangible benefits, namely higher order fulfilment rates, lower cost-to-serve metrics, and a company which is more agile in the face of market opportunities (Chien et al., 2023). Such benefits are not just intuitive, as shown by Li et al. (2004), where stronger SCM practices are associated with better organisational performance and competitive advantage.

The strategic significance of SCM has increased recently due to the digitalisation of supply chains. Supply chain resilience has been greatly improved by digital technologies, especially those related to Industry 4.0 and 5.0. To control disruption risks, for example, Ivanov et al. (2018) suggested an integrated approach that combines engineering, analytics, and business. On the specific disruption related to the COVID-19 pandemic, research by Ning et al. (2022) and Birkel et al. (2023) also showed how a company's digital maturity and traceability systems enhanced sustainability and responsiveness in the event of such a large-scale disruption. Additionally, research from Wang et al. (2024) has shown that artificial intelligence has a significant impact at both the strategic level, enabling data-driven decision-making, but also at an operational level, where it is mostly applied in dynamic inventory management and more accurate demand forecasting.

In sum, SCM is no longer confined to logistical coordination but has actually evolved into a multidimensional discipline that integrates technology, strategy, and cross-organisational collaboration to deliver value across the supply chain. Its evolving role in supporting resilience,

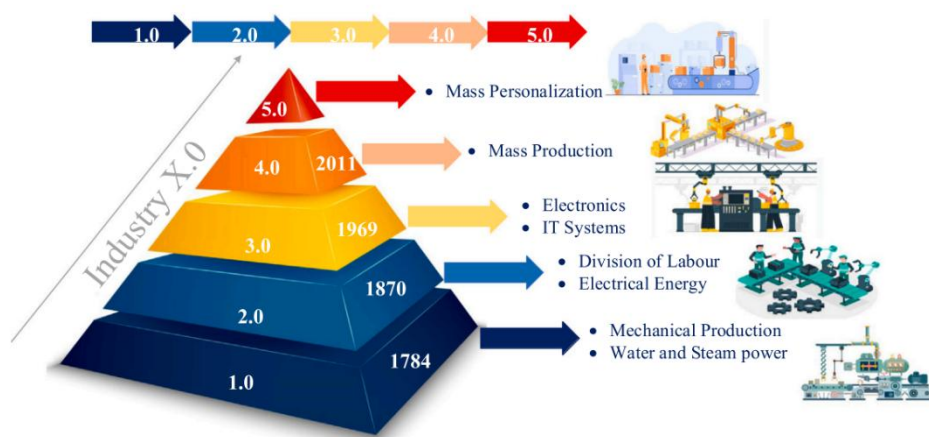
innovation, and sustainability underscores its foundational importance in the contemporary business environment.

2.2. Artificial Intelligence (AI) in the industry

Nowadays, when companies think about improving their processes and efficiency, they automatically embrace new technologies and the digital world. Among the different types of technologies, Artificial Intelligence (AI) (Toorajipour et al., 2020) is one of the most transformative technologies impacting modern operations and supply chain management (Dubey et al., 2019; Grover et al., 2020; Wamba et al., 2021). According to John McCarthy (2007), the father of Artificial Intelligence, AI can be defined as “the science and engineering of making intelligent machines, especially intelligent computer programs” (McCarthy, 2007:206). These programs are then used to achieve given goals by approaching intelligence in ways that are not natural to humans or other animals.

The adoption of AI in supply chain management is closely linked to the evolution of industrial systems. As shown in Figure 1, the transition towards Industry 4.0 and Industry 5.0 has enabled intelligent, connected, and human-centric supply chain operations (Maddikunta et al., 2021). Figure 2 provides a conceptual overview of how AI integrates with technologies such as IoT, digital twins, and robotics to support intelligent and human-centric supply chain operations, illustrating these key enabling technologies of Industry 5.0 and their interactions, highlighting the central role of AI within this technological ecosystem (Maddikunta et al., 2021).

Figure 1: Illustration of Industrial Evolution



(Adapted from Maddikunta et al., 2021)

Figure 2: Key enabling technologies of Industry 5.0



(Adapted from Maddikunta et al., 2021)

When considering a supply chain, if there is a process or activity that can have its efficiency, productivity, or sustainability improved in one of the companies, this will lead to a positive impact on all the other companies involved, as well as on the whole ecosystem. This is the core reasoning for the applicability of AI in the SCM. A recent systematic review of the literature by Beta et al. (2025) has demonstrated that artificial intelligence enhances supply chain resilience through improved forecasting, task efficiency, problem-solving capabilities, and customer service performance. Many of the articles studied by these authors highlight the positive impact of artificial intelligence on companies' daily operations and its effects throughout the supply chain. Nonetheless, several obstacles and challenges must be considered when adopting AI, as discussed later in this section.

AI can be applied to optimise inventory management, scheduling, quality control, operational efficiency, maintenance, fault identification, demand forecasting, routing, and delivery, as well as control, process, job design, and sustainability improvements. (Ennajeh & Najjar, 2023; Guner et al., 2015; Gupta et al., 2021; Kobbacy et al., 2006; Shoushtari et al., 2021). It helps with effectiveness and efficiency, but it also helps to improve innovation capabilities (Gupta et al., 2021).

With increasing pressure to adopt eco-friendly practices, AI has also been applied across several environmental fronts within manufacturing, from how energy is consumed on the production floor to the volume of material sent to waste and the reuse and recovery of resources. These AI-driven sustainability efforts are particularly relevant not only because they lower a

company's environmental impact but also because eco-conscious consumers will perceive the company as an ideal choice given their preferences (Rakholia et al., 2024).

Although recent literature has shown that AI applied in SCM generates a lot of benefits for the industry and companies, it is also important to mention that AI tools in isolation do not generate any kind of benefit or competitive advantage, meaning that managers need to create a business strategy and understand how to use them (Deloitte, 2020; Wamba et al., 2021). In other words, AI cannot make decisions independently or replace managers, but must be used as a tool that guides them toward the best decisions (Helo & Hao, 2021). More specifically, AI integration requires a skilled workforce and a possible culture shift to align human expertise with machine capabilities. As shown by Rakholia et al. (2024), these requirements may be harder to meet for smaller companies, which may struggle with the burden of high initial investments and a lack of specialised AI talent. Regardless of company size, the authors also show that some manufacturers struggle to implement effective AI systems due to a lack of large amounts of high-quality data. Compliance with regulations and ethical guidelines is also essential, as is ongoing R&D to enhance AI's role in manufacturing and address current limitations (Rakholia et al., 2024).

2.3 AI Technologies in Supply Chain Management

2.3.1 AI and its relevance in SCM

In recent years, as globalisation, digital transformation, and Industries 4.0 and 5.0 have reshaped the manufacturing and logistics landscape, AI has emerged as a critical enabler of smarter, faster, and more adaptive supply chains.

AI has become an increasingly influential driver of transformation in supply chain management (SCM), playing a pivotal role in enhancing efficiency across procurement, production, logistics, and distribution functions (Pournader et al., 2021). Digital technologies, particularly AI tools, are now recognised for their ability to streamline processes, reduce uncertainty, and support data-driven decision-making (Hendriksen, 2023; Shahzadi et al., 2024). Despite the growing awareness of AI's potential, full-scale adoption in supply chain operations remains limited (Wang et al., 2023).

The connection between AI and SCM is quite important. According to Richey et al. (2023), AI applications in supply chain and logistics differ according to data availability, contextual uncertainty, and levels of human involvement. The framework proposed by these authors indicates that the role of AI varies from automation-oriented tasks to decision-support functions in more complex contexts.

A central concept within this domain is Industrial AI, which refers to the systematic design and application of AI technologies to industrial contexts. Rather than replacing human labour, Industrial AI aims to augment it, improving productivity by automating routine tasks and supporting complex decision-making (Peres et al., 2020). Core technologies include machine learning (ML), deep learning (DL), natural language processing (NLP), and the Internet of Things (IoT), all of which enable greater levels of autonomy and adaptability in operations (Garg et al., 2021; Agarwal et al., 2019).

The literature also categorises and highlights specific AI technologies, such as agent-based systems, expert systems, genetic algorithms, artificial neural networks, and others, currently used in various SCM functions, including demand forecasting, inventory planning, logistics, production scheduling, and supplier management (Sharma et al., 2022; Baryannis et al., 2019).

One of these techniques, Agent-based Systems, is mostly used in demand planning and forecasting, customer relationship management, negotiation, and order picking. For example, if we are trying to understand the likelihood of a customer buying a certain product, an agent-based system can be used to simulate multiple customer types and their respective cognitive models, which influence this possibility (Baxter et al., 2003).

Genetic Algorithms, on the other hand, are used in network planning. For example, with a distribution route, these algorithms take the network's multiple parameters, generate an initial network with all the relevant distribution points, and find the optimal route between them (Zhao & Xie, 2023).

When it comes to Expert Systems, these are used in inventory planning, make-or-buy decisions, and supplier selection by using predictive analytics and real-time data. They forecast important supply chain factors, such as product demand and lead times for essential components (Min, 2009; Plathottam et al., 2023). Additionally, artificial neural networks, support vector machines, and regression trees have proven effective in identifying trends and predicting future outcomes (Carbonneau et al., 2007; Feizabadi, 2020). These models allow firms to respond proactively to demand fluctuations, mitigate stockouts, and manage inventory more efficiently. Additionally, advancements in point-of-sale (POS) analytics allow businesses to capture Stock Keeping Unit (SKU) level data and adjust inventory at a granular level (Feizabadi, 2020).

Beyond forecasting, AI contributes to several functional areas in supply chains, including predictive maintenance, quality assurance, human-robot collaboration (HRC), and employee training (Arinez et al., 2020). Predictive maintenance, in particular, enables companies to detect machinery faults before breakdowns occur, reducing downtime and operational disruptions.

HRC further enhances workplace productivity by combining human cognitive capabilities with the precision and reliability of AI-powered robots (Arinez et al., 2020).

Process optimisation is another key domain in which AI delivers value by analysing real-time and historical data to reduce energy consumption, predict bottlenecks, and improve customer service (Peres et al., 2020). AI-powered Digital Twins, built on Industrial IoT (IIoT) frameworks, simulate supply chain systems, enabling scenario analysis and proactive decision-making (Boyes et al., 2018; Maddikunta et al., 2021). These innovations improve operational resilience and facilitate real-time interventions in case of disruptions.

Recent developments in large language models (LLMs) have further broadened AI's application in SCM. With capabilities in text generation and reasoning, LLMs support tasks such as supplier evaluation, risk modelling, logistics planning, and warehouse layout design (Hendriksen, 2023; Richey et al., 2023). However, their use also raises concerns related to transparency, ethical use, and data privacy.

AI is applied across the three primary levels of supply chain decision-making: strategic, tactical, and operational (Min, 2009). At the strategic level, AI aids in long-term planning such as network design; at the tactical level, it helps in forecasting, scheduling, and resource allocation; while at the operational level, it supports real-time decision-making such as routing and demand fulfilment (Min, 2009). Technologies like artificial neural networks are particularly effective at recognising anomalies, such as demand spikes or transport delays, thereby minimising risks and enhancing responsiveness (Min, 2009).

Expert systems also play a critical role in SCM, especially in warehouse operations and production scheduling. For instance, knowledge-based systems have been used to optimise order-picking routes and equipment utilisation (Min, 2009). Practical implementations from firms like Nestlé and General Motors demonstrate how AI improves operational efficiency, reduces emissions, and enhances predictive maintenance (Wamba et al., 2021).

AI technologies are further empowered by the broader framework of Industry 4.0, which integrates AI with cloud computing, IoT, and Big Data analytics. This convergence facilitates real-time optimisation of manufacturing processes and promotes adaptive responses to market shifts (Xu et al., 2018; Zeba et al., 2021; Zheng et al., 2018). Such digital innovations not only improve operational and environmental performance but also support more sustainable and resilient supply chains (Shahzadi et al., 2024).

Nonetheless, the integration of AI in SCM also presents challenges, ranging from implementation costs and workforce upskilling to ethical dilemmas and cybersecurity risks. As digital technologies increasingly reshape global supply networks, managing disruption risks

and ensuring responsible AI use have become critical strategic priorities (Dolgui & Ivanov, 2020).

2.4. Enablers and Benefits of AI in Supply Chain Management

The integration of Artificial Intelligence (AI) into supply chain management (SCM) has revolutionised traditional operational models by enhancing decision-making, responsiveness, and overall efficiency. AI technologies are being deployed across various supply chain functions, offering benefits in forecasting, inventory control, production scheduling, logistics, and sustainability performance (Wamba et al., 2021).

The growing interest in AI within supply chain management is also reflected in broader evidence synthesised by Hangl et al. (2022), who conducted a tertiary study examining AI adoption in SCM. Their analysis indicates that organisations increasingly recognise AI as a strategic enabler for improving supply chain performance and competitiveness.

One of the most widely acknowledged advantages of AI in SCM is its capacity to improve forecasting accuracy. Accurate demand forecasting helps companies avoid overproduction or stockouts, which are critical to minimising the bullwhip effect and maintaining customer satisfaction. As highlighted by Shahzadi et al. (2024), AI's predictive analytics support precise demand forecasting and dynamic inventory management. Similarly, Yeh et al. (2016) demonstrated how simplified swarm optimisation algorithms improve the global optimisation of supply chain networks, reducing operating costs and enhancing customer satisfaction.

AI also contributes significantly to predictive maintenance, a function that reduces equipment downtime and prevents disruptions. By leveraging machine learning (ML) techniques such as computer vision, regression, classification, and anomaly detection, companies can predict failures based on sensor data and conduct timely maintenance (Plathottam et al., 2023). This proactive approach not only reduces unexpected downtime but also supports worker safety and environmental protection.

In the domain of inventory management, AI offers substantial improvements in accuracy, cost-efficiency, and speed. Osman et al. (2022) argue that AI improves data accuracy and productivity, enables faster decision-making, and leads to greater customer satisfaction. Time series models and reinforcement learning (RL) help optimise stock levels and automate reorder decisions, reducing inventory-related costs.

Furthermore, AI contributes to supply chain optimisation through advanced problem-solving methods that traditional mathematical models often struggle to handle. Techniques like genetic algorithms (GA), neural networks, fuzzy systems, and ant colony optimisation provide flexible and efficient alternatives (Plathottam et al., 2023). These methods have been

successfully applied in distribution routing, inventory planning, supplier selection, and minimising operational costs.

Another key benefit lies in the personalisation and enhancement of customer experience. AI enables supply chains to respond to customer-specific needs by analysing behaviour patterns and tailoring offerings accordingly. Shahzadi et al. (2024) note that this personalisation boosts customer satisfaction and loyalty, contributing to competitive advantage.

From a sustainability perspective, AI helps improve environmental performance. Through energy forecasting and optimised resource usage, companies can align operations with sustainability goals. Plathottam et al. (2023) report that deep neural networks and support vector machines are being used to forecast energy consumption at both facility and process levels. These capabilities reduce operational costs and environmental impact. Kurrahman et al. (2025) examine how generative AI capabilities contribute to green supply chain management (GSCM) by integrating the dynamic capabilities view with organisational learning theory. The study emphasises the role of sensing, seizing, and reconfiguring capabilities, supported by dynamic knowledge and innovative learning processes. In particular, reflexive control and measurement capabilities within sensing, and co-evolution capabilities within seizing, are identified as key priorities. The authors also highlight the importance of high-quality data gathering and analysis, especially for predictive maintenance and sales and operations strategy identification, to improve resource utilisation and reduce environmental impact.

Moreover, AI strengthens economic and social performance. Shahzadi et al. (2024) found that AI and big data analytics enhance managerial decision-making, improve supply chain resilience, and support economic growth (Wamba et al., 2017). AI technologies also facilitate more efficient logistics networks, ensuring the reliable distribution of essential goods and improving companies' social responsibility profile.

The introduction of AI-driven Enterprise Resource Planning (ERP) systems also helps streamline cross-functional processes by reducing data duplication and enabling informed, unified decision-making. As described by Oracle (2023), ERP integration improves supply chain performance and resource allocation, reinforcing overall operational effectiveness.

AI's contribution to process optimisation is equally noteworthy. Real-time optimisation using reinforcement learning and digital twins enables faster simulation and smarter factory layouts (Plathottam et al., 2023). These systems help manufacturers adjust processes dynamically and avoid disruptions without halting production.

Finally, the deployment of AI in human-robot collaboration (HRC) adds further value. According to Arinez et al. (2020), AI systems support planning, learning, and monitoring

functions in collaborative environments. Tools such as Bayesian decision-making, natural language processing, and reinforcement learning enhance coordination between humans and robots, improving safety and productivity.

