

MASTERS IN MANAGEMENT AND INDUSTRIAL STRATEGY

MASTER'S FINAL WORK DISSERTATION

ARTIFICIAL INTELLIGENCE AND SUPPLY CHAIN
INNOVATION: A MULTIPLE CASE STUDY OF
PORTUGUESE COMPANIES

MARGARIDA DOS SANTOS DIOGO

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*“Humans are allergic to change.
They love to say,
‘We’ve always done it this way.’
I try to fight that.”*

- Grace Hopper

GLOSSARY

AI – Artificial Intelligence

BMI – Business Model Innovation

ERP – Enterprise Resource Planning

Gen-AI – Generative Artificial Intelligence

ML – Machine Learning

NLP – Natural Language Processing

OM – Operations Management

RO – Research Objective

ROI – Return On Investment

RQs – Research Questions

SCM – Supply Chain Management

SCI – Supply Chain Innovation

SCOR Model – Supply Chain Operations Reference Model

SME – Small and Medium-sized Enterprises

WMS – Warehouse Management System

During the preparation of this work, the author used Claude (Anthropic) for the purposes of defining the structure, reviewing and improving the use of correct academic English, clarifying doubts and helping to organize ideas according to the structure defined in the methodology, translating interview materials from Portuguese into English, assisting in the analysis and organization of the interviews according to the themes aligned with the research questions, and verifying that all references used were listed in the References section and with APA style format. After using this tool, the author reviewed and edited the content as necessary and takes full responsibility for the content of this work.

ABSTRACT

Artificial Intelligence is playing an increasingly prominent role across supply chain operations, however empirical evidence of how it drives supply chain innovation in early-adoption, SME-dominated environments remains limited.

This study addresses that gap by exploring how AI is driving innovation in Portuguese supply chains – a context characterized by low AI adoption rates, fragmented data infrastructures, and a business landscape composed predominantly of small and medium-sized enterprises.

Through a qualitative multiple case study approach, seven semi-structured interviews were conducted with managers and specialists from six Portuguese organizations – three consulting firms and three companies at varying stages of AI adoption. The empirical analysis was guided by two complementary frameworks: the extended SCOR model, which identified where AI is being applied across supply chain phases, and the Supply Chain Innovation framework, which classified what type of innovation that application is generating. The findings reveal that AI adoption in Portugal is predominantly reactive, driven by competitive pressure rather than strategic intent, and concentrated in the Plan and Enable phases of the supply chain. When mapped against the SCI framework, the innovation being generated is almost entirely incremental, manifesting primarily as technology and process innovation through the automation of repetitive tasks, the improvement of analytical capabilities, and the shift from reactive to proactive operational management. Business model innovation is emerging but remains the exception. Three transversal conditions shape this picture: data quality and governance as the universal precondition for effective AI adoption, human and organizational readiness as a persistent change management challenge, and structural and financial constraints reflecting the realities of Portugal's SME-dominated business landscape.

The study concludes that AI is driving supply chain innovation in Portugal, but predominantly at the incremental end of the innovation spectrum. The gap between AI's transformative potential and its current organizational reality in Portugal is explained not by a lack of technology or awareness but by the absence of the foundational conditions, data quality, organizational readiness, and strategic intent, that genuine supply chain innovation requires.

Keywords: Artificial Intelligence, Supply Chain Innovation, SCOR MODEL, Supply Chain Management, Process Innovation

RESUMO

A Inteligência Artificial está a desempenhar um papel cada vez mais proeminente nas operações da cadeia de abastecimento. No entanto, as evidências empíricas sobre a forma como esta impulsiona a inovação na cadeia de abastecimento em ambientes de adoção precoce, dominados por PME, continuam a ser limitadas.

Este estudo aborda essa lacuna, explorando a forma como a IA está a impulsionar a inovação nas cadeias de abastecimento portuguesas – um contexto caracterizado por baixas taxas de adoção da IA, infraestruturas de dados fragmentadas e um panorama empresarial composto predominantemente por pequenas e médias empresas.

Seguindo um modelo de investigação qualitativo e recorrendo a um *case-study* múltiplo, foram realizadas sete entrevistas semiestruturadas com gestores e especialistas de seis organizações portuguesas – três empresas de consultoria e três empresas que apresentavam diferentes fases de adoção de IA. A análise empírica foi orientada por dois *frameworks* complementares: a versão alargada do modelo SCOR, que permitiu identificar onde a IA está a ser aplicada nas diferentes fases da cadeia de abastecimento, e o *framework* de Inovação da Cadeia de Abastecimento, que classificou o tipo de inovação que essa aplicação está a gerar. Os resultados revelam que a adoção da IA em Portugal é predominantemente reativa, impulsionada pela pressão competitiva em vez de por uma intenção estratégica, e concentrada nas fases de Planeamento (*Plan*) e Capacitação (*Enable*) da cadeia de abastecimento. Quando analisada segundo os componentes do modelo de Inovação da Cadeia de Abastecimento, a inovação gerada é quase inteiramente incremental, manifestando-se principalmente como inovação tecnológica e de processos através da automatização de tarefas repetitivas, da melhoria das capacidades analíticas e da transição de uma gestão operacional reativa para uma proativa. A inovação do modelo de negócio está a surgir, mas continua a ser a exceção. Três condições transversais moldam este cenário: a qualidade e o modelo de governo de dados como pré-requisito universal para uma adoção eficaz da IA, a preparação humana e organizacional como um desafio persistente na gestão da mudança e as restrições estruturais e financeiras que refletem as realidades do tecido empresarial português, dominado pelas PMEs.

O estudo conclui que a IA está a impulsionar a inovação na cadeia de abastecimento em Portugal, mas predominantemente de forma incremental. O fosso entre o potencial transformador da IA e a sua realidade organizacional atual em Portugal explica-se não

por falta de tecnologia ou de sensibilização, mas pela ausência das condições fundamentais – qualidade dos dados, preparação organizacional e intenção estratégica, que a verdadeira inovação na cadeia de abastecimento requer.

Palavras-chave: Inteligência Artificial, Inovação na Cadeia de Abastecimento, Modelo SCOR, Gestão da Cadeia de Abastecimento, Inovação de Processos

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1. INTRODUCTION

Artificial Intelligence (AI) is reshaping the way organizations manage their supply chains. In today's economy, the pressure to adapt has reached unprecedented levels, as organizations and individuals navigate through constant consumer demand changes, unpredictable market conditions, geopolitical supply-chain disruptions and the rapid acceleration of technology development. In this context, organizations that fail to ensure innovation are at risk of being left behind. Supply chain management (SCM) has become one of the most critical areas in which competitive advantages can make a difference in leading or stalling; equally the ability to respond quickly and intelligently to the surrounding environment has become a necessity, rather than a luxury (Al-Omoush et al., 2025; Kwak et al., 2018).

AI is emerging as one of the most powerful tools available to organizations that are struggling with these challenges. Useful across the full scope of supply chain operations, AI is enabling faster decisions, more efficient processes and new forms of value creation – from demand forecasting and inventory optimization to supplier risk monitoring and logistics automation. As digital transformation advances across industries, the capacity to leverage AI as a driver of Supply Chain Innovation (SCI) is becoming a strategic priority that organizations can no longer ignore.

Despite the sudden increase of research documenting AI's transformative potential in SCM, there are gaps remaining in academic literature. Studies on AI-driven SCI have been overly concentrated in large organizations, manufacturing sectors and also geographically, on the United States (Wong & Ngai, 2019). Smaller economies, SME-dominated business landscapes and early-adoption contexts have received less attention, leaving a gap in understanding of how AI-driven innovation occurs when the foundational conditions, such as data infrastructure, financial capacity, organizational readiness, are still being built. Portugal is the perfect example of this type of setting. With only 8.8% of Portuguese companies currently using AI in supply chain operations (Oliveira et al., 2024) and 11.5% overall (INE, 2025) the country offers an underexplored ground in which to examine what AI-driven SCI looks like at an early stage of adoption and what conditions shape its implementation and scope. The findings of this study are applicable out of the academic context, for Portuguese companies going through the early stages of AI adoption, for managers trying to comprehend what true AI-driven innovation requires and

for a business landscape still building the foundations necessary to reach AI's full potential.

It is in this context that the central question of this study arises: “*How is AI driving innovation in the supply chains of Portuguese companies?*” (RQ). Two research objectives were also set in order to guide this dissertation. The first strives “*to identify and characterize the implementation and utilization of AI in supply chain operations within Portuguese organizations*” (RO1). The second objective explores “*how organizations experience and interpret the impact of AI on supply chain processes, including efficiency, responsiveness, and decision-making*” (RO2). Together these objectives provide both a descriptive and an interpretive recollection of AI-driven SCI in the Portuguese context.

The empirical analysis is guided by two complementary analytical frameworks. The extend SCOR Model, structured by the Plan, Source, Make, Deliver, Return, and Enable phases, provides an operational lens for identifying where AI is being applied across supply chain functions. Secondly, the SCI framework, using the dimensions proposed by Kwak et al. (2018) and Wong and Ngai (2022), provides the analytical lens for classifying what type of innovation that application is generating, whether a technology, process, or emerging business model innovation.