In summary, AI adoption across supply chain functions yields multifaceted benefits: it improves forecasting, automates inventory control, enhances customer experience, reduces costs, supports sustainability, and enables real-time responsiveness (Wamba et al., 2021). These advantages collectively strengthen a firm's resilience, competitiveness, and adaptability in an increasingly volatile global market (Calatayud et al., 2018; Hendriksen, 2023; Yue et al., 2025).

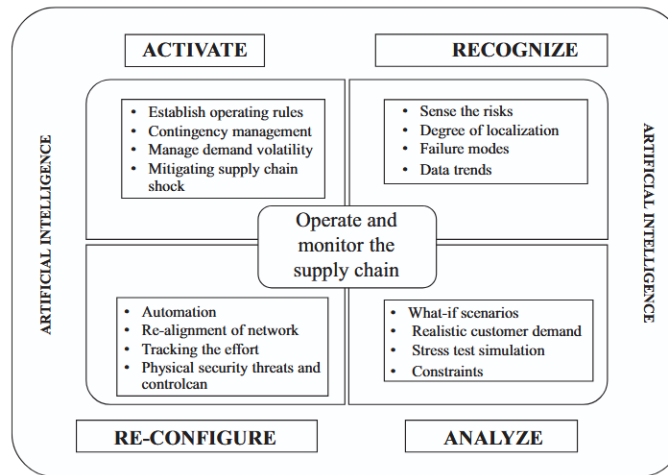
2.5. AI and Supply Chain Resilience

The resilience of supply chains is challenged by frequent shocks, including natural or environmental disasters, health or sanitary crises, economic or political instability, cyber-attacks and wars (Craighead et al., 2007). The increasing frequency and severity of such disruptions have drawn significant attention to the concept of supply chain resilience (SCR). This has become a critical capability for organisations seeking to maintain operational continuity and competitive advantage amid supply failures, delivery delays and demand fluctuations (Brandon-Jones et al., 2014; Christopher & Peck, 2004; Dai et al., 2025; Nikookar & Yanadori, 2021; Ponomarov & Holcomb, 2009). Consequently, the potential of AI to enhance supply chain resilience has been examined in numerous studies (Belhadi et al., 2021; Dabbous et al., 2026; Dai et al., 2025; Modgil et al., 2021; Smyth et al., 2024; Zamani et al., 2022). In particular, AI-powered demand forecasting has emerged as a critical capability for enhancing both SCR and supply chain visibility. During the 2020's pandemic, advanced forecasting models enabled organisations to anticipate supply shortages, optimise inventory levels and adapt procurement strategies in response to rapidly changing market conditions (Zaoui et al., 2025). This supported more informed and timely decision-making in uncertain circumstances (Ivanov & Dolgui, 2020). These capabilities demonstrate how AI can assist organisations in proactively identifying risks and responding effectively to disruptions before they escalate into significant operational challenges.

Modgil et al. (2021) emphasise the importance of AI technologies in enhancing supply chain resilience during periods of disruption, such as the one caused by the pandemic. Their framework identifies four interconnected capabilities that support the continuous operation and monitoring of the supply chain: recognize, analyze, reconfigure and activate. The '*recognize*' capability refers to AI's ability to identify risks, detect failure patterns, assess localisation levels and interpret emerging data trends, thereby improving visibility across supply networks. The

‘*analyze*’ dimension involves scenario evaluation, stress testing and assessing demand conditions and operational constraints. The ‘*re-configure*’ capability enables automation and network realignment in response to disruptions. Finally, the ‘*activate*’ capability involves implementing contingency measures, demand management practices, and mitigating supply shocks. Together, these capabilities demonstrate how AI can enhance visibility, adaptability and responsiveness in turbulent environments, as shown in Figure 3.

Figure 3: AI technologies in developing resilience in supply chains



(Adapted from Modgil et al., 2021)

AI not only contributes to supply chain resilience but also strengthens several dynamic capabilities that enable organisations to adapt and compete in increasingly volatile environments (Teece et al., 1997). AI enhances supply chain agility, which is defined as the ability to rapidly sense and respond to changes in market conditions and operational disruptions (Braunscheidel & Suresh, 2009; Patrucco et al., 2025). It also improves responsiveness, referring to the speed and effectiveness with which organisations react to such changes. AI can process large volumes of structured and unstructured data to generate actionable insights that support faster and more accurate decision-making across supply chain activities (Dubey et al., 2021; Ivanov & Dolgui, 2020; Wamba et al., 2021). AI-based analytics transform data into organisational knowledge, enabling firms to anticipate environmental changes more effectively, identify emerging opportunities and adapt their operations continuously (Lamees & Ramayah, 2025). Consequently, organisations can transition from reactive to proactive and adaptive decision-making approaches.

AI also plays a crucial role in improving collaboration within supply chain networks (Cao & Zhang, 2011). Effective AI applications require information to be integrated and actions coordinated among suppliers, manufacturers, logistics providers and customers. AI improves

visibility and facilitates real-time information sharing, reducing information asymmetries and supporting a common understanding of risks, demand conditions, and operational constraints (Dubey et al., 2019; Srinivasan & Swink, 2018). This allows supply chain partners to synchronise planning activities, align strategic objectives, and coordinate responses more effectively. Furthermore, AI-driven risk management capabilities strengthen collaborative relationships by facilitating joint problem-solving and more coordinated responses to disruptions, ultimately contributing to greater supply chain agility (Wong et al., 2022). From an intellectual capital perspective, these collaborative processes also enhance relational capital and organisational learning, thereby fostering innovation and long-term adaptability across supply networks (Lamees & Ramayah, 2025). Similarly, Wong et al. (2022) demonstrate that collaborative supply chain relationships reinforce the effectiveness of AI-driven risk management by facilitating information exchange and coordinated responses to emerging threats. This collaborative dimension is particularly important in increasingly complex and interconnected supply networks, where resilience depends not only on the capabilities of individual firms but also on the collective ability of network members to share information and respond effectively to unexpected events.

Consequently, AI should not merely be viewed as a technological tool for operational optimisation but as a means of enabling organisational adaptability and network-level capabilities. By improving visibility, accelerating decision-making, strengthening risk management, supporting inter-organisational collaboration, and facilitating adaptive responses to uncertainty, AI helps organisations develop more agile, responsive, and resilient supply chains capable of operating effectively in turbulent and rapidly changing environments (Dubey et al., 2019; Ivanov & Dolgui, 2020; Wamba et al., 2021; Wong et al., 2022). Moreover, by strengthening human, structural, and relational capital, AI-based analytics contribute to continuous learning and innovation, enabling firms not only to respond to disruptions more effectively but also to develop sustainable competitive advantages in increasingly digital supply chain ecosystems (Lamees & Ramayah, 2025). Furthermore, recent research suggests that generative AI may amplify these benefits by augmenting planners' cognitive capabilities, facilitating knowledge integration, and supporting cross-functional decision-making. However, realising these advantages requires maintaining human oversight to prevent information overload and excessive reliance on algorithmic recommendations (Shurrab & Jonsson, 2026).

2.6. Barriers to AI adoption in SCM / Challenges

This section addresses the limitations and ethical considerations that organisations face when implementing AI. These include the need for high-quality data, strategic alignment, a skilled workforce and responsible governance. Despite the growing adoption of AI in SCM, its implementation is accompanied by significant technical, organisational, economic and ethical challenges. One of the main technical barriers is the vast amount of data generated across supply chains, which can impede efficient inventory tracking and real-time decision-making. Osman et al. (2022) highlight data overload, tracking difficulties and inefficient business planning as ongoing problems that AI has not yet fully resolved. These issues are intensified by high operational costs, particularly as inventory levels and the complexity of digital systems increase.

Economic challenges are also prevalent. Implementing AI requires a significant initial investment, as well as ongoing financial input for maintenance, training and hardware updates (Shahzadi et al., 2024). The costs of integrating AI systems, including sensors, processors and software, can be prohibitive for small and medium-sized enterprises. Furthermore, operational costs do not diminish over time as hardware components require regular replacement and updates (Osman et al., 2022).

Organisational and human-related barriers can further complicate the deployment of AI. Resistance to change, a lack of support from senior management, and poor internal communication can all hinder the successful integration of AI. The absence of skilled personnel and limited digital maturity within firms can also restrict effective adoption (Shahzadi et al., 2024). Furthermore, AI-driven automation may reduce the need for human workers, raising concerns about job displacement. Addressing this requires investment in upskilling and reskilling, adding further to implementation costs (Osman et al., 2022).

Significant barriers to AI adoption in supply chain management also include practical implementation challenges related to data, organisational readiness, and stakeholder acceptance. Issues relating to data quality, availability, and connectivity are particularly critical, as information is often siloed, poorly standardised, incomplete, or difficult to integrate across suppliers, customers, and internal systems. This limits the effectiveness of AI-driven decision-making (Choi et al., 2017; Wamba et al., 2020). Organisational readiness, including the availability of digital infrastructure, analytical capabilities, and managerial support, has been identified as a prerequisite for the successful implementation of AI (Dubey et al., 2019). Resistance to change in traditionally conservative industries further complicates adoption, particularly when employees and supply chain partners are not sufficiently involved in

evaluation, design and implementation (Baryannis et al., 2019). A lack of understanding of and trust in AI systems, which often stems from their perceived ‘black box’ nature and limited explainability, can also hinder deployment and reduce users’ acceptance of AI-supported decisions (Choi et al., 2017; Dwivedi et al., 2019). Furthermore, integrating AI solutions into existing business processes and operational workflows is often complex, resource-intensive and time-consuming. This requires careful alignment of technological capabilities, organisational processes, and strategic objectives to avoid operational disruption (Hangl et al., 2023; Wamba et al., 2020).

From a technical standpoint, several studies have highlighted limitations specific to AI, including the difficulty of obtaining high-quality training data. As Plathottam et al. (2023) point out, manufacturing environments frequently comprise proprietary systems and restricted data access, resulting in expensive and time-consuming data acquisition. Similar issues are also reported in the operations management literature, where fragmented data infrastructures, diverse information sources and limited data availability are recognised as significant obstacles to effectively deploying AI and advanced analytics solutions (Choi et al., 2017; Wamba et al., 2020). Preprocessing requirements, sensor inconsistencies and the rarity of key events (e.g. equipment failures) further complicate model training and reduce predictive performance in industrial settings (Baryannis et al., 2019; Plathottam et al., 2023). Furthermore, the energy-intensive nature of training AI and machine learning models raises environmental concerns due to the carbon emissions associated with prolonged computational activity (Plathottam et al., 2023).

Security and privacy risks also remain critical challenges. AI systems require access to sensitive operational, customer and employee data, which increases exposure to cyber threats and data breaches. Research on digital transformation and AI adoption shows that concerns about data governance, privacy protection and cybersecurity can greatly reduce an organisation’s willingness to implement AI-enabled solutions (Dubey et al., 2019; Dwivedi et al., 2019). Furthermore, Plathottam et al. (2023) emphasise that while AI can enhance security monitoring and anomaly detection capabilities, it does not eliminate vulnerabilities, particularly when personal information or industrial control system data is involved. Consequently, the ethical handling of employee-related data is essential to safeguard individual rights and maintain organisational trust. This includes anonymisation procedures and compliance with data protection regulations (Dwivedi et al., 2019).

The explainability of AI models has also emerged as a key research priority in operations and supply chain management, as user trust and adoption are strongly influenced by the ability

to understand and justify algorithmic decisions (Dwivedi et al., 2019; Baryannis et al., 2019). Similarly, safety concerns in human-robot collaboration (HRC) have risen from the difficulty AI systems face in accurately interpreting human behaviour and intentions. This limits the broader deployment of AI systems in shared workspaces and complex manufacturing environments (Arinez et al., 2020). These challenges emphasise the importance of designing AI systems that balance autonomy, transparency and human oversight, ensuring safe and effective implementation in operational settings.

Furthermore, definitional ambiguity and evolving public perceptions present significant challenges to the adoption of AI. As Sheikh et al. (2023) explain, AI is an inherently dynamic and contested concept whose boundaries and capabilities are continuously redefined as the technology evolves. The so-called ‘AI effect’, whereby systems are no longer perceived as AI once they become widely adopted or routine, further contributes to conceptual uncertainty regarding what constitutes AI and what it can realistically achieve. Such ambiguity can result in inconsistent interpretations among practitioners, policymakers and the public, influencing regulatory approaches, investment decisions and levels of trust and acceptance.

In summary, although AI has the potential to transform supply chain optimisation and decision-making, its effective deployment is hindered by complex, multidimensional challenges in technical, organisational, ethical and conceptual domains. Overcoming these barriers requires strategic planning, sustained investment in data and digital capabilities, robust governance frameworks, ethical safeguards and continuous organisational learning to ensure the responsible, transparent and effective use of AI in supply chains.

2.7. Ethical, Social, and Human Implications of AI in SCM

The ethical and social implications of artificial intelligence (AI) in supply chain management go far beyond technological performance and operational efficiency. As AI automates more routine and data-intensive activities, such as forecasting, planning, analytics, logistics operations and supplier management, it is fundamentally reshaping the nature of work, organisational structures and decision-making processes within supply chains. Rather than merely replacing human labour, AI is transforming job roles by shifting responsibilities from operational execution to more strategic, analytical and supervisory tasks. This evolution has led to the emergence of hybrid work environments, where human expertise and AI capabilities complement each other by combining algorithmic processing power with human judgement and contextual understanding. Consequently, successful AI adoption requires technological investment and organisational adaptation, including reskilling the workforce, encouraging

continuous learning, and developing new competencies to support effective human-AI collaboration (Burger et al., 2023; Culot et al., 2024). These developments raise important ethical, social and managerial questions regarding transparency, accountability, trust, workforce adaptation and the appropriate balance between automated and human decision-making in supply chain contexts.

The ethical and social implications of artificial intelligence (AI) in supply chain management (SCM) are closely linked to transparency, trust and human oversight. Hangl et al. (2023) emphasise that AI systems in SCM should complement human judgement rather than replace it. They should operate as decision support tools under continuous human supervision. Their qualitative evidence suggests that current AI applications are not yet capable of fully autonomous decision-making and require ongoing monitoring, validation and contextual interpretation by human experts. The ‘black box’ nature of many AI algorithms and their inconsistent outputs raise concerns and highlight the importance of explainability and transparency in sustaining stakeholder trust. This is particularly important when such systems influence high-impact operational decisions such as pricing, production planning, and supply chain coordination, as it is essential to ensure that AI-generated recommendations can be understood, justified, and audited.

In addition to technical transparency, the literature also highlights the broader organisational and social responsibilities that are associated with the adoption of AI. Effective implementation requires the involvement of multiple stakeholder groups, such as supply chain managers, IT specialists, end users and experts in ethics and the social sciences (Hangl et al., 2023). Differences in organisational culture, risk tolerance levels, and data privacy attitudes further influence the acceptance and spread of AI across industries and geographic contexts. Consequently, AI adoption should be understood as a socio-technical transformation requiring structured governance mechanisms, cross-functional collaboration and sustained capability development, not merely as a technological upgrade. Namely, continuous employee training and upskilling are essential to ensure the responsible use of AI systems, alongside transparent data-sharing practices across supply chain partners.

Pandey et al. (2024) further reinforce the human dimension of AI implementation, highlighting the relevance of behavioural operations management and social psychological factors in shaping the acceptance of AI and machine learning technologies. They challenge the assumption of purely rational decision-making in supply chains by demonstrating that cognitive biases, perceptions of fairness and behavioural responses significantly influence the interpretation and adoption of AI-enabled recommendations. This perspective emphasises the

importance of designing AI systems that are technically robust and aligned with human decision-making processes and behavioural realities.

At a structural level, digitalisation is reshaping organisational configurations and inter-organisational relationships within supply networks. Holmström et al. (2019) introduce the concept of digital encapsulation, whereby information relating to design, production, delivery and use is embedded in digital artefacts. This enables activities to be redistributed across organisational and geographic boundaries. This facilitates more open and interactive supply networks in which customers and external stakeholders can participate in product development and operational decision-making processes. However, such developments also challenge traditional supply chain structures, which are characterised by stable interfaces, predefined roles and predictable workflows. This requires firms to reconsider their coordination mechanisms, organisational boundaries and value creation logic.

Similarly, the growing adoption of artificial intelligence and digital twin technologies in supply chain risk management gives rise to novel governance challenges. Ivanov and Dolgui (2020) conceptualise the digital supply chain twin as a cyber-physical decision support system integrating real-time data, simulation, optimisation and machine learning in order to represent and manage the dynamic state of supply networks. While these systems improve visibility, predictive capability and resilience, they also shift decision-making towards algorithm-supported, data-driven control environments. Consequently, decision-making authority becomes increasingly distributed between human managers and AI-driven systems, raising important questions regarding accountability, responsibility, and the appropriate level of human oversight in automated decision-making processes.