To address the research question (RQ), a qualitative and exploratory research design was adopted, implemented through a multiple case study approach. Seven semi-structured interviews were conducted with managers and specialists from six Portuguese organizations: three consulting firms with direct experience implementing AI across client supply chains, and three companies at varying stages of AI adoption. The selection of both consulting firms and company perspectives was deliberate since consulting participants can offer a broad and realistic view of AI adoption in Portugal, while company participants provide direct evidence of how AI is impacting operations and generating innovation within specific contexts.

The thesis is structured as follows. Chapter 2 contains the Literature Review, that covers three main sections: first, a comprehensive examination of AI in SCM, including its definition and evolution, the types of AI models used in SCM contexts, their main applications across supply chain functions, and the benefits and challenges of adoption. Chapter 3 covers the Methodology applied and details the research design, analytical

framework, sample selection, and data collection and analysis techniques. Chapter 4 presents the findings and discussion, organized around three empirical themes: the current state of AI adoption in Portuguese supply chains, the nature of AI-driven SCI, and the conditions shaping how that innovation manifests, followed by a discussion of results. Finally, Chapter 5 presents the conclusions of the study, including theoretical implications, managerial implications and limitations and directions for future research.

2. LITERATURE REVIEW

2.1. Artificial Intelligence in Supply Chain Management

2.1.1 Definition and evolution of AI in a SCM context

Supply Chain Management (SCM) is fundamental to any business, serving as its core. No company can survive or thrive without effective SCM, making its development a focal point across industries (Dash et al. 2019). SCM is defined as the coordination of relationships both within organizations and across interconnected business units, including suppliers, production facilities, logistics operators, and marketing systems, in order to enable the multidirectional flow of materials, services, finances, and information from original producers to end customers, ultimately creating value, improving operational efficiency, and ensuring customer satisfaction (Toorajipour et al., 2021). In today's globalized markets, well-functioning supply chains are essential for maintaining cost efficiency, operational continuity, and overall financial performance (Khedr & Rani, 2024).

With the progression of times, this inherently complex system continues to encounter new challenges: globalization, the rise of disruptive technologies and the worldwide dispersion of raw materials, suppliers, and distributors have fundamentally reshaped the SCM landscape, increasing its complexity, costs, and operational demands while requiring organizations to continuously adapt to new conditions, customer preferences, and emerging disruptions. Failing to do so can lead companies to a loss of competitiveness, making the ability to sense and satisfy new consumer needs not only an operational advantage but a strategic imperative in today's economy (Baldi et al., 2024).

According to Joel et al. (2024; p. 708), variants such as “*limited real-time visibility into operations, inefficiencies in demand forecasting and inventory management*”, extended lead times, higher transportation costs or even risks of disruptions caused by uncontrollable external factors – for instance, geopolitical instability (wars - military or

trade) or natural disasters make indispensable the adoption of advanced approaches, strategies and systems. In this context, Artificial Intelligence (AI) can be used as leverage, acting as a transformative managerial innovation which can support decision-making processes and boost operational efficiency. Toorajipour et al. (2021), acknowledged that SCM is one of the areas expected to most benefit from AI applications.

Artificial Intelligence, as a term, was first introduced by John McCarthy in 1955. Initially focused on exploring machines' abilities to use language and logic-based programming, AI has since evolved into a groundbreaking analytics tool capable of tackling complex problems once thought only solvable by human capacity (Pournader et al., 2021).

In Operations Management (OM) literature, some authors define AI as a system's ability to independently interpret and learn through data gathered from external environments. Using such acquired knowledge, AI can generate, adjust or propose new solutions and inputs that support decision making processes, amplifying human intelligence and facilitating tasks – all while considering multiple variables present in its operating environment (Belhadi et al., 2024; Grover et al., 2022).

AI is composed of several interconnected technological branches.

Machine Learning (ML) can be understood as the systems' ability to automatically learn from problems, patterns, relationships and observations, rather than following explicitly programmed rules (Janiesch et al., 2021). It is the most foundational technology, having more advanced subsets such as Deep Learning, extending this capacity to process large volumes of unstructured data through multi-layer neural networks (Janiesch et al., 2021).

Computer vision gives machines the ability to extract meaning from visual inputs such as images and video, making it particularly relevant in physical supply chain environments where it supports tasks like detecting production defects and monitoring workplace safety in ways that manual inspection cannot match at scale (Dash et al., 2019).

Natural Language Processing (NLP), which enables systems to interpret and respond to human language, generates applications such as voice assistants and chatbot interfaces that are increasingly present in supply chain operations (Pournader et al., 2021).

Together these branches of AI have unlocked new opportunities to manage operational flows more efficiently and effectively while also supporting managers in making informed decisions (Eyo-Udo, 2024; Richey et al., 2023).