Baryannis et al. (2019) further emphasise these concerns, highlighting the inherent tension between predictive performance and interpretability in machine learning applications for supply chain risk management. While advanced AI techniques can greatly enhance the prediction of disruptions and the detection of risks, they have limited practical value if decision-makers cannot interpret or validate the underlying reasoning. The authors propose a framework that emphasises the need for close collaboration between AI specialists and supply chain practitioners to ensure that algorithmic outputs are interpretable, actionable, and aligned with operational objectives. The authors argue that prioritising interpretability may involve trade-offs in predictive accuracy, but that such trade-offs are necessary to ensure trust, accountability and effective risk mitigation in practice.

Overall, the literature indicates that the integration of AI in supply chain management extends far beyond technological implementation, being deeply embedded in governance,

organisational, ethical, and behavioural dimensions. Therefore, ethical and social considerations are central to how AI systems are designed, deployed, and supervised within increasingly complex and interconnected supply networks, rather than being peripheral.

Finally, the challenges of governance and interpretability become even more pronounced in the context of generative AI applications. Recent empirical evidence by Wamba et al. (2023) shows that although organisations anticipate significant benefits from generative AI, such as automation, cost reduction, improved operational efficiency, and enhanced customer responsiveness, substantial barriers persist. These include concerns relating to data quality, privacy, and cybersecurity, as well as difficulties integrating with legacy systems and dependence on external technology providers. Furthermore, issues such as employee resistance, the need for reskilling, and concerns about algorithmic bias and error propagation are widespread. The study also highlights differences across industries in terms of perceived benefits and implementation readiness, suggesting that organisational maturity plays a key role in shaping adoption outcomes. These findings reinforce the view that the responsible deployment of generative AI in supply chains requires advanced technological infrastructure, strong governance frameworks, skilled human capital and robust data management practices.

3. METHODOLOGY

This study seeks to analyse the benefits of Artificial Intelligence in Supply Chain Management from the perspective of companies. To address this objective, a quantitative research approach was employed to enable the systematic collection and analysis of numerical data. As noted by Yin (2001), this approach allows for a structured examination of the research problem, helping to direct respondents' answers toward the subject under investigation, while ensuring anonymity and supporting the analysis of relationships between variables.

3.1 Research design

This study adopts a quantitative, cross-sectional research design grounded in a structured survey strategy, which is widely recommended in Operations Management (OM) research for empirical investigations of firm-level constructs (Forza, 2002; Rungtusanatham et al., 2003). The objective is exploratory and theory-building in nature, aiming to examine Artificial Intelligence (AI) capabilities, perceived barriers, and benefits, as well as their relationships with supply chain (SC) capabilities in Portuguese manufacturing firms. Rather than testing predefined hypotheses, the study focuses on identifying patterns of association among constructs, which is appropriate in emerging research domains such as AI capabilities. This approach follows established methodological guidance suggesting that survey research is

particularly suitable for capturing complex organisational phenomena and enabling statistical analysis of relationships between latent constructs (Ketokivi & Schroeder, 2004).

Data were collected through an online survey administered to Portuguese manufacturing companies, targeting respondents in managerial roles with knowledge of operations, supply chain management, or digital transformation initiatives. The use of an online survey is consistent with contemporary OM and information systems research due to its efficiency, scalability, and ability to reach geographically dispersed populations.

The final dataset was analysed using descriptive statistics and correlation analysis to explore associations between AI capabilities and SC capabilities, as well as related constructs such as barriers and benefits, providing empirical insights into how these capabilities co-exist within manufacturing environments.

The research is based on a deductive approach, as it builds on existing literature related to artificial intelligence and supply chain management, which guided the formulation of the research survey (Saunders et al., 2019). Data were collected through a survey distributed to companies and was later analysed to draw conclusions that can be generalised to the target population, allowing for the identification of relationships between the variables under study.

In addition, the study incorporates both descriptive and exploratory research designs. The descriptive component focuses on presenting and characterising the phenomena under analysis, including identifying possible correlations between variables without any manipulation. The exploratory dimension aims to provide further insight into the topic by clarifying key aspects related to the role and benefits of artificial intelligence in supply chain management (Saunders et al., 2019).

3.2. Sample and Data Collection

The target population in this study comprises SMEs manufacturing firms located in Portugal given the increasing digitalisation among them (EIB, 2021), which provides a pertinent data source for analysis, in particular AI technologies. The study's sampling frame was derived from the Informa D&B database, a comprehensive database listing over 26322 manufacturing companies operating in Portugal, classified under CAE codes 10 to 32 (inclusive), that were active and had a valid corporate email address. The database contained information on the company name, Portuguese email address, CAE code and description, date of incorporation, sales and services provided, the most recent year with available financial data, the number of employees (latest year), and the export rate of each company. No duplicate entries were identified in the database; therefore, no data cleaning was required in this regard.

An email was sent to the corporate address targeting respondents in managerial roles with knowledge of operations, supply chain management, or digital transformation initiatives. The survey was sent to the companies via a link in an email. To ensure that respondents had adequate knowledge to answer the survey, they were asked to indicate their current role and the number of years they had been working in the company.

3.2.1 Survey Development

In quantitative research, surveys are commonly used as a data collection method, particularly when the objective is to analyse relationships between variables across a large number of respondents. According to Saunders et al. (2019), survey strategies enable the collection of standardised data cost-effectively, facilitating comparisons between responses and making them relatively easy to implement and understand. In the context of this study, which examines the benefits of artificial intelligence in supply chain management, the use of a survey allows for the efficient collection of comparable data from companies.

The survey consisted primarily of closed-ended questions, which limited the range of possible responses participants could provide, and was structured into six sections:

- Section A: Company profile;
- Section B: Adoption of artificial intelligence in supply chain management;
- Section C: Capabilities and resources for artificial intelligence;
- Section D: Perceived benefits of artificial intelligence in supply chain management;
- Section E: Supply chain management strategies and practices;
- Section F: Barriers to the adoption of artificial intelligence in supply chain management;
- Section G: Respondent profile.

For this study, an online survey was developed using LimeSurvey software (<https://www.limesurvey.org/pt>). The survey was available from 26 January 2026 to 20 April 2026. An invitation to participate was sent via email on 26 January 2026, in which respondents were informed about the purpose of the study, the estimated time required to complete the survey, and the confidentiality of the data (Appendix A).

Following the initial invitation, three reminder emails were sent to improve the response rate (Frohlich, 2002) (Appendix B). Participants were automatically removed from the database as responses were received. Participants who requested exclusion were also removed.

During the period in which the survey was open, a total of 1,860 responses were recorded, corresponding to a response rate of 7.06% (1,860/26,322). The final sample consists of 514 complete responses. Following established recommendations for survey-based research, procedural remedies were applied to reduce common method bias, including assuring respondent anonymity, improving item clarity, and carefully structuring the survey to reduce respondent fatigue (Dillman et al., 2014; Podsakoff et al., 2003).

3.2.2 Measurement scales

The scales used to measure the constructs were based on previously validated scales from the OM and IS literature and were adapted to the management context to ensure content validity. Different measurement approaches were employed, including open-ended, either-or, multiple-choice, and scaled questions (Misner & Carr, 2023). Most constructs were measured using a five-point Likert scale, where respondents were asked to indicate their level of agreement with each statement (1 = “Strongly disagree” to 5 = “Strongly agree”).

Artificial Intelligence Adoption was measured using items adapted from Jackson et al. (2024) and Sharma et al. (2022). This scale was developed to assess the extent to which organisations adopt and apply artificial intelligence technologies in supply chain management activities. The Artificial Intelligence Adoption scale consisted of 13 items, reflecting various applications of AI in supply chain processes, including forecasting, planning, inventory management, logistics, decision-making, and operational optimisation.

Artificial Intelligence Capabilities were measured using items adapted from Mikalef and Gupta (2021) and Sahoo et al. (2024). This scale comprised six dimensions, covering the resources and organisational capabilities required for the adoption and implementation of artificial intelligence. Technological infrastructure was measured using a four-item scale adapted from Sahoo et al. (2024). The remaining dimensions were adapted from Mikalef and Gupta (2021), namely data management (5 items), human and technical skills (5 items), business alignment (7 items), interdepartmental coordination (8 items), and risk management (7 items).

Perceived Benefits of Artificial Intelligence were measured using items adapted from Riahi et al. (2023). This scale comprised six dimensions, covering the main benefits associated with the implementation of artificial intelligence in supply chain management. These dimensions include data-driven decision-making and forecasting (5 items), operational efficiency and optimisation (7 items), quality management (5 items), network and supply chain

management (6 items), resilience and disruption management (4 items), and sustainability, safety and maintenance (3 items).

Supply Chain Management Strategies and Practices were measured using items adapted from Belhadi et al. (2021), Iftikhar et al. (2024), and Nikookar & Yanadori (2021). This scale comprised three dimensions, covering key supply chain practices related to organisational performance and adaptability. These dimensions include supply chain resilience (5 items), collaboration in the supply chain (5 items), and supply chain responsiveness (4 items).

Artificial Intelligence Barriers were measured using items adapted from Cannas et al. (2023), Riahi et al. (2023), and Sharma et al. (2022). This scale comprised two dimensions, covering the main obstacles that may hinder the implementation of artificial intelligence in supply chain management. These dimensions include technological barriers (7 items) and business and strategic barriers (24 items).

4. FINDINGS AND DISCUSSION

4.1 Companies Characterisation

The sample obtained through the survey consists of 514 companies (Table I). The majority of these companies (53.9%) have been in operation for over 20 years. The mean firm age is 26.9 years ($SD = 25.3$), which suggests considerable heterogeneity in terms of organisational maturity across the sample.

Regarding the location of the companies' headquarters, the sample was predominantly composed of European organisations (98.2%), with a very small proportion of the companies headquartered in Asia (0.4%). Concerning the number of employees in 2025, most of the surveyed companies employed less than 50 employees (88.1%), while 9.1% employed between 51 and 250 employees. These numbers suggest that most of the companies are Small and Medium-sized Enterprises.

When asked about the types of customers served, 48.6% of the respondents indicated that their organisations operate simultaneously in both Business to Business (B2B) and Business to Consumer (B2C) markets. Additionally, 42.2% reported serving exclusively other businesses (B2B), while only 9.1% indicated that their companies focus solely on end consumers (B2C).

In terms of the geographic scope of supply chain operations, 208 of the surveyed companies reported operating at a national level, representing the largest proportion of the sample (40.5%). 170 have indicated performing international operations (33.1%), while 21.6% of the companies stated that their operations are purely local, within a single city or region. Lastly, 4.9% stated

that they maintain global operations, across several countries. As depicted in Table I, these results suggest that most companies in the sample operate beyond just local scope.

The results on the number of countries involved in supply chain operations demonstrate significant variation among the surveyed companies, with 33.7% of the organisations indicating they operate in a single country, while most of the respondents reported supply chain activities extending across multiple countries (Appendix C - Table I). Regarding the number of suppliers, most surveyed companies stated they work with between 0 and 10 suppliers (56.2%). Furthermore, 23.0% indicated having between 11 and 20 suppliers, whereas only 14.4% reported collaborating with more than 30 suppliers (Table I).

Table I: Companies Characterisation

	Respondents	Frequency
Company age		
< 5	54	10,5%
5 - 10	92	17,9%
11 - 20	87	16,9%
> 20	277	53,9%
<i>Missing Values</i>	4	0,8%
Headquarters		
Asia	2	0,4%
Europe	505	98,2%
<i>Missing Values</i>	7	1,4%
Employees		
< 50	453	88,1%
51 - 250	47	9,1%
> 250	14	2,7%
Type of customers		
B2B - Business to Business	217	42,2%
B2C - Business to Consumer	47	9,1%
Both (B2B & B2C)	250	48,6%
Geographical scope		
Local	111	21,6%
National	208	40,5%
International	170	33,1%
Global	25	4,9%
Number of Suppliers		
0-10	289	56,2%
11-20	118	23,0%
21-30	33	6,4%
> 30	74	14,4%
Total	514	100%

Source: Author's own elaboration.

Lastly, the respondents were also asked to identify the role their organisations performed within the supply chain. Table II shows that the most frequently reported role was that of main manufacturer, selected by 48.7% of companies. Being a multiple-choice option, the results suggest that several organisations simultaneously perform more than one role within the supply chain structure. In addition, 18.3% identified themselves as suppliers or raw material suppliers, while 17.5% reported operating as service providers or logistics providers. The remaining roles, including distributor, wholesaler, retailer, and store operator, were reported less frequently.

Table II: Role of the surveyed companies in the supply chain

	Respondents	Frequency
Supplier / Raw material supplier (upstream)	129	18,3%
Main manufacturer	343	48,7%
Distributor	46	6,5%
Wholesaler	15	2,1%
Retailer (downstream)	19	2,7%
Shopkeeper	29	4,1%
Logistics provider	123	17,5%
Total	704	100%

Source: Author's own elaboration.

Note: Multiple response question.

4.2 Respondents Characterisation

Table III summarises the demographic and professional characteristics of the respondents. The majority have worked for their current company for over 15 years and are aged between 45 and 54. In terms of educational attainment, the most common qualification is a bachelor's degree (31.9%). The sample is relatively balanced in terms of gender, comprising 44.7% female and 53.7% male respondents. Regarding the respondents' position within the company, the majority indicated that they hold the role of Owner / Chairman / CEO.

Table III: Respondents Characterisation

	Respondents	Frequency
Seniority with the company		
< 5 years	147	28,6%
6 - 10 years	117	22,8%
11 - 15 years	55	10,7%
> 16 years	195	37,9%
Position in the company		
Owner / Chairman / CEO	213	41,4%
Managing Director / General Manager	181	35,2%
Logistics Manager / Supply chain	27	5,3%
Other	62	12,1%
<i>Missing Values</i>	31	6,0%
Total	514	100%

Source: Author's own elaboration.

Note: The seniority intervals used were adapted from Patrucco et al. (2025).

4.3 Reliability Analysis

Reliability is important to ensure that the data collected provide consistent measurements of the constructs being analysed. It refers to the degree to which a measurement instrument produces stable and consistent results across different items designed to assess the same construct (Nunnally & Bernstein, 1994). According to Fornell & Larcker (1981), a Cronbach's alpha coefficient of 0.70 or higher is acceptable.

The study used multi-item scales adapted from previous research to measure the constructs under investigation. The survey was divided into sections corresponding to the following constructs: competencies and resources; perceived benefits; supply chain capabilities; and barriers to AI adoption. The items used to measure each construct are presented in Appendix C – Table II.

The internal consistency of these constructs was evaluated using Cronbach's alpha (Table IV). All constructs exceeded the recommended reliability threshold of 0.70, indicating strong internal consistency. Cronbach's alpha values ranged from 0.880 for the 'Technological Infrastructure' dimension of the 'AI Competencies and Resources' construct to the highest value of 0.974 for the 'Disruption Resilience' construct of 'Perceived Benefits' and for 'Business and strategic barriers' construct of 'Barriers'. Given these satisfactory reliability levels, items associated with each construct were aggregated into mean composite scores for further analysis.

Table IV: Cronbach's Alpha

Construct	Abbreviation	Cronbach's Alpha
Technological infrastructure	TI	0,880
Data-related capabilities	DRC	0,910
Human-related capabilities	HRC	0,920
Business competencies and tangible resources that support the implementation of AI	BCTR	0,949
Organisational capabilities	OC	0,967
Capability to manage organisational change and AI-related risks	CMOR	0,920
Benefits of data-driven decision-making and forecasting	BDDDMF	0,946
Benefits relating to operational efficiency and optimisation	BROEO	0,955
Quality management	QM	0,936
Network and supply chain management	NSCM	0,973
Disruption resilience	DR	0,974
Benefits associated with sustainability, safety and maintenance	BASSM	0,936
Supply chain resilience	SCR	0,948
Supply chain collaboration	SCCoI	0,937
Supply chain responsiveness	SCResp	0,886
Technological barriers	TB	0,932
Business and strategic barriers	BSB	0,974
AI Capabilities	AIC	0,899
AI Benefits	AIB	0,964

Source: Author's own elaboration.

AI adoption in SC activities

As shown in Table V, the adoption of AI is most prevalent in operational and analytical supply chain activities. This is particularly evident in sales and demand forecasting (40.9%), inventory and warehouse management (39.5%), process management (33.9%), cost forecasting (31.2%), and production planning and control (30.2%). In contrast, adoption is considerably lower in activities requiring greater inter-organisational integration and strategic coordination, such as supply chain network design (8.6%), risk management and resilience (10.6%), supply chain integration (13.1%), and sustainability management (16.3%).

Table V: AI Adoption in Supply Chain Activities

Supply Chain Activity	Respondents	Frequency	Frequency of Cases
Sales and Demand Forecasting	181	13,3%	40,9%
Supplier and Procurement Management (e.g., supplier selection and evaluation)	125	9,2%	28,2%
Inventory and Warehouse Management (e.g., stock levels, replenishment)	175	12,9%	39,5%
Supply Chain Risk Management and Resilience	47	3,5%	10,6%
Supply Chain Sustainability (e.g., waste reduction, energy consumption forecasting)	72	5,3%	16,3%
Process Management (e.g., process mapping, performance monitoring, automation)	150	11,1%	33,9%
Supply Chain Integration (e.g., information sharing, systems integration)	58	4,3%	13,1%
Supply Chain Network Design (e.g., warehouse location, network configuration)	38	2,8%	8,6%
Maintenance Management (e.g., predictive maintenance)	69	5,1%	15,6%
Logistics and Distribution (e.g., transportation and distribution strategy, route management, reverse logistics)	66	4,9%	14,9%
Production/Manufacturing (e.g., production planning and control, capacity forecasting)	134	9,9%	30,2%
Quality Management	104	7,7%	23,5%
Cost Forecasting	138	10,2%	31,2%

Source: Author's own elaboration.**Note:** Multiple-choice question.

This pattern aligns with the existing literature on AI in supply chains, which suggests that organisations initially adopt AI in domains where data is readily available, implementation is relatively straightforward, and operational benefits can be realised quickly. Riahi et al. (2021) and Sharma et al. (2022) identify forecasting, planning, inventory management, logistics optimisation and decision support as the most mature AI application areas in supply chains. Similarly, Choi et al. (2017) argue that advanced analytics and AI technologies primarily create value by improving information processing and prediction accuracy in data-intensive environments, as well as operational decision-making.

From an organisational information processing perspective, AI enhances capabilities by enabling firms to transform large volumes of data into actionable insights. This supports more accurate planning and resource allocation (Fan et al., 2018).

The strong adoption of AI in process management and production planning also reflects broader digital transformation trends. Studies have demonstrated that AI, automation and smart manufacturing technologies can optimise processes, increase operational flexibility and enhance performance (Frank et al., 2019; Queiroz et al., 2020). Furthermore, digital supply chain technologies enable real-time monitoring and decision-making, helping organisations to boost efficiency and responsiveness across operational processes (Ivanov & Dolgui, 2020; Hohenstein et al., 2015).

In contrast, the lower adoption of AI in supplier management, supply chain integration and collaborative activities suggests that many organisations are still in the early stages of AI development. Such applications usually necessitate extensive data sharing, systems interoperability, and robust collaborative relationships between supply chain partners. Previous studies have consistently demonstrated the critical role of information integration, supply chain visibility, and analytics in enabling digital transformation and improving supply chain performance (Fan et al., 2018; Srinivasan & Swink, 2018). This finding is also consistent with research on supply chain collaboration, which highlights the challenges associated with inter-organisational information sharing and coordinated decision-making (Cao & Zhang, 2011; Min et al., 2005).

Of particular note is the low level of AI adoption in supply chain risk management and resilience (10.6%). This finding is somewhat surprising, given the increasing frequency of disruptions and the growing emphasis on supply chain resilience in research and practice. Existing literature suggests that AI can significantly improve disruption detection, risk prediction, visibility, and adaptive decision-making capabilities (Baryannis et al., 2019; Ivanov & Dolgui, 2020). More recent studies demonstrate that AI capabilities directly contribute to the development of resilience by improving firms' ability to anticipate, absorb and respond to disruptions (Belhadi et al., 2021; Dai & Zhang, 2026). However, implementing AI for resilience purposes usually requires sophisticated analytical capabilities, high-quality data infrastructures, and advanced organisational preparedness, which may account for its more limited adoption among the firms surveyed (Dabbous et al., 2026; Lu et al., 2025).

Similarly, the modest adoption of AI in sustainability management suggests that many organisations prioritise operational efficiency over broader environmental and sustainability goals. Although AI has considerable potential to support waste reduction, energy optimisation and resource efficiency, applications in these areas are less developed than traditional forecasting and planning uses (Riahi et al., 2023; Zamani et al., 2022). This finding is consistent with evidence indicating that firms usually prioritise efficiency-oriented digital transformation

initiatives before applying digital technologies to sustainability and resilience objectives (Hohenstein et al., 2015).

Overall, the findings suggest that the adoption of AI in supply chains is an evolutionary process. In line with the literature on digital transformation, organisations appear to start by adopting AI for forecasting, planning, inventory management and process optimisation, as the benefits are more immediate and the implementation requirements are less complex in these areas. As technology becomes more mature, AI applications gradually expand to include more strategic activities involving supply chain integration, collaboration, resilience and sustainability (Hohenstein et al., 2015; Queiroz et al., 2020). This progression is consistent with the organisational information processing view, which suggests that firms increase their information-processing capabilities incrementally as environmental complexity and coordination requirements grow (Srinivasan & Swink, 2018). Consequently, the future expansion of AI-enabled supply chains will depend on investments in technology, as well as the development of complementary organisational capabilities related to data management, integration, collaboration and change management (Dabbous et al., 2026; Dubey et al., 2021). Therefore, the future expansion of AI-enabled supply chains will depend not only on technological investment, but also on complementary capabilities relating to data management, collaboration and organisational readiness (Dubey et al., 2021).

4.4 Correlation Analysis

Pearson's correlation coefficient was used to evaluate the strength and direction of relationships between the variables in the study. In line with Hair et al. (2010), positive coefficients suggest that an increase in one variable is associated with an increase in another, and larger absolute values indicate a stronger relationship.

AI Competencies and Perceived AI Benefits

The first correlation analysis examined the relationship between AI competencies and the perceived benefits of adopting AI. As shown in Table VI, all AI competency dimensions were significantly and positively correlated with the benefits of AI adoption ($p < 0.01$). These results imply that organisations with stronger AI-related capabilities are more likely to recognise the value of implementing AI in supply chain management.

The strongest relationship was observed between the *capability to manage organisational change and AI-related risks*, and the *benefits relating to operational efficiency and optimisation* ($r = 0.498$, $p < 0.01$). This suggests that successfully realising AI benefits depends not only on

technological investment, but also on an organisation's ability to manage change, adapt processes and overcome implementation risks. This interpretation is consistent with digital transformation literature emphasising that organisational readiness, leadership commitment and change management are critical determinants of technology-enabled performance improvement (Hohenstein et al., 2015; Wamba et al., 2021). Similarly, dynamic capabilities theory suggests that firms create value from emerging technologies when they can reconfigure resources and adapt organisational routines to changing environments (Teece et al., 1997).

A moderate positive relationship was also found between *data-related capabilities* and *benefits associated with sustainability, safety and maintenance* ($r = 0.490$, $p < 0.01$). This is consistent with research that highlights the importance of data quality, accessibility, and integration for AI-enabled predictive maintenance, sustainability monitoring, and operational risk management (Baryannis et al., 2019; Zamani et al., 2022).

AI applications rely heavily on large volumes of accurate, integrated data in order to generate actionable insights. Consequently, organisations with stronger data infrastructures are more likely to reap the benefits of predictive and preventive decision-making processes.

Similarly, *business competencies and tangible resources that support the implementation of AI* were positively associated with the *benefits of data-driven decision-making and forecasting* ($r = 0.475$, $p < 0.01$). This finding corroborates previous research indicating that managerial support, strategic alignment and investment in digital infrastructure are essential enablers of analytical and predictive capabilities (Choi et al., 2017; Wamba et al., 2017). From an organisational information processing theory (OIPT) perspective, these competencies enhance a firm's capacity to process information and mitigate uncertainty, resulting in more informed and precise decision-making (Fan et al., 2018; Srinivasan & Swink, 2018).

Overall, these findings suggest that organisations with more advanced AI-related capabilities are more likely to take advantage of the benefits of AI implementation. This aligns with recent AI readiness frameworks that identify data capabilities, organisational resources, workforce skills and change management as critical factors in creating AI value (Shahzadi et al., 2024). More broadly, the findings support the view that AI-generated benefits emerge not only from the technology itself, but also from the organisational capabilities required to deploy and exploit it effectively (Dabbous et al., 2026; Dubey et al., 2021).

Table VI: Correlation analysis between Competencies and Perceived Benefits

Variables	BDDDMF	BROEO	QM	NSCM	DR	BASSM
TI	0.393**	0.386**	0.370**	0.346**	0.349**	0.385**
DRC	0.459**	0.443**	0.437**	0.454**	0.447**	0.490**
HRC	0.441**	0.436**	0.426**	0.428**	0.402**	0.440**
BCTR	0.475**	0.453**	0.456**	0.473**	0.457**	0.468**
OC	0.440**	0.445**	0.437**	0.422**	0.435**	0.421**
CMOR	0.465**	0.498**	0.473**	0.430**	0.431**	0.408**

Source: Author's own elaboration.

Note: * $p < 0.05$; ** $p < 0.01$ and *** $p < 0.001$.

AI Competencies and Supply Chain Capabilities

A second correlation analysis was conducted to examine the relationship between AI competencies and three key supply chain capabilities: resilience, collaboration and responsiveness. As shown in Table VII, all AI competency dimensions were significantly and positively associated with all three supply chain capabilities.

The strongest relationship was identified between the *capability to manage organisational change and AI-related risks*, and *supply chain resilience* ($r = 0.617$, $p < 0.01$). This strong positive association suggests that organisations that are better prepared to manage technological change and uncertainty are also more capable of anticipating, absorbing and recovering from disruptions. This finding is highly consistent with the emerging literature linking AI adoption and resilience development. AI can enhance a firm's ability to detect disruptions, process large volumes of information, support risk assessment and improve response decisions in uncertain environments (Belhadi et al., 2021; Dai & Zhang, 2026).

The results also showed a strong positive association between the *capability to manage organisational change and AI-related risks* and *supply chain responsiveness* ($r = 0.600$, $p < 0.01$). This suggests that organisations with stronger AI capabilities can respond more quickly to changes in demand, supply conditions and operational disruptions. This is consistent with OM literature demonstrating that information processing capabilities support supply chain agility and responsiveness by improving visibility, flexibility and decision-making speed (Braunscheidel & Suresh, 2009; Swafford et al., 2008). AI technologies further strengthen these capabilities by enabling real-time analytics and predictive insights (Sharma et al., 2022).

Similarly, the *capability to manage organisational change and AI-related risks* was strongly associated with *supply chain collaboration* ($r = 0.586$, $p < 0.01$). This result suggests that organisations with stronger AI-related capabilities tend to develop more collaborative

relationships with their supply chain partners. Previous studies have demonstrated that digital technologies enhance information sharing, visibility and coordination across organisational boundaries, thereby strengthening supply chain integration and collaborative performance (Cao & Zhang, 2011). From an OIPT perspective, AI improves an organisation's capacity to process and exchange information, thereby reducing uncertainty and facilitating joint decision-making among supply chain partners (Fan et al., 2018; Srinivasan & Swink, 2018).

Taken together, these findings suggest that AI-related competencies contribute to both operational improvements and the development of strategic supply chain capabilities and corroborate recent studies demonstrating that AI readiness and AI-enabled innovation bolster resilience, responsiveness, and integration within increasingly intricate supply chain environments (Dabbous et al., 2026; Dai et al., 2025; Lu et al., 2025). Additionally, they reinforce the argument that AI functions as a capability-enabling resource, strengthening firms' ability to sense, respond to, and adapt to environmental changes, which are all core elements of supply chain resilience and agility (Ambulkar et al., 2015; Christopher & Peck, 2004).

Table VII: Correlation analysis between Competencies and Strategies and Practices

Variables	TI	DRC	HRC	BCTR	OC	CMOR
SC Resilience	0.384**	0.471**	0.441**	0.449**	0.476**	0.617**
SC Collaboration	0.379**	0.447**	0.412**	0.440**	0.415**	0.586**
SC Responsiveness	0.335**	0.422**	0.380**	0.421**	0.483**	0.600**

Source: Author's own elaboration.

Note: * $p < 0.05$; ** $p < 0.01$ and *** $p < 0.001$.

AI Competencies and Barriers to AI Adoption

The final correlation analysis examined the relationship between AI competencies and perceived barriers to AI adoption in supply chain management (Table VIII). The results revealed significant positive associations, indicating that organisations with stronger AI competencies also tend to report greater awareness of AI implementation barriers.

A moderate positive correlation was observed between *organisational capabilities* and *business and strategic barriers (BSB)* ($r = 0.341$, $p < 0.01$). Rather than indicating resistance to AI, this finding suggests that organisations with higher maturity levels have a more sophisticated understanding of the strategic challenges involved in AI implementation. These organisations are likely to be more aware of issues relating to governance, organisational alignment, workforce readiness and change management.

Similarly, the *capability to manage organisational change and AI-related risks* was positively associated with *business and strategic barriers (BSB)* ($r = 0.302$, $p < 0.01$). This indicates that organisations actively engaged in managing AI-related transformation processes are more aware of the cultural, organisational and managerial challenges associated with digital transformation initiatives. Research on AI implementation consistently identifies change management, employee acceptance, leadership support and organisational culture as critical barriers to successful adoption (Hangl et al., 2022; Riahi et al., 2023).

A significant positive relationship was also found between *organisational capabilities* and *technological barriers (TB)* ($r = 0.251$, $p < 0.01$). This suggests that firms with more advanced AI initiatives are more likely to recognise challenges related to infrastructure, system integration, data quality, interoperability and technological complexity. Similar observations have been reported in studies of AI implementation and digital transformation, which show that organisations often become more aware of technological constraints as they advance in their implementation journey (Hohenstein et al., 2015; Sharma et al., 2022).

Overall, the findings suggest that organisations with stronger AI competencies are more aware of the technological, organisational and strategic challenges associated with AI adoption. These results are consistent with Dynamic Capabilities Theory and Organisational Information Processing Theory, which propose that companies with more advanced knowledge and capabilities are better able to recognise, assess, and manage opportunities and risks related to emerging technologies (Srinivasan & Swink, 2018; Teece et al., 1997).

Notably, the correlations between AI competencies and adoption barriers were considerably weaker than those observed between AI competencies and AI benefits or supply chain capabilities. This suggests that, while barriers remain relevant, their influence may be outweighed by the perceived benefits and capability-enhancing potential of AI. Consequently, organisations with higher AI maturity appear to recognise implementation challenges while simultaneously perceiving AI as a valuable strategic resource for improving supply chain performance, resilience, integration and responsiveness (Dabbous et al., 2026; Zamani et al., 2022).

Table VIII: Correlation analysis between Competencies and Barriers to AI adoption

Variables	TI	DRC	HRC	BCTR	OC	CMOR
TB	0,132**	0,200**	0,199**	0,213**	0,251**	0,242**
BSB	0,184**	0,238**	0,217**	0,245**	0,341**	0,302**

Source: Author's own elaboration.

Note: * $p < 0.05$; ** $p < 0.01$ and *** $p < 0.001$.

4.5 ANOVA Analysis

AI Capabilities (AIC) and Supply Chain Complexity

Supply chain complexity is commonly examined through two key dimensions: structural and dynamic complexity (Bode & Wagner, 2015; Iftikhar et al., 2023). Structural complexity arises from the number and diversity of entities within the supply chain, including suppliers, customers, products, and their geographical distribution (Bozarth et al., 2009; Iftikhar et al., 2023). In contrast, dynamic complexity reflects variability and uncertainty in operational processes, such as fluctuations in lead times and supplier delivery performance (Akin Ateş et al., 2022; Sivadasan et al., 2002; Wu et al., 2006).

This study focuses on structural complexity, using the geographic dispersion of supply chain actors as an indicator of different complexity levels. To examine whether AI capabilities (AIC) differ according to the complexity of supply chain operations, a one-way analysis of variance (ANOVA) was conducted. The null and alternative hypotheses were formulated as follows:

$$H_0: \mu_{AIC1} = \mu_{AIC2} = \mu_{AIC3} = \mu_{AIC4}$$

$$H_1: \mu_{AICi} \neq \mu_{AICj} \text{ for at least one pair of groups } (i, j = 1, 2, 3, 4)$$

where the four groups correspond to firms operating in supply chains with different levels of complexity: local (1), national (2), international (3), and global (4).