Fundamentally, what sets modern AI apart from primitive rule-based automation is the inherent ability to automatically learn from available data, adapt to its inputs and environment and continuously improve the outputs. It is this capability that makes AI particularly suited to the dynamic ecosystem of SCM and promises a greater shift in operations and practices (Richey et al., 2023; Toorajipour et al., 2021).

2.1.2 Types of AI models in SCM

- Predictive Analytics

Predictive analytics is among the most established and widely studied forms of AI application in SCM (Toorajipour et al., 2021). Its integration in SCM has increasingly been considered a vital strategic tool for organizations that want to yield competitive advantages and stay on the edge in today's fast paced and complex economy (Oyewole et al., 2024). It can be defined as the usage of ML, statistical algorithms and data mining techniques to scrutinize vast amounts of data to generate predictions about future outcomes or trends (Oyewole et al., 2024). It has been considered a groundbreaking application of ML since traditional forecasting methods have become obsolete, pressuring organizations to continuously adapt their supply chains to meet rapidly evolving expectations (Baldi et al., 2024; Eyo-Udo, 2024). According to Oyewole et al. (2024; p. 570), with the power to "*leverage(s) historical data, market trends, and external factors to develop sophisticated models*", predictive analytics can "*enhance the accuracy of demand predictions*", assist in decision making, adjust the inventory needed and improve production processes for greater efficiency.

- Prescriptive Analytics

According to Lepenioti et al., (2020), prescriptive analytics is the most advance type of analytics tool, bringing higher value to businesses. It differs not only from its advanced analytical depth but also because it builds upon the outputs from the predictive models and employs AI, expert systems and optimization algorithms to generate automated, adaptive and ideal decisions that facilitate the development and execution of both proactive and reactive measures. A necessary tool for managing complex, unpredictable and fast-paced environments, such as the contemporary SCM (Smyth et al., 2024) where prompt decision-making is crucial.

- Generative AI

In recent years, another category of AI models relevant to SCM has been rapidly evolving and with high degrees of implementation (Jackson et al., 2024). Generative AI (Gen-AI) can be described as AI systems that integrate ML and Deep Learning, in order to generate new content, for example, texts, images, documents, videos, simulations and even audio, with the knowledge gathered from large data sets in which the model was trained on (Fosso Wamba et al., 2024; Teixeira et al., 2025; Richey et al., 2023). What sets this new model aside from the previous ones is that traditional AI still needs extensive programming in order to know how to execute tasks, while Gen-AI can generate content from something as simple as human-machine conversations, e.g. Chat-GPT (Fosso Wamba et al., 2024). Gen-AI, with all the above-described capabilities, can bring a disruptive shift in the field of logistics and SCM (Fosso Wamba et al., 2024; Jackson et al., 2024; Richey et al., 2023). Fosso Wamba et al. (2024) and Richey et al. (2023) described some of the possible uses of Gen-AI in SCM: strengthened customer connections, better sourcing evaluation, possibility to mitigate risk across the supply chain, better management and forecasting of procurement and inventory, logistics coordination, more sustainable practices and empower decision-making processes.

Table I, presented in Appendix A, provides an overview of the main types of AI models, as well as their relevance to SCM.

2.1.3 Main applications of AI in SCM

AI has become an increasingly integral part of modern supply chain operations, with practical applications found at virtually every stage. A systematic analysis of recent literature reveals a convergence in the classification of AI applications across strategic and operational SCM phases rather than by the technology types used (Daios et al., 2025; Richey et al., 2023; Teixeira et al., 2025). Therefore, it is practical to highlight the main AI applications according to the different supply chain phases, following the logic presented by the extended Supply Chain Operations Reference (SCOR) Model.

The extended SCOR Model is a strategic planning framework used by senior managers to deconstruct and simplify SCM. It has been widely adopted as a reference framework for supply chain analysis (Huan et al., 2004) and structures supply chain operations into six core processes: Plan, Source, Make, Deliver, Return and Enable (APICS, 2017). The 'Enable' process was later incorporated into the model and relates to governance, data management, and risk management.

Plan – Demand Forecasting and Inventory Optimization

The planning phase is one of the most crucial in SCM. It guides the way inventories, production and distribution decisions are made. According to Jackson et al., (2024), AI has played a significant role in redesigning the way this process is conducted. The introduction of this new tool has allowed businesses to decipher, understand and learn from complex data gathered from multiple sources, thus helping to rapidly understand and design plans for upcoming demand, capabilities' development and supply availability (Belhadi et al., 2024). With AI's ability to learn from available information and adapt over time, patterns are learned and predictions generated, used to increase the accuracy of forecasts and contribute to decision making, efficiency of operations and an optimization of inventories and supply chains (Jackson et al., 2024). Without this essential help, companies are forced to maintain high inventory levels and rely on human capabilities to manage operations, which can be limited and impact the execution quality and even profits (Belhadi et al., 2024). More recently, with the development of Gen-AI, accuracy has been improved regarding both demand and forecast of expected sales. This development is key to enable companies to program needs, orders and optimal quantities. On the long run, this process allows to reduce waste, opens way for lean management practices and increases the possibility of more efficient operations management (Jackson et al., 2024; Richey et al., 2023).