The null hypothesis (H_0) assumes that the mean level of AI capabilities is equal across all four supply chain complexity groups. Conversely, the alternative hypothesis (H_1) posits that at least one group exhibits a significantly different mean level of AI capabilities. The ANOVA results (see Table IX) show statistically significant differences in AI capabilities among firms operating at various levels of supply chain complexity ($F = 10.891$; $p < 0.001$). This suggests that developing AI-related competencies is linked to the geographical scope and structural complexity of supply chain operations. Specifically, firms operating in international and global supply chains exhibit significantly higher levels of AI capability than those operating at a local or national level.

Table IX: Comparison of means of each variable and SC complexity

Variables	AIC	AIB	SCR	SCCol	SCResp
F - Test	10.891	8.875	6.151	3.467	4.659
Significance	< .001***	< .001***	< .001***	.016*	.003**

Source: Author's own elaboration.

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$;

Abbreviations in Appendix C.

From an organisational information processing theory (OIPT) perspective, this finding is theoretically expected. As supply chains become more geographically dispersed and structurally complex, organisations face greater information processing requirements due to increased uncertainty, coordination challenges and interdependencies among supply chain actors (Galbraith, 1974; Srinivasan & Swink, 2018). Under these conditions, firms must develop advanced analytical and digital capabilities to process larger volumes of information and support effective decision-making. AI capabilities are an important mechanism through which organisations can increase their information processing capacity and cope with growing environmental complexity.

These findings are also consistent with research on supply chain complexity. Traditionally, structural complexity has been associated with larger supplier bases, wider geographical dispersion, increased network interdependencies and higher coordination requirements (Bode & Wagner, 2015; Bozarth et al., 2009; Choi & Krause, 2005). As complexity increases, firms become increasingly dependent on data-intensive technologies to support planning, forecasting, coordination and monitoring activities. Consequently, organisations operating in international and global supply chains are likely to invest more heavily in AI-related resources, competencies and infrastructures.

Additionally, the results of the post hoc *Tukey* test (See Appendix D) showed that AI capabilities differ primarily between local/national and international/global firms, with no significant differences observed between the latter two. This pattern may indicate the existence of a capability threshold effect. Once organisations reach a certain level of geographical complexity, they develop the minimum set of AI capabilities necessary to manage it effectively. Further expansion may increase operational scale but does not necessarily require proportionally greater development of AI capabilities.

These findings are consistent with recent digital supply chain literature. Big data analytics and AI technologies improve visibility, decision-making quality and coordination in complex supply networks (Choi et al., 2017; Fan et al., 2018; Wamba et al., 2017). Similarly, research on digital transformation emphasises that organisations facing greater network complexity are increasingly relying on intelligent technologies to enhance information sharing, process integration and operational responsiveness (Hohenstein et al., 2015; Queiroz et al., 2020).

Recent AI literature provides further support for these findings. Dabbous et al. (2026), for example, argue that AI readiness is becoming increasingly valuable as organisations operate in more complex environments, as AI can enhance information processing and adaptive decision-making capabilities. Likewise, Lu et al. (2025) demonstrate that AI capability orientation has a

stronger impact on organisational outcomes in complex supply chain settings. Therefore, the present findings suggest that complexity acts as both a challenge and a catalyst for AI capability development.

Overall, the results support the argument that increasing supply chain complexity stimulates investment in AI-related competencies and resources, as firms seek to improve visibility, coordination and decision-making in an increasingly interconnected supply chain environment.

AI Benefits (AIB) and Supply Chain Complexity

Following the analysis of AI Capabilities, an additional ANOVA was performed to examine whether AI Benefits (AIB) differ according to the complexity of supply chain operations. The null and alternative hypotheses were formulated as follows:

$$H_0: \mu_{AIB1} = \mu_{AIB2} = \mu_{AIB3} = \mu_{AIB4}$$

$$H_1: \mu_{AIBi} \neq \mu_{AIBj} \text{ for at least one pair of groups } (i, j = 1, 2, 3, 4)$$

where the four groups correspond to firms operating in supply chains with different levels of complexity: local (1), national (2), international (3), and global (4).

The null hypothesis (H_0) assumes that the mean level of perceived AI Benefits is equal across all four supply chain complexity groups. Conversely, the alternative hypothesis (H_1) posits that at least one group exhibits a significantly different mean level of perceived AI Benefits.

The ANOVA results presented in Table IX show statistically significant differences in perceived AI Benefits among firms operating at different levels of supply chain complexity ($F = 8.875$; $p < 0.001$). Therefore, the null hypothesis is rejected, indicating that the mean levels of AI Benefits vary according to supply chain complexity.

The results of the post hoc *Tukey* test (See Appendix E) showed no statistically significant differences between organisations operating locally and nationally ($p > 0.05$). However, statistically significant differences were found between local and international organisations ($p < 0.001$), as well as between local and global organisations ($p < 0.05$). Similarly, national organisations reported significantly different levels of perceived AI benefits compared to international ($p < 0.001$) and global organisations ($p < 0.05$). No statistically significant differences were identified between international and global organisations ($p > 0.05$). For these reasons, while organisations operating internationally and globally perceive greater benefits from AI adoption than local and national organisations, the perceived benefits do not differ significantly between international and global firms. This difference may be associated with the greater need to manage information in geographically wider supply chains.

This finding is closely aligned with the organisational information processing theory (OIPT), which proposes that advanced technologies generate greater value when organisations encounter higher levels of uncertainty and information processing demands (Galbraith, 1974; Srinivasan & Swink, 2018). International and global supply chains generate larger volumes of operational data, involve multiple actors across different geographical locations and require extensive coordination mechanisms. In such circumstances, AI-enabled systems can generate substantial benefits by enhancing forecasting accuracy, visibility, decision-making speed and resource allocation.

The absence of significant differences between international and global organisations suggests that AI benefits may also exhibit diminishing marginal returns. Once firms are operating in highly complex supply chain environments, the incremental benefits associated with further geographical expansion may become less pronounced. This finding is broadly consistent with complexity research, which suggests that increasing complexity does not always generate proportionally greater performance improvements (Akin Ateş et al., 2022; Choi & Krause, 2005).

These results are also in line with research on analytics and digital technologies. For example, Choi et al. (2017) and Wamba et al. (2017) demonstrate that analytics capabilities generate greater performance benefits when organisations face higher levels of uncertainty and complexity. Similarly, Dubey et al. (2021) argue that data analytics capabilities enhance organisational flexibility and resilience, enabling firms to manage increasingly complex operating environments more effectively.

A comparable pattern has recently emerged in AI research. Sharma et al. (2022) argue that AI primarily generates value through improved prediction, automation and decision support. Other studies demonstrate that AI is particularly beneficial when organisations need to manage large-scale, dynamic, interconnected supply networks (Belhadi et al., 2021; Dai & Zhang, 2026). Consequently, international and global organisations may perceive greater benefits because AI technologies help them to process larger quantities of information, coordinate geographically dispersed operations and respond more effectively to disruptions.

Overall, these results suggest that the business value derived from AI increases with supply chain complexity, which reinforces the argument that AI technologies are becoming increasingly important as organisations operate across geographically dispersed and structurally complex supply networks.

Supply Chain Capabilities and Supply Chain Complexity

A) Supply Chain Resilience

This study further examines whether three supply chain capabilities (SCCs), namely supply chain resilience, supply chain collaboration, and supply chain responsiveness, differ according to the complexity of supply chain operations. The following hypotheses were tested:

$$H_0: \mu_{SCC1} = \mu_{SCC2} = \mu_{SCC3} = \mu_{SCC4}$$

$$H_1: \mu_{SCCi} \neq \mu_{SCCj} \text{ for at least one pair of groups } (i, j = 1, 2, 3, 4)$$

where the four groups represent organisations operating in local, national, international, and global supply chains, respectively. The null hypothesis assumes that the mean levels of supply chain resilience, collaboration, and responsiveness are equal across the four levels of supply chain complexity, whereas the alternative hypothesis proposes that at least one group differs significantly.

The ANOVA results presented in Table IX show statistically significant differences in supply chain resilience across organisations operating at different levels of supply chain complexity ($F = 6.151$, $p < 0.001$). Therefore, the null hypothesis is rejected, indicating that resilience varies according to the geographical complexity of supply chain operations. *Tukey's* post hoc analysis (See Appendix F) shows that organisations operating in international supply chains exhibit significantly higher resilience than local ($p < 0.05$) and national organisations ($p < 0.05$). Likewise, global organisations report significantly higher SC resilience than both local ($p < 0.01$) and national firms ($p < 0.05$). No significant differences were identified between local and national organisations ($p > 0.05$) or between international and global organisations ($p > 0.05$).

The results show that firms operating in international and global supply chains are significantly more resilient than those operating in local and national ones. This suggests that supply chain complexity is an important driver of resilience capability development.

These results are consistent with foundational supply chain resilience research. Christopher and Peck (2004) and Craighead et al. (2007), for example, argue that geographically dispersed supply chains are exposed to greater disruption risks due to increased interdependencies, longer lead times and greater environmental uncertainty. Consequently, organisations operating in such environments must develop stronger capabilities to anticipate, absorb and recover from disruptions.

The findings also support the dynamic capability view of resilience. Resilience is increasingly viewed as a strategic organisational capability that develops through learning, adaptation and repeated exposure to uncertainty, rather than as a static organisational attribute

(Ambulkar et al., 2015; Ponomarov & Holcomb, 2009). Firms operating in complex international supply networks are more likely to encounter disruptions and therefore accumulate greater experience in managing uncertainty, resulting in stronger resilience capabilities. Bode and Wagner (2015) also demonstrate that structural complexity increases the frequency of disruptions by creating more vulnerability pathways. Similarly, Iftikhar et al. (2024) argue that complexity can have a positive effect by prompting firms to develop exploitative and exploratory capabilities, which ultimately bolster resilience and robustness.

These findings are also consistent with the literature on emerging AI and digital transformation. Iftikhar et al. (2023) demonstrate that analytics capabilities mediate the relationship between complexity and resilience. Dabbous et al. (2026), Dai et al. (2025) and Belhadi et al. (2021) have also concluded that AI can improve resilience through enhanced visibility, risk detection, forecasting accuracy and adaptive decision-making. Consequently, higher resilience among international and global firms may reflect accumulated experience and greater investment in digital and AI-based capabilities.

The lack of significant differences between international and global organisations suggests that resilience may reach a maturity stage beyond a certain level of complexity. Once organisations have developed the routines, collaborative mechanisms and information-processing capabilities required to manage highly complex networks, further geographical expansion may offer limited additional benefits.

B) Supply Chain Collaboration

Regarding supply chain collaboration, the results presented in Table IX reveal statistically significant differences in collaboration capabilities across organisations operating at different levels of supply chain complexity ($F = 3.467$, $p < 0.05$). Therefore, the null hypothesis is rejected, indicating that supply chain collaboration varies according to the geographical complexity of supply chain operations. However, the *Tukey* post hoc analysis (See Appendix G) did not identify statistically significant differences among the groups.

Nevertheless, the overall ANOVA result suggests that geographical expansion and increasing supply chain complexity are associated with variations in collaborative capability development.

This finding is consistent with SC research highlighting that complex and geographically dispersed supply chains require stronger inter-organisational collaboration mechanisms to facilitate coordination, information sharing, and joint problem solving (Cao & Zhang, 2011; Simatupang & Sridharan, 2005). In particular, supply chain collaboration becomes increasingly

important as firms rely on external partners across multiple locations and organisational boundaries to manage uncertainty and improve operational performance (Brandon-Jones et al., 2014; Fawcett et al., 2011). Moreover, greater coordination, information sharing and joint decision-making are required among supply chain partners as network complexity increases (Cao & Zhang, 2011; Min et al., 2005; Simatupang & Sridharan, 2005). As organisations expand geographically, collaborative mechanisms become increasingly important for managing information flows and reducing uncertainty.

From an Organisational Information Processing Theory (OIPT) perspective, collaboration constitutes a critical information-processing mechanism that enables firms to manage increasing levels of supply chain complexity and uncertainty by facilitating information exchange, joint decision-making, and coordinated action across organisational boundaries (Srinivasan & Swink, 2018). As supply chains become more interconnected, globalised, and geographically dispersed, organisations face greater information-processing requirements that exceed the capacity of traditional coordination mechanisms. Consequently, collaborative relationships become increasingly important for enhancing supply chain visibility, synchronising activities, and aligning decisions among supply chain partners (Cao & Zhang, 2011; Fan et al., 2018).

Recent research on digital transformation further reinforces this perspective by demonstrating that digital capabilities - including big data analytics, artificial intelligence, and digital connectivity - expand firms' information-processing capacity through real-time information sharing, enhanced visibility, and improved supply chain integration (Dubey et al., 2021; Holmström et al., 2019; Wamba et al., 2017). These capabilities improve organisational responsiveness and flexibility, enabling firms to coordinate more effectively across complex supply networks and respond more rapidly to environmental uncertainty (Ivanov & Dolgui, 2020; Modgil et al., 2021; Pournader et al., 2021).

C) Supply Chain Responsiveness

A different pattern emerged for supply chain responsiveness. The ANOVA results (see Table IX) reveal statistically significant differences among the analysed groups ($F = 4.659$, $p < 0.01$), while the *Tukey* post hoc analysis (See Appendix H) indicates that international organisations report significantly higher responsiveness levels than local ($p < 0.05$) and national organisations ($p < 0.05$). However, no statistically significant differences were observed between global organisations and the remaining groups or between international and global organisations. These findings suggest that responsiveness improves as organisations expand

beyond domestic markets, but this capability may not continue increasing once firms reach a highly complex global operational scope.

This pattern can be explained by the increasing need for agility and rapid decision-making in internationally distributed supply chains. SCM studies indicate that supply chain responsiveness is strongly influenced by visibility, coordination mechanisms, and the ability to process information quickly across organisational boundaries (Christopher & Peck, 2004; Swafford et al., 2008). Firms operating internationally are exposed to diverse markets, suppliers, and customer requirements, which may stimulate the development of responsive capabilities to manage greater uncertainty and variability. Similarly, studies on supply chain agility suggest that companies facing dynamic environments develop capabilities related to flexibility, speed, and adaptation to maintain competitiveness (Braunscheidel & Suresh, 2009; Swafford et al., 2008).

The results also show that international organisations are significantly more responsive than local and national organisations. These findings suggest that geographical expansion stimulates the development of responsiveness capabilities by exposing firms to greater uncertainty, market diversity and operational variability. This result is aligned with the supply chain literature. Braunscheidel and Suresh (2009) and Swafford et al. (2008) demonstrate that responsiveness depends heavily on information processing capabilities, flexibility and integration mechanisms. International firms face greater pressure to coordinate globally dispersed activities and respond swiftly to changes in the market, creating an incentive to develop responsiveness capabilities.

The findings also support the organisational information processing theory perspective. Increasing complexity raises the volume and velocity of information processing requirements, encouraging firms to invest in technologies and processes that improve visibility and accelerate decision-making (Fan et al., 2018; Srinivasan & Swink, 2018).

However, the absence of significant differences between international and global organisations suggests that responsiveness may not increase indefinitely with complexity. This finding supports Choi and Krause's (2005) argument that complexity has nonlinear effects. While moderate increases in complexity can stimulate capability development, excessive complexity may create coordination issues that offset potential gains in responsiveness. Similarly, Bozarth et al. (2009) argue that highly complex supply networks may introduce managerial challenges that hinder performance improvements. Consequently, global firms may reach a point where additional complexity generates both benefits and coordination costs, resulting in a plateau in responsiveness performance.

Overall, the findings suggest that supply chain complexity acts as both a challenge and a mechanism for building capabilities. As organisations expand geographically, they appear to develop stronger AI capabilities, resilience, collaboration and responsiveness. However, these benefits do not increase indefinitely, indicating the existence of maturity effects and diminishing returns on capabilities at very high levels of supply chain complexity.

5. CONCLUSION

This study aimed to analyse how managers perceive the adoption of Artificial Intelligence (AI) within their organisations, the extent to which AI is being adopted across supply chain activities, and how AI capabilities are associated with supply chain resilience. A quantitative approach was adopted, based on survey data from a final sample of 514 companies operating in Portugal, analysed through descriptive statistics and Pearson correlation analysis. Overall, the results show that AI capabilities and organisational resources are positively associated with the perceived benefits of AI in SCM, and that these benefits are, in turn, positively related to supply chain resilience, responsiveness and collaboration.

With respect to the extent of adoption, AI is used mainly in operational and analytical activities such as sales and demand forecasting, inventory and warehouse management, process management, and cost forecasting. In contrast, its use remains more limited in strategic and inter-organisational activities, such as supply chain network design, risk management, integration and sustainability. In response to the first research question (RQ1), managers in Portuguese manufacturing companies perceive AI adoption as relevant for improving supply chain activities, mainly through operational efficiency, data-driven decision-making, forecasting, sustainability and disruption management. In response to the second research question (RQ2), AI capabilities and perceived AI benefits are positively associated with supply chain resilience, with the strongest relationship observed between the capability to manage organisational change and AI-related risks and supply chain resilience, responsiveness, and collaboration. Moreover, organisations operating at international and global levels report higher levels of AI capabilities, benefits and resilience than those operating locally or nationally. The study therefore concludes that value creation from AI in SCM should not be understood only as a technological implementation, but also as an organisational process that depends on adequate resources, managerial awareness, data capabilities and organisational readiness, reinforcing the importance of developing internal capabilities to strengthen resilience in increasingly complex supply chain environments.

Theoretical Implications

This study extends the AI-SCM literature by providing empirical evidence from Portuguese manufacturing firms, an underexplored context. The findings support the dynamic capabilities perspective by showing that AI value creation depends on complementary organisational capabilities rather than technological resources alone. In particular, organisational change and AI risk management exhibit stronger associations with resilience, responsiveness, and operational performance than purely technological capabilities.

The study also contributes to the emerging literature on AI-enabled supply chain resilience by empirically confirming that AI capabilities are positively associated with resilience, collaboration, and responsiveness. Furthermore, the results suggest that AI adoption follows a staged process, with firms prioritising operational applications before extending AI to more strategic and inter-organisational activities. Finally, the higher AI capabilities observed among internationally operating firms indicate that environmental complexity and international exposure may accelerate capability development and AI value creation.

Managerial Implications

The findings suggest that managers should approach AI implementation as an organisational transformation rather than a technological investment. Realising AI benefits requires complementary investments in data quality, organisational capabilities, employee skills, and change management.

The results further indicate that firms currently concentrate AI adoption on forecasting, inventory, and production planning, while underutilising AI for resilience, risk management, and supply chain integration. Managers should therefore expand AI applications towards these strategic areas to strengthen resilience and competitive advantage. Finally, organisations should align AI initiatives with broader supply chain strategy, supported by governance mechanisms, workforce development, and continuous organisational learning, to maximise long-term value.

Limitations and further research

This study is subject to some limitations that should be considered when interpreting the findings. First, the sample consisted exclusively of organisations operating in Portugal, so the results may not be fully generalisable to other national contexts, where economic conditions, technological maturity, regulatory frameworks and supply chain structures may differ. Second, a cross-sectional design was adopted, collecting data at a single point in time; the results therefore reflect respondents' perceptions during the data collection period and do not allow an

assessment of how AI capabilities, benefits and supply chain outcomes evolve. Finally, the analysis relied on self-reported survey data, capturing managers' perceptions rather than objective measures of organisational performance, which may be subject to respondent bias.

Regarding future research, it would be valuable to include organisations from a broader range of countries and supply chain contexts to assess whether the findings hold across different economic, technological, and regulatory environments. Larger and more diverse samples would also enable more detailed comparisons across industries, organisational sizes and supply chain configurations. In addition, future studies could examine the impact of specific AI technologies, such as machine learning, generative AI, predictive analytics or digital twins, since different applications may generate distinct capabilities, benefits and outcomes. Finally, longitudinal studies could investigate how AI capabilities, perceived benefits and supply chain outcomes evolve over time, providing a deeper understanding of the long-term effects of AI adoption in supply chains.

REFERENCES

- Agarwal, A., Jayant, A. (2019). Application of Machine Learning Techniques in Supply Chain Management. *International Research Journal of Management Science & Technology*. <http://www.irjmst.com/abstractview/8007>
- Akın Ateş, M., Suurmond, R., Luzzini, D., & Krause, D. R. (2022). Order from chaos: A meta-analysis of supply chain complexity and firm performance. *Journal of Supply Chain Management*, 58(1), 3–30. <https://doi.org/10.1111/jscm.12274>
- Ambulkar, S., Blackhurst, J., & Grawe, S. (2015). Firm's resilience to supply chain disruptions: Scale development and empirical examination. *Journal of Operations Management*, 33–34(1), 111–122. <https://doi.org/10.1016/j.jom.2014.11.002>
- Arinez, J. F., Chang, Q., Gao, R. X., Xu, C., & Zhang, J. (2020). Artificial intelligence in Advanced Manufacturing: current status and future outlook. *Journal of Manufacturing Science and Engineering*, 142(11). <https://doi.org/10.1115/1.4047855>
- Baryannis, G., Dani, S., & Antoniou, G. (2019). Predicting supply chain risks using machine learning: The trade-off between performance and interpretability. *Future Generation Computer Systems*, 101, 993–1004. <https://doi.org/10.1016/j.future.2019.07.059>
- Baryannis, G., Dani, S., & Antoniou, G. (2019). Predictive analytics and artificial intelligence in supply chain management: Review and implications for the future. *Computers & Industrial Engineering*, 137, 106024.
- Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2019). Supply chain risk management and artificial intelligence: state of the art and future research directions. *International Journal of Production Research*, 57(7), 2179–2202. <https://doi.org/10.1080/00207543.2018.1530476>
- Baxter, N., Collings, D., & Adjali, I. (2003). Agent-Based Modelling — Intelligent Customer Relationship Management. *BT Technology Journal*, 21(2), 126–132. <https://doi.org/10.1023/a:1024455405112>
- Belhadi, A., Mani, V., Kamble, S. S., Khan, S. a. R., & Verma, S. (2021). Artificial intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: an empirical investigation. *Annals of Operations Research*, 333(2–3), 627–652. <https://doi.org/10.1007/s10479-021-03956-x>
- Beta, K., Nagaraj, S. S., & Weerasinghe, T. D. (2025). The role of artificial intelligence on supply chain resilience. *Journal of Enterprise Information Management*, 38(3), 950–973. <https://doi.org/10.1108/jeim-12-2023-0674>

- Birkel, H., Hohenstein, N., & Hähner, S. (2023). How have digital technologies facilitated supply chain resilience in the COVID-19 pandemic? An exploratory case study. *Computers & Industrial Engineering*, 183, 109538. <https://doi.org/10.1016/j.cie.2023.109538>
- Bode, C., & Wagner, S. M. (2015). Structural drivers of upstream supply chain complexity and the frequency of supply chain disruptions. *Journal of Operations Management*, 36(1), 215–228. <https://doi.org/10.1016/j.jom.2014.12.004>
- Boyes, H., Hallaq, B., Cunningham, J., & Watson, T. (2018). The industrial internet of things (IIoT): An analysis framework. *Computers in Industry*, 101, 1–12. <https://doi.org/10.1016/j.compind.2018.04.015>
- Bozarth, C. C., Warsing, D. P., Flynn, B. B., & Flynn, E. J. (2009). The impact of supply chain complexity on manufacturing plant performance. *Journal of Operations Management*, 27(1), 78–93. <https://doi.org/10.1016/j.jom.2008.07.003>
- Brandon-Jones, E., Squire, B., Autry, C. W., & Petersen, K. J. (2014). A contingent resource-based perspective of supply chain resilience and robustness. *Journal of Supply Chain Management*, 50(3), 55–73. <https://doi.org/10.1111/jscm.12050>
- Braunscheidel, M. J., & Suresh, N. C. (2009). The organizational antecedents of a firm's supply chain agility for risk mitigation and response. *Journal of Operations Management*, 27(2), 119–140. <https://doi.org/10.1016/j.jom.2008.09.006>
- Burger, M., Nitsche, A., & Arlinghaus, J. (2023). Hybrid intelligence in procurement: Disillusionment with AI's superiority? *Computers in Industry*, 150, 103946. <https://doi.org/10.1016/j.compind.2023.103946>
- Calatayud, A., Mangan, J., & Christopher, M. (2018). The self-thinking supply chain. *Supply Chain Management an International Journal*, 24(1), 22–38. <https://doi.org/10.1108/scm-03-2018-0136>
- Cannas, V. G., Ciano, M. P., Saltalamacchia, M., & Secchi, R. (2023). Artificial intelligence in supply chain and operations management: a multiple case study research. *International Journal of Production Research*, 62(9), 3333–3360. <https://doi.org/10.1080/00207543.2023.2232050>
- Cao, M., & Zhang, Q. (2011). Supply chain collaboration: Impact on collaborative advantage and firm performance. *Journal of Operations Management*, 29(3), 163–180. <https://doi.org/10.1016/j.jom.2010.12.008>

- Carbonneau, R., Laframboise, K., & Vahidov, R. (2007). Application of machine learning techniques for supply chain demand forecasting. *European Journal of Operational Research*, 184(3), 1140–1154. <https://doi.org/10.1016/j.ejor.2006.12.004>
- Chien, C., Ku, C., & Lu, Y. (2023). Ensemble learning for demand forecast of After-Market spare parts to empower data-driven value chain and an empirical study. *Computers & Industrial Engineering*, 185, 109670. <https://doi.org/10.1016/j.cie.2023.109670>
- Choi, T. Y., & Krause, D. R. (2005). The supply base and its complexity: Implications for transaction costs, risks, responsiveness, and innovation. *Journal of Operations Management*, 24(5), 637–652. <https://doi.org/10.1016/j.jom.2005.07.002>
- Choi, T., Wallace, S. W., & Wang, Y. (2017). Big Data Analytics in operations management. *Production and Operations Management*, 27(10), 1868–1883. <https://doi.org/10.1111/poms.12838>
- Christopher, M., & Peck, H. (2004). Building the resilient supply chain. *The International Journal of Logistics Management*, 15(2), 1–14. <https://doi.org/10.1108/09574090410700275>
- CSCMP (n.d.). *SCM Definitions and Glossary of Terms*. https://cscmp.org/CSCMP/Educate/SCM_Definitions_and_Glossary_of_Terms.aspx
- Craighead, C. W., Blackhurst, J., Rungtusanatham, M. J., & Handfield, R. B. (2007). The severity of supply chain disruptions: Design characteristics and mitigation capabilities. *Decision Sciences*, 38(1), 131–156. <https://doi.org/10.1111/j.1540-5915.2007.00151.x>
- Culot, G., Podrecca, M., & Nassimbeni, G. (2024). Artificial intelligence in supply chain management: A systematic literature review of empirical studies and research directions. *Computers in Industry*, 162, 104132. <https://doi.org/10.1016/j.compind.2024.104132>
- Dabbous, A., Sayegh, M. M., Barakat, K. A., & Veglianti, E. (2026). Corporate artificial intelligence readiness and its contribution to supply chain resilience: insights from complexity theory. *International Journal of Production Research*, 64(6), 2331–2353. <https://doi.org/10.1080/00207543.2025.2578299>
- Dai, J., Geng, R., Xu, D., Shangguan, W., & Shao, J. (2025). Unveiling the impact of the congruence between artificial intelligence and explorative learning on supply chain resilience. *International Journal of Operations & Production Management*, 45(2), 570–593. <https://doi.org/10.1108/ijopm-12-2023-0990>

- Dai, J., & Zhang, A. (2026). Does artificial intelligence (AI) adoption enable resilience to disruptions among firms? An in-depth examination. *Technological Forecasting and Social Change*, 227, 124546. <https://doi.org/10.1016/j.techfore.2026.124546>
- Deloitte. (2020). “The window for AI competitive advantage is narrowing how can AI adopters keep their edge?” <https://www2.deloitte.com/us/en/insights/industry/technology/ai-competitive-advantage-narrowing.html>.
- Dillman, D. A., Smyth, J. D., & Christian, L. M. (2014). *Internet, phone, mail, and mixed-mode surveys: The tailored design method* (4th ed.). Wiley.
- Dolgui, A., & Ivanov, D. (2020). Exploring supply chain structural dynamics: New disruptive technologies and disruption risks. *International Journal of Production Economics*, 229, 107886. <https://doi.org/10.1016/j.ijpe.2020.107886>
- Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Giannakis, M., Foropon, C., Roubaud, D., & Hazen, B. T. (2019). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations. *International Journal of Production Economics*, 226, 107599. <https://doi.org/10.1016/j.ijpe.2019.107599>
- Dubey, R., Gunasekaran, A., Childe, S. J., Wamba, S. F., Roubaud, D., & Foropon, C. (2021). Empirical investigation of data analytics capability and organizational flexibility as complements to supply chain resilience. *International Journal of Production Research*, 59(1), 110–128. <https://doi.org/10.1080/00207543.2019.1582820>
- Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., . . . Williams, M. D. (2019). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, 101994. <https://doi.org/10.1016/j.ijinfomgt.2019.08.002>
- Ennajeh, L., & Najar, T. (2023). Artificial Intelligence and Supply Chain Management: An Integrative Literature Review. *IEEE*. <https://doi.org/10.1109/amcai59331.2023.10431506>
- European Investment Bank. (2021). *EIB Investment Survey 2021: Portugal overview*. European Investment Bank. <https://doi.org/10.2867/614689>

- Fan, Y., & Stevenson, M. (2018). A review of supply chain risk management: definition, theory, and research agenda. *International Journal of Physical Distribution & Logistics Management*, 48(3), 205–230. <https://doi.org/10.1108/ijpdlm-01-2017-0043>
- Fan, Y., Stevenson, M., & Li, C. (2018). How supply chain analytics enables operational supply chain transparency: An organizational information processing theory perspective. *International Journal of Physical Distribution & Logistics Management*, 48(1), 47–68. <https://doi.org/10.1108/IJPDLM-11-2017-0341>
- Fawcett, S. E., Magnan, G. M., & McCarter, M. W. (2011). Benefits, barriers, and bridges to effective supply chain management. *Supply Chain Management: An International Journal*, 16(1), 6–20. <https://doi.org/10.1108/13598541111103467>
- Feizabadi, J. (2020). Machine learning demand forecasting and supply chain performance. *International Journal of Logistics Research and Applications*, 25(2), 119–142. <https://doi.org/10.1080/13675567.2020.1803246>
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 29–50.
- Forza, C. (2002). Survey research in operations management: a process-based perspective. *International Journal of Operations & Production Management*, 22(2), 152–194. <https://doi.org/10.1108/01443570210414310>
- Frank, A. G., Dalenogare, L. S., & Ayala, N. F. (2019). Industry 4.0 technologies: Implementation patterns in manufacturing companies. *International Journal of Production Economics*, 210, 15–26. <https://doi.org/10.1016/j.ijpe.2019.01.004>
- Frohlich, M. T. (2002). Techniques for improving response rates in OM survey research. *Journal of Operations Management*, 20(1), 53–62. [https://doi.org/10.1016/s0272-6963\(02\)00003-7](https://doi.org/10.1016/s0272-6963(02)00003-7)
- Galbraith, J. R. (1974). Organization Design: an information processing view. *INFORMS Journal on Applied Analytics*, 4(3), 28–36. <https://doi.org/10.1287/inte.4.3.28>
- Garg, R., Kiwelekar, A. W., & Netak, L. D. (2021). Logistics and Freight Transportation Management: An NLP based Approach for Shipment Tracking. *Pertanika Journal of Science & Technology*, 29(4). <https://doi.org/10.47836/pjst.29.4.28>
- Grover, P., Kar, A. K., & Dwivedi, Y. K. (2020). Understanding artificial intelligence adoption in operations management: insights from the review of academic literature and social media discussions. *Annals of Operations Research*, 308(1–2), 177–213. <https://doi.org/10.1007/s10479-020-03683-9>

- Guner, H. U., Chinnam, R. B., & Murat, A. (2015). Simulation platform for anticipative plant-level maintenance decision support system. *International Journal of Production Research*, 54(6), 1785–1803. <https://doi.org/10.1080/00207543.2015.1064179>
- Gupta, S., Modgil, S., Bhattacharyya, S., & Bose, I. (2021). Artificial intelligence for decision support systems in the field of operations research: review and future scope of research. *Annals of Operations Research*, 308(1–2), 215–274. <https://doi.org/10.1007/s10479-020-03856-6>
- Hair, J., Black, W., Babin, B., & Anderson, R. (2010). *Multivariate data analysis with readings* (7th ed.). Prentice Hall.
- Hangl, J., Behrens, V. J., & Krause, S. (2022). Barriers, Drivers, and Social Considerations for AI adoption in Supply Chain Management: a Tertiary study. *Logistics*, 6(3), 63. <https://doi.org/10.3390/logistics6030063>
- Hangl, J., Krause, S., & Behrens, V. J. (2023). Drivers, barriers and social considerations for AI adoption in SCM. *Technology in Society*, 74, 102299. <https://doi.org/10.1016/j.techsoc.2023.102299>
- Helo, P., & Hao, Y. (2021). Artificial intelligence in operations management and supply chain management: an exploratory case study. *Production Planning & Control*, 33(16), 1573–1590. <https://doi.org/10.1080/09537287.2021.1882690>
- Hendriksen, C. (2023). Artificial intelligence for supply chain management: Disruptive innovation or innovative disruption? *Journal of Supply Chain Management*, 59(3), 65–76. <https://doi.org/10.1111/jscm.12304>
- Hohenstein, N., Feisel, E., Hartmann, E., & Giunipero, L. (2015). Research on the phenomenon of supply chain resilience. *International Journal of Physical Distribution & Logistics Management*, 45(1/2), 90–117. <https://doi.org/10.1108/ijpdlm-05-2013-0128>
- Holmström, J., Holweg, M., Lawson, B., Pil, F. K., & Wagner, S. M. (2019). The digitalization of operations and supply chain management: Theoretical and methodological implications. *Journal of Operations Management*, 65(8), 728–734. <https://doi.org/10.1002/joom.1073>
- IBM Corporation. (2021). *IBM SPSS Statistics for Windows* (Version 28.0). IBM Corporation.
- Iftikhar, A., Ali, I., & Stevenson, M. (2024). The silver lining of supply chain complexity: Building supply chain resilience and robustness through exploitation and exploration. *Supply Chain Management: An International Journal*, 29(2), 244–259. <https://doi.org/10.1108/SCM-01-2023-0022>