Source – Procurement, Supplier Selection, and Sourcing Assessment

In the sourcing phase AI helps to provide a shift in how the organizations identify, evaluate and manage their supply chain players. Traditionally, supplier selection involves a labor-intensive, judgment-dependent process which is constrained due to manual analysis and either incomplete or overwhelming amounts of information. AI overcomes these limitations since it has the capacity of processing vast amounts of supplier data across multiple dimensions. As Richey et al. (2023) mention, the application of AI in evaluating and choosing suppliers offers a faster way of going through prospective candidates, since AI has a large capacity of analyzing and categorizing data while also considering parameters of interest for companies, including quality, cost-effectiveness, reliability and sustainability to gather an optimal portfolio of suitable suppliers (Daio et al., 2025). Besides this, Daio et al. (2025) also highlight AI's ability to automate processes in routine procurement operations, such as order entry, invoice processing or

even order managing, resulting in the reduction of administrative work and an improvement of the workflow.

Intelligence agent-based systems can take the role of the human decision maker or assist managers with structural decision support for both strategic and operational procurement choices (Daios et al., 2025), contributing to a shift from reactive procurement toward a more anticipatory and intelligence-driven sourcing strategy (Samuels, 2025).

Make – Production Optimization and Smart Manufacturing

The Make phase encompasses all production and manufacturing activities within the supply chain. The constant development of new technologies, in the context of Industry 4.0, has fundamentally changed how these activities are conducted. As Zhong et al. (2017) describe, intelligent manufacturing is a new concept that takes advantage of information and technological developments in order to optimize production. In practical terms, Dash et al. (2019) identify four key areas where AI has boosted production operations: optimizing assets and processes, combining effective human-robot teams, improving quality and reliability and preventing downtime through predictive maintenance. Dash et al. (2019) also mention that the use of collaborative robots can increase productivity by up to 20 percent, showcasing the possibility of improved efficiency through AI applications. Quality control can also be affected significantly by these developments: in semiconductor manufacturing, for example, testing costs and yield losses can represent up to 30 percent of total production cost, and AI engines are now being deployed to identify the root causes of these losses in real time, enabling immediate process adjustments that reduce defects (Dash et al., 2019). Finally, Daios et al. (2025) showcased that data collected from production machinery can be used to anticipate equipment failure and, in that sense, scheduled maintenance can be applied, avoiding unplanned stops that can put production at risk. Together, the aforementioned applications allow the move from reactive production management, where problems are dealt with, to a more intelligent, prevention-oriented model where AI optimizes operations in advance, minimizes human involvement in routine tasks while supporting complex decision-making (Zhong et al., 2017).

Deliver - Logistics, Transportation, and Distribution

The delivery phase encompasses activities that are cost-intensive and some of the most complex in the supply chain. According to Samuels (2025), AI technologies, such as

robotics and automation, have revolutionized warehouse and distribution operations, being a driver for strategic innovation and operational efficiency. For example, autonomous robots and smart picking systems are gradually taking the place of manual procedures in distribution centers (Dash et al. 2019). In the matter of transportation, as described by Richey et al. (2023), Gen-AI is a powerful tool since it can formulate distribution strategies and logistic routes that take into consideration specific constraints and objectives, such as maximization of the service level, cost reduction, disruptions (i.e. traffic), weather conditions and environmental factors. The ability to analyze vast amounts of information in real time allows the most efficient transportation routes rather than depending on static, prearranged schedules.

Return – Reverse Logistics and Circular Supply Chains

The Return phase of the supply chain concerns product returns, recycling, refurbishment, and end-of-life management and has historically been one of the least optimized areas of SCM, largely due to the unpredictability and complexity of reverse material flows. AI applications in this phase are less mature than in the operational phases discussed above, reflecting a broader pattern in the literature where forward logistics has received substantially more research attention than reverse logistics. Nevertheless, the strategic importance of this phase is growing, particularly as regulatory pressure around circular economy practices and extended producer responsibility intensifies across European markets. Teixeira et al. (2025) note that in closed loop/circular supply chains AI can have a role in helping with resource recovery and waste reduction, indicating the highest-value recovery pathway.

Enable – Risk Management, Resilience, and Sustainability

The Enable phase of the extended SCOR model highlights activities that are transversal to the entirety of the supply chain, rather than in one operational stage, including governance, data management, risk management, and sustainability practices.

- **Governance and Data Management**

At the governance level, AI is changing how organizations manage information access and data quality, two functions that previously relied heavily on manual processes and human judgment. By continuously scanning information from multiple sources such as supplier audits, regulatory databases, and industry reports, AI tools can flag potential

compliance issues early and propose ways to address them before they become operational or legal problems (Richey et al., 2023). On the data management side, AI is helping organizations automate routine data processing tasks and activities related to quality control in order to maintain more consistent and reliable information flows across supply chain functions. These developments are supporting the building of data infrastructure that effective decision-making increasingly depends on (Daivos et al., 2025).

- **Risk Management and Resilience**

Supply chain resilience can be described as the ability to anticipate and recover from disruptions. This has been one of the areas where AI's contributions have been strategically applied. As Richey et al. (2023) describe, Gen-AI has the ability to explore different scenarios and thus, generating risk assessments of various disruptions – including strikes, natural disasters, pandemics, supply constraints, enabling organizations to formulate resilient strategies and contingency plans that support business continuity through adverse conditions. This capability is supported by Daivos et al. (2025) who outline that AI improves transparency through continuous monitoring and can diminish the negative impacts of worldwide crises, such as COVID-19. Therefore, AI presents the possibility to transform risk management from a reactive discipline, responding to disruptions after they occur, into an anticipatory one, in which organizations can identify and promptly mitigate threats.

- **Sustainability and Ethical Supply Chain Practices**

AI also contributes to supply chain sustainability across environmental, social, and governance dimensions. As Teixeira et al. (2025) note, AI can optimize operations, contribute to the reduction of greenhouse gas emissions, correctly manage resources, aid responsible sourcing and allow transparency across the supply chain, generating efficiency and operational performance.

This multi-dimensional contribution positions AI as a lever for systemic, values-driven supply chain transformation, increasingly relevant within the European Union regulatory context that frames the operational environment of Portuguese companies. Table II, presented in Appendix A, provides a summary of AI applications across the extended SCOR Model phases and respective authors citing those applications.

2.1.4 Benefits and Challenges of AI Adoption in Supply Chain Management

- **Benefits**

Besides operational gains explained across the individual SCOR processes, AI generates strategic value at an organizational level beyond only process efficiency. Companies that successfully adopt AI are well positioned to develop a sustained competitive advantage, consequence of fast and accurate decision-making, service level improvements and the capability of responding to market changes and demands with an agility that competitors still using traditional methods are not able to match (Richey et al., 2023). Cohen et al. (2026) reinforce this, arguing that the true potential of AI in SCM is not achieved through isolated applications but through its integration with OM knowledge and principals to create systems that are both reliable and capable of handling complex real-world supply chain environments.

AI's contribution to organizational learning is equally significant. By continuously processing data from across the supply chain, AI enables companies to learn from past performance, adapt to new constraints and perpetually improve in ways that human-managed systems cannot replicate due to their limitations (Belhadi et al., 2024).

Regarding the relationship between human judgment and machine intelligence in supply chain operations. Rather than replacing human expertise, AI works most effectively when used to complement it, handling the analytical and data-intensive dimensions of decision-making while freeing human decision-makers to focus on contextual understanding, oversight, and adaptive thinking (Cohen et al., 2026). As Cohen et al. (2026, p.694) state directly "*AI's role is not to replace people in supply chains but to augment them*".

On a structural level, AI also allows cross-functional integration across supply chain phases that were previously isolated. As stated by Teixeira et al. (2025), connecting planning, sourcing, production, and delivery through shared data and intelligence, potentiates a more responsive and coherent supply chain.

Together these benefits position AI not merely as an operational tool but as a source of strategic differentiation and, increasingly, as a foundation for innovation.

- **Challenges**

Despite the advantages presented, AI's adoption in SCM faces significant barriers. Data quality and governance are fundamental topics for concern since AI systems are entirely

dependent on the quality, accessibility and integrity of the data to be used, and many organizations, particularly SMEs, frequently lack the technical infrastructure, strong data management processes and governance models necessary to effectively leverage AI (Richey et al., 2023; Teixeira et al., 2025). Gaps, inconsistencies or inaccuracies in data can turn AI models ineffective or counterproductive, resulting in unreliable outputs that impair rather than support decision-making (Richey et al., 2023).