- Iftikhar, A., Purvis, L., Giannoccaro, I., & Wang, Y. (2023). The impact of supply chain complexities on supply chain resilience: The mediating effect of big data analytics. *Production Planning & Control*, 34(16), 1562–1582. <https://doi.org/10.1080/09537287.2022.2032450>
- Ivanov, D., & Dolgui, A. (2020). A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. *Production Planning & Control*, 32(9), 775–788. <https://doi.org/10.1080/09537287.2020.1768450>
- Ivanov, D., Dolgui, A., & Sokolov, B. (2018). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal of Production Research*, 57(3), 829–846. <https://doi.org/10.1080/00207543.2018.1488086>
- Jackson, I., Ivanov, D., Dolgui, A., & Namdar, J. (2024). Generative artificial intelligence in supply chain and operations management: a capability-based framework for analysis and implementation. *International Journal of Production Research*, 62(17), 6120–6145. <https://doi.org/10.1080/00207543.2024.2309309>
- Ketokivi, M. A., & Schroeder, R. G. (2004). Perceptual measures of performance: fact or fiction? *Journal of Operations Management*, 22(3), 247–264. <https://doi.org/10.1016/j.jom.2002.07.001>
- Kobbacy, K. a. H., Vadera, S., & Rasmy, M. H. (2006). AI and OR in management of operations: history and trends. *Journal of the Operational Research Society*, 58(1), 10–28. <https://doi.org/10.1057/palgrave.jors.2602132>
- Kurrahman, T., Tsai, F. M., Lim, M. K., Sethanan, K., & Tseng, M. (2025). Generative AI capabilities for green supply chain management improvement: extended dynamic capabilities view. *International Journal of Logistics Research and Applications*, 1–28. <https://doi.org/10.1080/13675567.2025.2479006>
- Lamees, A., & Ramayah, T. (2025). How artificial intelligence-based supply chain analytics enable supply chain agility and innovation? An intellectual capital perspective. *Supply Chain Management an International Journal*, 30(2), 233–249. <https://doi.org/10.1108/scm-09-2024-0558>
- Li, S., Ragu-Nathan, B., Ragu-Nathan, T., & Rao, S. S. (2004). The impact of supply chain management practices on competitive advantage and organizational performance. *Omega*, 34(2), 107–124. <https://doi.org/10.1016/j.omega.2004.08.002>
- Lu, X., Chiang, C.-Y., Wu, F., & Xu, X. (2025). Whose AI matters? Examining the bilateral effects of AI capability orientation on supply chain resilience. *International Journal of*

- Operations & Production Management*, 45(8), 1549–1577.
<https://doi.org/10.1108/IJOPM-09-2024-0790>
- Maddikunta, P. K. R., Pham, Q., B, P., Deepa, N., Dev, K., Gadekallu, T. R., Ruby, R., & Liyanage, M. (2021). Industry 5.0: A survey on enabling technologies and potential applications. *Journal of Industrial Information Integration*, 26, 100257.
<https://doi.org/10.1016/j.jii.2021.100257>
- McCarthy, J. (2007). “WHAT IS ARTIFICIAL INTELLIGENCE?”, <https://www-formal.stanford.edu/jmc/whatisai.pdf>
- Mentzer, J. T., DeWitt, W., Keebler, J. S., Min, S., Nix, N. W., Smith, C. D., & Zacharia, Z. G. (2001). DEFINING SUPPLY CHAIN MANAGEMENT. *Journal of Business Logistics*, 22(2), 1–25. <https://doi.org/10.1002/j.2158-1592.2001.tb00001.x>
- Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, 58(3), 103434.
<https://doi.org/10.1016/j.im.2021.103434>
- Min, H. (2009). Artificial intelligence in supply chain management: theory and applications. *International Journal of Logistics Research and Applications*, 13(1), 13–39.
<https://doi.org/10.1080/13675560902736537>
- Min, S., Roath, A. S., Daugherty, P. J., Genchev, S. E., Chen, H., Arndt, A. D., & Richey, R. G. (2005). Supply chain collaboration: What’s happening? *The International Journal of Logistics Management*, 16(2), 237–256. <https://doi.org/10.1108/09574090510634539>
- Misner, J., & Carr, G. (2023, May 15). *Survey research*. Messages That Matter: Public Speaking in the Information Age - Third Edition.
<https://nic.pressbooks.pub/messageshatmatter/chapter/survey-research/>
- Modgil, S., Gupta, S., Stekelorum, R., & Laguir, I. (2021). AI technologies and their impact on supply chain resilience during COVID-19. *International Journal of Physical Distribution & Logistics Management*, 52(2), 130–149. <https://doi.org/10.1108/ijpdlm-12-2020-0434>
- Nikookar, E., & Yanadori, Y. (2021). Preparing supply chain for the next disruption beyond COVID-19: managerial antecedents of supply chain resilience. *International Journal of Operations & Production Management*, 42(1), 59–90. <https://doi.org/10.1108/ijopm-04-2021-0272>
- Ning, Y., Li, L., Xu, S. X., & Yang, S. (2022). How do digital technologies improve supply chain resilience in the COVID-19 pandemic? Evidence from Chinese manufacturing

- firms. *Frontiers of Engineering Management*, 10(1), 39–50.
<https://doi.org/10.1007/s42524-022-0230-4>
- Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.).
- Oracle. (2023, September 21). *What is ERP?* <https://www.oracle.com/erp/what-is-erp/>
- Osman, B. M., Alinkeel, S., & Bhavshar, D. (2022). A study on role of artificial intelligence to improve inventory management system. *International Research Journal of Modernization in Engineering Technology and Science*, 4(3), 226-233.
https://www.irjmets.com/uploadedfiles/paper/issue_3_march_2022/19468/final/fin_irj_mets1646486656.pdf
- Pandey, B. K., Paramashivan, M. A., Hasan, A., Pramanik, S., Dadheech, P., Manaktala, S. S., & George, A. S. (2024). Social psychological obstacles to the implementation of artificial intelligence in supply chain management. In *Advances in logistics, operations, and management science book series* (pp. 17–24). <https://doi.org/10.4018/979-8-3693-1347-3.ch002>
- Patrucco, A. S., Rodrigues, V. P., Fransoo, J. C., & Mejia-Argueta, C. (2025). Resilient supply chains amid uncertainty: Do agility, adaptability, and alignment mitigate the effects of major disruptions? *Journal of Business Logistics*, 46(4).
<https://doi.org/10.1111/jbl.70037>
- Peres, R. S., Jia, X., Lee, J., Sun, K., Colombo, A. W., & Barata, J. (2020). Industrial Artificial Intelligence in Industry 4.0 - Systematic Review, Challenges and Outlook. *IEEE Access*, 8, 220121–220139. <https://doi.org/10.1109/access.2020.3042874>
- Plathottam, S. J., Rzonca, A., Lakhnori, R., & Iloeje, C. O. (2023). A review of artificial intelligence applications in manufacturing operations. *Journal of Advanced Manufacturing and Processing*, 5(3). <https://doi.org/10.1002/amp2.10159>
- Podsakoff, P. M., MacKenzie, S. B., Lee, J., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>
- Ponomarov, S. Y., & Holcomb, M. C. (2009). Understanding the concept of supply chain resilience. *The International Journal of Logistics Management*, 20(1), 124–143.
<https://doi.org/10.1108/09574090910954873>
- Pournader, M., Ghaderi, H., Hassanzadegan, A., & Fahimnia, B. (2021). Artificial intelligence applications in supply chain management. *International Journal of Production Economics*, 241, 108250. <https://doi.org/10.1016/j.ijpe.2021.108250>

- Queiroz, M. M., Wamba, S. F., Machado, M. C., & Telles, R. (2020). Smart production systems drivers for business process management improvement. *Business Process Management Journal*, 26(5), 1075–1092. <https://doi.org/10.1108/bpmj-03-2019-0134>
- Rakholia, R., Suárez-Cetrulo, A. L., Singh, M., & Carbajo, R. S. (2024). Advancing Manufacturing through Artificial intelligence: current landscape, perspectives, best practices, challenges and future direction. *IEEE Access*, 1. <https://doi.org/10.1109/access.2024.3458830>
- Riahi, Y., Saikouk, T., Badraoui, I., & Wamba, S. F. (2023). Researched topics, patterns, barriers and enablers of artificial intelligence implementation in supply chain: a Latent-Dirichlet-allocation-based topic-modelling and expert validation. *Production Planning & Control*, 36(5), 565–592. <https://doi.org/10.1080/09537287.2023.2286523>
- Riahi, Y., Saikouk, T., Gunasekaran, A., & Badraoui, I. (2021). Artificial intelligence applications in supply chain: A descriptive bibliometric analysis and future research directions. *Expert Systems With Applications*, 173, 114702. <https://doi.org/10.1016/j.eswa.2021.114702>
- Richey, R. G., Chowdhury, S., Davis-Sramek, B., Giannakis, M., & Dwivedi, Y. K. (2023). Artificial intelligence in logistics and supply chain management: A primer and roadmap for research. *Journal of Business Logistics*, 44(4), 532–549. <https://doi.org/10.1111/jbl.12364>
- Rungtusanatham, M., Choi, T. Y., Hollingworth, D. G., Wu, Z., & Forza, C. (2003). Survey research in operations management: historical analyses. *Journal of Operations Management*, 21(4), 475–488. [https://doi.org/10.1016/s0272-6963\(03\)00020-2](https://doi.org/10.1016/s0272-6963(03)00020-2)
- Sahoo, S., Kumar, S., Donthu, N., & Singh, A. K. (2024). Artificial intelligence capabilities, open innovation, and business performance—Empirical insights from multinational B2B companies. *Industrial marketing management*, 117, 28–41.
- Saunders, M. N. K., Lewis, P., & Thornhill, A. (2019). *Research Methods for Business Students*. (8th ed.). Pearson Education.
- Shahzadi, G., Jia, F., Chen, L., & John, A. (2024a). AI adoption in supply chain management: a systematic literature review. *Journal of Manufacturing Technology Management*, 35(6), 1125–1150. <https://doi.org/10.1108/jmtm-09-2023-0431>
- Sharma, R., Shishodia, A., Gunasekaran, A., Min, H., & Munim, Z. H. (2022). The role of artificial intelligence in supply chain management: mapping the territory. *International Journal of Production Research*, 60(24), 7527–7550. <https://doi.org/10.1080/00207543.2022.2029611>

- Sheikh, H., Prins, C., & Schrijvers, E. (2023). Artificial intelligence: definition and background. In *Research for policy* (pp. 15–41). https://doi.org/10.1007/978-3-031-21448-6_2
- Shoushtari, F., Ghafourian, E., & Talebi, M. (2021). Improving Performance of Supply Chain by Applying Artificial Intelligence. *International Journal of Industrial Engineering and Operational Research*, 3(1), 14-23. Retrieved from <https://bgsiran.ir/journal/ojs-3.1.1-4/index.php/IJIEOR/article/view/43>
- Shurrab, H., & Jonsson, P. (2026). Augmentation or overwhelm? GenAI and the recoding of supply chain planning's DNA. *International Journal of Physical Distribution & Logistics Management*, 56(11), 241–264. <https://doi.org/10.1108/ijpdlm-08-2025-0444>
- Simatupang, T. M., & Sridharan, R. (2005). The collaboration index: A measure for supply chain collaboration. *International Journal of Physical Distribution & Logistics Management*, 35(1), 44–62. <https://doi.org/10.1108/09600030510577421>
- Sivadasan, S., Efstathiou, J., Frizelle, G., Shirazi, R., & Calinescu, A. (2002). An information-theoretic methodology for measuring the operational complexity of supplier-customer systems. *International Journal of Operations & Production Management*, 22(1), 80–102. <https://doi.org/10.1108/01443570210412088>
- Smyth, C., Dennehy, D., Wamba, S. F., Scott, M., & Harfouche, A. (2024). Artificial intelligence and prescriptive analytics for supply chain resilience: a systematic literature review and research agenda. *International Journal of Production Research*, 62(23), 8537–8561. <https://doi.org/10.1080/00207543.2024.2341415>
- Srinivasan, R., & Swink, M. (2018). An investigation of visibility and flexibility as complements to supply chain analytics: An Organizational Information Processing Theory perspective. *Production and Operations Management*, 27(10), 1849–1867. <https://doi.org/10.1111/poms.12746>
- Swafford, P. M., Ghosh, S., & Murthy, N. (2008). Achieving supply chain agility through IT integration and flexibility. *International Journal of Production Economics*, 116(2), 288–297. <https://doi.org/10.1016/j.ijpe.2008.09.002>
- Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18(7), 509-533.
- Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., & Fischl, M. (2020). Artificial intelligence in supply chain management: A systematic literature review. *Journal of Business Research*, 122, 502–517. <https://doi.org/10.1016/j.jbusres.2020.09.009>

- Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J.-F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, 70, 356–365. <https://doi.org/10.1016/j.jbusres.2016.08.009>
- Wamba, S. F., Guthrie, C., Queiroz, M. M., & Minner, S. (2023). ChatGPT and generative artificial intelligence: an exploratory study of key benefits and challenges in operations and supply chain management. *International Journal of Production Research*, 62(16), 5676–5696. <https://doi.org/10.1080/00207543.2023.2294116>
- Wamba, S. F., Queiroz, M. M., Guthrie, C., & Braganza, A. (2021). Industry experiences of artificial intelligence (AI): benefits and challenges in operations and supply chain management. *Production Planning & Control*, 33(16), 1493–1497. <https://doi.org/10.1080/09537287.2021.1882695>
- Wamba, S. F., Queiroz, M. M., & Trinchera, L. (2020). Dynamics between blockchain adoption determinants and supply chain performance: An empirical investigation. *International Journal of Production Economics*, 229, 107791. <https://doi.org/10.1016/j.ijpe.2020.107791>
- Wang, H., Liu, M., & Shen, W. (2023). Industrial-generative pre-trained transformer for intelligent manufacturing systems. *IET Collaborative Intelligent Manufacturing*, 5(2). <https://doi.org/10.1049/cim2.12078>
- Wang, Y., Gao, J., Cheng, T., Jin, M., Yue, X., & Wang, H. (2024). Is it necessary for the supply chain to implement artificial intelligence-driven sales services at both the front-end and back-end stages? *Transportation Research Part E Logistics and Transportation Review*, 194, 103923. <https://doi.org/10.1016/j.tre.2024.103923>
- Wei, Z., & Xiang, W. (2013). The importance of Supply Chain Management. *International Journal of Business and Social Science*, 4.
- Wong, L., Tan, G. W., Ooi, K., Lin, B., & Dwivedi, Y. K. (2022). Artificial intelligence-driven risk management for enhancing supply chain agility: A deep-learning-based dual-stage PLS-SEM-ANN analysis. *International Journal of Production Research*, 62(15), 5535–5555. <https://doi.org/10.1080/00207543.2022.2063089>
- Wu, Y., Frizelle, G., & Efstathiou, J. (2006). A study on the cost of operational complexity in customer–supplier systems. *International Journal of Production Economics*, 106(1), 217–229. <https://doi.org/10.1016/j.ijpe.2006.06.004>
- Yeh, W., Lin, W., Lai, C., Lee, Y., Chung, Y. Y., & Lin, J. (2016). Application of simplified swarm optimization algorithm in deteriorate supply chain network problem. *2016 IEEE*

- Congress on Evolutionary Computation (CEC)*, 2695–2700.
<https://doi.org/10.1109/cec.2016.7744127>
- Yin, R. K. (2001). *Estudo de caso: planejamento e métodos*. (2ª Ed.). Porto Alegre: Bookman.
- Yue, X., Kang, M., & Zhang, Y. (2025). The impact of artificial intelligence usage on supply chain resilience in manufacturing firms: a moderated mediation model. *Journal of Manufacturing Technology Management*. <https://doi.org/10.1108/jmtm-07-2024-0379>
- Zamani, E. D., Smyth, C., Gupta, S., & Dennehy, D. (2022). Artificial intelligence and big data analytics for supply chain resilience: A systematic literature review. *Annals of Operations Research*, 327(2), 605–632. <https://doi.org/10.1007/s10479-022-04983-y>
- Zaoui, S., Foguem, C., Tchuenté, D., & Kamsu-Foguem, B. (2025). The application of artificial intelligence technologies in the resilience and the viability of supply chains: a systematic literature review. *Production Planning & Control*, 36(16), 2429–2446. <https://doi.org/10.1080/09537287.2025.2563616>
- Zeba, G., Dabić, M., Čičak, M., Daim, T., & Yalcin, H. (2021). Technology mining: Artificial intelligence in manufacturing. *Technological Forecasting and Social Change*, 171, 120971. <https://doi.org/10.1016/j.techfore.2021.120971>
- Zhao, L., & Xie, J. (2023). Optimization of the supply chain network planning problem using an improved genetic algorithm. *International Journal for Simulation and Multidisciplinary Design Optimization*, 14, 9. <https://doi.org/10.1051/smdo/2023014>
- Zheng, P., Wang, H., Sang, Z., Zhong, R. Y., Liu, Y., Liu, C., Mubarak, K., Yu, S., & Xu, X. (2018). Smart manufacturing systems for Industry 4.0: Conceptual framework, scenarios, and future perspectives. *Frontiers of Mechanical Engineering*, 13(2), 137–150. <https://doi.org/10.1007/s11465-018-0499-5>

APPENDIX

Appendix A - Initial Email

Exmo(a), GESTAMP CERVEIRA, LDA,

O meu nome é Margarida e estou, neste momento, a realizar um projeto de investigação no âmbito do Mestrado em Gestão e Estratégia Industrial do ISEG – Instituto Superior de Economia e Gestão da Universidade de Lisboa. O projeto tem como objetivo estudar a situação das empresas da indústria transformadora portuguesa relativamente à adoção e aplicação da Inteligência Artificial na Gestão da Cadeia de Abastecimento.

Venho por este meio solicitar a sua contribuição, que é fundamental para atingir o objetivo acima mencionado, através da resposta a um questionário ao qual poderá aceder através do endereço abaixo:

<https://margarida-iseg.limesurvey.net/213265?token=72&lang=pt>

Ao responder ao questionário, o mais importante é a sua experiência e/ou opinião, não havendo, por conseguinte, respostas certas ou erradas. Peço-lhe que, nas suas respostas, tenha como referência a empresa ou organização onde se encontra atualmente. Toda a informação fornecida é estritamente confidencial. Não será possível identificar pessoalmente as pessoas e empresas envolvidas neste estudo e os dados recolhidos serão utilizados exclusivamente para efeitos de tratamento estatístico, sendo apresentados de forma agregada. O tempo estimado para o preenchimento do questionário é de 15 minutos.

Agradeço, desde já, a sua atenção e colaboração, colocando-me à disposição para qualquer esclarecimento, através do seguinte endereço de correio eletrónico: margaridagoncalves@aln.iseg.ulisboa.pt.

Devido à nova Política de Proteção de Dados, por favor, informe-me caso não pretenda receber lembretes para participar no inquérito, através de um dos meios já referidos.

Atentamente,

Margarida Gonçalves

Clique aqui para aceder ao inquérito:

<https://margarida-iseg.limesurvey.net/213265?token=72&lang=pt>

Se não quer participar deste inquérito e não deseja receber mais convites clique p.f. na seguinte ligação:

<https://margarida-iseg.limesurvey.net/optout/tokens/213265?token=72&langcode=pt>

Se estiver na lista negra mas quiser participar neste inquérito e pretender receber convites, por favor clique no seguinte link:

<https://margarida-iseg.limesurvey.net/optin/tokens/213265?token=72&langcode=pt>

Appendix B - Reminder Email

Exmo(a) Senhor(a),

O meu nome é Margarida e estou, neste momento, a realizar uma investigação no âmbito do Mestrado em Gestão e Estratégia Industrial do ISEG — Instituto Superior de Economia e Gestão da Universidade de Lisboa, que tem como objetivo estudar a situação das empresas da indústria transformadora portuguesa relativamente à adoção e aplicação da Inteligência Artificial na Gestão da Cadeia de Abastecimento.

Para alcançar o objetivo acima mencionado, gostaria de solicitar a sua preciosa colaboração, solicitando-lhe que responda individualmente a um questionário.

Se já respondeu a este questionário, agradeço que ignore este e-mail. Caso ainda não tenha respondido, agradeço que o faça, pois até ao momento o número de respostas obtidas é muito reduzido, o que invalida a realização do meu projeto. Por conseguinte, seria extremamente importante para mim obter a sua resposta. Para preencher o questionário, deverá aceder ao seguinte endereço:

<https://margarida-iseg.limesurvey.net/213265?token=107?=&pt>

Não existem respostas certas ou erradas; apenas a sua experiência e/ou opinião são importantes. Ao responder a estas questões, considere a empresa ou organização onde se encontra atualmente.

Toda a informação fornecida é estritamente confidencial. Não será possível identificar pessoalmente as pessoas e empresas envolvidas neste estudo e os dados recolhidos serão utilizados exclusivamente para efeitos de tratamento estatístico, sendo apresentados de forma agregada. O tempo estimado para preencher o questionário é 15 minutos.

Agradeço, desde já, a sua atenção e colaboração, colocando-me à disposição para qualquer esclarecimento, através do seguinte endereço de correio eletrónico: margaridagoncalves@aln.iseg.ulisboa.pt.

Atentamente,

Margarida Gonçalves

Clique aqui para aceder ao inquérito:

<https://margarida-iseg.limesurvey.net/213265?token=107?=&pt>

Se não quer participar deste inquérito e não deseja receber mais convites clique p.f. na seguinte ligação:

<https://margarida-iseg.limesurvey.net/optout/tokens/213265?token=107&langcode=pt>

Appendix C – Tables

Table I: Number of countries covered by the supply chain

Countries	Respondents	Frequency
0	35	6.8%
1	173	33.7%
2	70	13.6%
3	64	12.5%
4	38	7.4%
5	42	8.2%
6	16	3.1%
7	9	1.8%
8	8	1.6%
9	2	0.4%
10	20	3.9%
12	8	1.6%
14	2	0.4%
15	5	1.0%
18	3	0.6%
20	5	1.0%
24	1	0.2%
25	3	0.6%
30	1	0.2%
35	1	0.2%
38	1	0.2%
40	1	0.2%
50	1	0.2%
52	1	0.2%
55	1	0.2%
70	1	0.2%
100	1	0.2%
150	1	0.2%
Total	514	100,0%

Source: Author's own elaboration.

Table II - List of abbreviations

Constructs	Abbreviations
Competencies and Resources	
Technological infrastructure	TI
Data-related capabilities	DRC
Human-related capabilities	HRC
Business competencies and tangible resources that support the implementation of AI	BCTR
Organisational capabilities	OC
Capability to manage organisational change and AI-related risks	CMOR
Perceived Benefits	
Benefits of data-driven decision-making and forecasting	BDDDMF
Benefits relating to operational efficiency and optimisation	BROEO
Quality management	QM
Network and supply chain management	NSCM
Disruption resilience	DR
Benefits associated with sustainability, safety and maintenance	BASSM
Supply Chain Capabilities	
Supply Chain Resilience	SCR
Supply Chain Collaboration	SCCoI
Supply Chain Responsiveness	SCResp
Barriers to AI Adoption	
Technological Barriers	TB
Business and Strategic Barriers	BSB
AI Capabilities	AIC
AI Benefits	AIB

Appendix D – Post hoc *Tukey* test between AI Capabilities (AIC) and Supply Chain Complexity

Comparações múltiplas							
Variável dependente: Alcapability Tukey HSD							
(I) Operação geográfica da cadeia de abastecimento	(J) Operação geográfica da cadeia de abastecimento	Diferença média (I-J)	Erro Padrão	Sig.	Intervalo de Confiança 95%		
					Limite inferior	Limite superior	
Local (limitado a uma cidade ou região)	Nacional (em todo o país)	-,09070	,09601	,781	-,3382	,1568	
	Internacional (instalações no país, mas com exportação para vários países)	-,37390*	,09968	,001	-,6308	-,1170	
	Global (com instalações em vários países)	-,82397*	,18082	<,001	-1,2900	-,3579	
Nacional (em todo o país)	Local (limitado a uma cidade ou região)	,09070	,09601	,781	-,1568	,3382	
	Internacional (instalações no país, mas com exportação para vários países)	-,28320*	,08445	,005	-,5009	-,0655	
	Global (com instalações em vários países)	-,73327*	,17290	<,001	-1,1789	-,2876	
Internacional (instalações no país, mas com exportação para vários países)	Local (limitado a uma cidade ou região)	,37390*	,09968	,001	,1170	,6308	
	Nacional (em todo o país)	,28320*	,08445	,005	,0655	,5009	
	Global (com instalações em vários países)	-,45006	,17496	,051	-,9010	,0009	
Global (com instalações em vários países)	Local (limitado a uma cidade ou região)	,82397*	,18082	<,001	,3579	1,2900	
	Nacional (em todo o país)	,73327*	,17290	<,001	,2876	1,1789	
	Internacional (instalações no país, mas com exportação para vários países)	,45006	,17496	,051	-,0009	,9010	
*. A diferença média é significativa no nível 0.05.							

Appendix E – Post hoc *Tukey* test between AI Benefits (AIB) and Supply Chain Complexity

Comparações múltiplas						
Variável dependente: Albenefits						
Tukey HSD						
(I) Operação geográfica da cadeia de abastecimento	(J) Operação geográfica da cadeia de abastecimento	Diferença média (I-J)	Erro Padrão	Sig.	Intervalo de Confiança 95%	
					Limite inferior	Limite superior
Local (limitado a uma cidade ou região)	Nacional (em todo o país)	-,08553	,11038	,866	-,3700	,1990
	Internacional (instalações no país, mas com exportação para vários países)	-,46646 [*]	,11460	<,001	-,7618	-,1711
	Global (com instalações em vários países)	-,62102 [*]	,20789	,016	-1,1569	-,0852
Nacional (em todo o país)	Local (limitado a uma cidade ou região)	,08553	,11038	,866	-,1990	,3700
	Internacional (instalações no país, mas com exportação para vários países)	-,38094 [*]	,09709	<,001	-,6312	-,1307
	Global (com instalações em vários países)	-,53549 [*]	,19878	,037	-1,0479	-,0231
Internacional (instalações no país, mas com exportação para vários países)	Local (limitado a uma cidade ou região)	,46646 [*]	,11460	<,001	,1711	,7618
	Nacional (em todo o país)	,38094 [*]	,09709	<,001	,1307	,6312
	Global (com instalações em vários países)	-,15456	,20115	,869	-,6730	,3639
Global (com instalações em vários países)	Local (limitado a uma cidade ou região)	,62102 [*]	,20789	,016	,0852	1,1569
	Nacional (em todo o país)	,53549 [*]	,19878	,037	,0231	1,0479
	Internacional (instalações no país, mas com exportação para vários países)	,15456	,20115	,869	-,3639	,6730

*. A diferença média é significativa no nível 0.05.

Appendix F – Post hoc *Tukey* test between Supply Chain Resilience and Supply Chain Complexity

Comparações múltiplas						
Variável dependente: ResCABaste						
Tukey HSD						
(I) Operação geográfica da cadeia de abastecimento	(J) Operação geográfica da cadeia de abastecimento	Diferença média (I-J)	Erro Padrão	Sig.	Intervalo de Confiança 95%	
					Limite inferior	Limite superior
Local (limitado a uma cidade ou região)	Nacional (em todo o país)	-,08328	,11401	,885	-,3772	,2106
	Internacional (instalações no país, mas com exportação para vários países)	-,35629 [*]	,11836	,015	-,6614	-,0512
	Global (com instalações em vários países)	-,69182 [*]	,21473	,007	-1,2453	-,1383
Nacional (em todo o país)	Local (limitado a uma cidade ou região)	,08328	,11401	,885	-,2106	,3772
	Internacional (instalações no país, mas com exportação para vários países)	-,27301 [*]	,10029	,034	-,5315	-,0145
	Global (com instalações em vários países)	-,60854 [*]	,20532	,017	-1,1378	-,0793
Internacional (instalações no país, mas com exportação para vários países)	Local (limitado a uma cidade ou região)	,35629 [*]	,11836	,015	,0512	,6614
	Nacional (em todo o país)	,27301 [*]	,10029	,034	,0145	,5315
	Global (com instalações em vários países)	-,33553	,20777	,371	-,8711	,2000
Global (com instalações em vários países)	Local (limitado a uma cidade ou região)	,69182 [*]	,21473	,007	,1383	1,2453
	Nacional (em todo o país)	,60854 [*]	,20532	,017	,0793	1,1378
	Internacional (instalações no país, mas com exportação para vários países)	,33553	,20777	,371	-,2000	,8711

*. A diferença média é significativa no nível 0.05.

Appendix G – Post hoc *Tukey* test between Supply Chain Collaboration and Supply Chain Complexity

Comparações múltiplas						
Variável dependente: ColabCA						
Tukey HSD						
(I) Operação geográfica da cadeia de abastecimento	(J) Operação geográfica da cadeia de abastecimento	Diferença média (I-J)	Erro Padrão	Sig.	Intervalo de Confiança 95%	
					Limite inferior	Limite superior
Local (limitado a uma cidade ou região)	Nacional (em todo o país)	-,04508	,11526	,980	-,3422	,2520
	Internacional (instalações no país, mas com exportação para vários países)	-,24974	,11965	,159	-,5582	,0587
	Global (com instalações em vários países)	-,53939	,21707	,063	-1,0989	,0201
Nacional (em todo o país)	Local (limitado a uma cidade ou região)	,04508	,11526	,980	-,2520	,3422
	Internacional (instalações no país, mas com exportação para vários países)	-,20466	,10138	,182	-,4660	,0566
	Global (com instalações em vários países)	-,49431	,20756	,082	-1,0293	,0407
Internacional (instalações no país, mas com exportação para vários países)	Local (limitado a uma cidade ou região)	,24974	,11965	,159	-,0587	,5582
	Nacional (em todo o país)	,20466	,10138	,182	-,0566	,4660
	Global (com instalações em vários países)	-,28965	,21003	,513	-,8310	,2517
Global (com instalações em vários países)	Local (limitado a uma cidade ou região)	,53939	,21707	,063	-,0201	1,0989
	Nacional (em todo o país)	,49431	,20756	,082	-,0407	1,0293
	Internacional (instalações no país, mas com exportação para vários países)	,28965	,21003	,513	-,2517	,8310

Appendix H – Post hoc *Tukey* test between Supply Chain Responsiveness and Supply Chain Complexity

Comparações múltiplas						
Variável dependente: CapResCA						
Tukey HSD						
(I) Operação geográfica da cadeia de abastecimento	(J) Operação geográfica da cadeia de abastecimento	Diferença média (I-J)	Erro Padrão	Sig.	Intervalo de Confiança 95%	
					Limite inferior	Limite superior
Local (limitado a uma cidade ou região)	Nacional (em todo o país)	-,04582	,11120	,976	-,3325	,2408
	Internacional (instalações no país, mas com exportação para vários países)	-,31687 [*]	,11545	,032	-,6144	-,0193
	Global (com instalações em vários países)	-,49775	,20944	,083	-1,0376	,0421
Nacional (em todo o país)	Local (limitado a uma cidade ou região)	,04582	,11120	,976	-,2408	,3325
	Internacional (instalações no país, mas com exportação para vários países)	-,27104 [*]	,09781	,029	-,5232	-,0189
	Global (com instalações em vários países)	-,45192	,20026	,110	-,9681	,0642
Internacional (instalações no país, mas com exportação para vários países)	Local (limitado a uma cidade ou região)	,31687 [*]	,11545	,032	,0193	,6144
	Nacional (em todo o país)	,27104 [*]	,09781	,029	,0189	,5232
	Global (com instalações em vários países)	-,18088	,20265	,809	-,7032	,3414
Global (com instalações em vários países)	Local (limitado a uma cidade ou região)	,49775	,20944	,083	-,0421	1,0376
	Nacional (em todo o país)	,45192	,20026	,110	-,0642	,9681
	Internacional (instalações no país, mas com exportação para vários países)	,18088	,20265	,809	-,3414	,7032

*. A diferença média é significativa no nível 0.05.