Secondly, implementation costs and the immaturity of companies can also pose barriers. Integrating AI into existing supply chain systems requires significant investment in technology, infrastructure, and human expertise, and the complexity of this transition is frequently underestimated (Daios et al., 2025). Other problems that need facing before implementation reside within the organizations, since in most cases it is necessary to redefine roles and responsibilities, the way internal processes are carried out and to construct the digital maturity required in order to AI have the right conditions to deliver value (Daios et al., 2025). This challenge is aggravated due to the difficulties in measuring the ROI of AI developments, making it harder for managers to defend adoption and force many to have a caution and considerate position about AI's actual benefit for their operations (Daios et al., 2025). Cultural resistance and the need for workforce upskilling further slow adoption, as AI requires fundamental changes in how people work and make decisions across the organization (Samuels, 2025). Organizations, and respective employees, must adapt and develop capabilities that complement AI usage, rather than competing with it. Distinct human skills such as strategic thinking, problem solving and interpersonal assessment are areas where human intelligence still has a meaningful advantage (Richey et al., 2023). Adding to this, Cohen et al. (2026) point out that companies adopting AI usually face two types of interconnected gaps: one focused on technology, with outdated systems and fragmented data, and the other focused on people and culture, related to resistance to change and incorrect incentives. When both exist at the same time, AI tends to stay confined to small pilots instead of becoming part of the operations of an organization.

Finally, ethical concerns and regulatory uncertainty are becoming more important. Issues related to algorithmic bias, data privacy, and transparency in AI decision-making are increasingly subject to regulatory scrutiny, as evidenced by the EU Artificial Intelligence Act (European Parliament and Council of the European Union, 2024), which places direct

compliance obligations on organizations deploying AI systems across EU member states including Portugal (Daios et al., 2025; Richey et al., 2023).

2.2 Innovation in Supply Chains

2.2.1 Conceptualizing innovation: types and dimensions

Innovation within SCM has emerged as a strategic obligation. Organizations must keep on developing new capabilities across their supply chains to remain responsive to shifting market conditions, changing customer expectations, and accelerating technological change (Al-Omoush et al., 2025; Kwak et al., 2018). When pursued successfully, SCI has the potential to generate value beyond operational efficiency, in areas such as service quality, economic performance, environmental responsibility, and social impact, making it a foundation for competitive advantage that extends to both corporate and societal implications (Wong & Ngai, 2019).

Despite its growing strategic importance, SCI remains without a single universally accepted definition. The field is still highly fragmented, with multiple definitions each reflecting distinct thematic emphases and perspectives (Kahn & Cook, 2026; Wong & Ngai, 2022). Arlbjørn et al. (2011) offer one of the most cited and widely adopted definitions (Malacina & Teplov, 2022), defining SCI as any degree of change within supply chain networks, technologies, or processes, from gradual optimization to fundamental transformation, at any organizational level, as long as it creates new value for stakeholders in the form of new markets, products, services or network structures. Arlbjørn et al. (2011) also distinguish SCI from invention, stating that an innovation must demonstrate its commercial value through actual implementation, instead of only existing as an idea. Wong & Ngai (2022) complement this by characterizing SCI as a multifaceted process through which organizations leverage new technologies to navigate environmental uncertainty while simultaneously improving operational efficiency and strengthening customer value delivery

SCI is displayed across multiple dimensions, each capturing a distinct way in which change can be generated across supply chain networks. Kwak et al. (2018) propose two established core dimensions: technology innovation and process innovation, a classification supported by Kahn & Cook (2026), who find that technology features explicitly in ten of the thirteen SCI definitions reviewed across academic literature. Technology innovation focuses on upgrading the systems and infrastructure that make

supply chains work, from information platforms and tracking tools to logistics equipment, with the goal of making organizations more productive, gain more visibility across their operations, and better positioned to serve downstream customers (Kwak et al., 2018). Process innovation is related to how supply chain activities are carried out rather than what tools support them, focusing on the redesign of operational routines, coordination mechanisms, and service delivery approaches in ways that raise quality and reduce cost over time (Kwak et al., 2018).

While technology innovation presents the tools and infrastructure that enable supply chain improvement, Kwak et al. (2018) observe that the greatest gains in customer value tend to emerge from process innovation, specifically through the development of more agile and responsive ways of operating across global supply chains. Nonetheless, technology and process innovation are complementary, since it enables and accelerates the process changes that ultimately generate value for customers and supply chain partners. Beyond these two established dimensions, a third emerging dimension – business model innovation (BMI), is gaining analytical relevance as digital transformation compels organizations to move beyond operational improvement toward more fundamental reconfigurations of how they create, deliver, and capture value (Zhou et al., 2026; Kahn & Cook, 2026). As Foss & Saebi (2017) argue, a business model captures how a firm organizes the creation, delivery, and capture of value, and changing that architecture represents one of the most comprehensive and strategic forms of innovation a firm can pursue.

Across all three dimensions, SCI may range from incremental to radical. As Arlbjørn et al. (2011) establish, incremental SCI represents an optimization of current practices within networks, technology, and processes, while radical SCI sets entirely new rules within its application area, something with a transformative effect on how supply chain activities are organized and conducted. This distinction is significant because it shapes not only the nature of the change being generated but also the strategic conditions that are needed to make that change possible.

2.2.2 Evolution and Dynamics of Supply Chain Innovation

Innovation in SCM has evolved into a strategic phenomenon that extends beyond the boundaries of individual firms (Wong and Ngai, 2019). The dynamics of SCI are shaped by both internal capabilities and external relationships, given that organizations are

increasingly facing business environments where technological changes are rapid and frequent, making the ability to innovate not a strategic option but a competitive necessity (Al-Omoush et al., 2025; Malacina & Teplov, 2022). The relational dimension is equally important since buyer-supplier collaborations for innovation create significant benefits including knowledge sharing, economies of scale in research and development, and risk transfer across supply chain partners (Malacina & Teplov, 2022). Organizations where suppliers are disconnected from innovation efforts are significantly less likely to achieve their SCI objectives (Wong & Ngai, 2019).

Historically, innovation in SCM has been understood through the lens of process improvement (Hahn, 2020). However, the rise of Industry 4.0 is changing this perspective. The integration of digital technologies into supply chain operations is enabling new models of autonomous coordination between machines, systems, and organizations that go beyond what traditional process improvement frameworks were designed to capture (Hahn, 2020; Samuels, 2025). SCI is consequently shifting from a predominantly cost-reduction orientation toward a focus on customer value and, in the case of larger organizations, toward the emergence of entirely new ways of organizing and monetizing supply chain activities (Hahn, 2020; Zhou et al., 2026). Digital technologies, by giving organizations access to richer and more timely information, create the conditions for understanding stakeholder needs in depth, identifying emerging industry shifts, and making better resource allocation decisions in environments characterized by uncertainty (Li et al., 2024). This capacity to improve supply chain agility, traceability, and flexibility makes digital technologies a critical enabler of the dynamic capabilities organizations need to remain competitive (Li et al., 2024). This change reflects a dynamic transformation described by Vial (2019): digital technologies do not simply improve existing ways of working but disrupt them, forcing organizations to rethink how they create value and navigate the organizational and structural challenges that come with that change. It is within this context of accelerating digital disruption and evolving competitive demands that AI has emerged as one of the most significant tools reshaping SCI.

2.2.3 AI as an Enabler of Supply Chain Innovation

AI is gaining recognition as a source of competitive advantage in SCM, not just for the efficiency gains it delivers, but for its capacity to help organizations stay relevant in a world defined by constant disruption, shifting customer demands, and relentless pressure

to digitalize (Cannas et al., 2024). Haefner et al. (2021) observe that AI could change the economics of innovation for firms, making it less risky and less costly by expanding their ability to search for opportunities, process information at scale, and bring ideas to implementation faster than traditional methods. Bahoo et al. (2023) go further, suggesting that AI is not just improving existing innovation practices but has the capacity to push organizations toward more ambitious and transformative outcomes than they could achieve without it. For organizations that use it well, AI opens the door to disruptive innovation, not just better processes but entirely new ways of competing and creating value (Lee et al., 2019).

Within supply chain operations, AI's capacity to enable innovation is visible across multiple dimensions. Sullivan and Wamba (2024) show that AI expands what organizations can do in three directions: tackle repetitive operational tasks automatically, turn large volumes of data into actionable insights, and enable direct interaction with people, and is this combination that creates new pathways for market responsiveness and innovation. Richey et al. (2023) argue that AI can build the kind of organizational flexibility that allows supply chains to adapt their structures, rethink their processes, and create value in ways that go beyond what any single function could achieve on its own. Teixeira et al. (2025) argue that what AI is allowing goes beyond incremental improvements to individual supply chain functions, laying the groundwork for supply chains to become smarter, more adaptable, and more sustainable as a whole.

At the business model level, Gen-AI is presenting significant possibilities. What sets Gen-AI apart from earlier AI systems is its ability to create entirely new outputs rather than simply working with what already exists and in supply chain terms this opens new possibilities for how organizations assess suppliers, manage risk, coordinate logistics, and engage with customers (Fosso Wamba et al., 2024). Wamba et al. (2023) suggest that Gen-AI has the potential to change how supply chain partners work and communicate together, though they also acknowledge that most organizations have not yet developed the preparedness to fully explore what this technology can offer. Jorzik et al. (2024) show that AI can play very different roles in BMI depending on how organizations approach it, from simply supporting what already exists to generating new capabilities, creating new value propositions, or challenging the rules of how an industry operates.

However, the relationship between AI adoption and SCI is not automatically positive – how organizations adopt matters as much as whether they adopt. Richey et al. (2023) observe that traditional AI applications are reactive, leveraging data for prediction and optimization without necessarily generating new value. This distinction matters because organizations that adopt AI in response to competitive pressure – what Al-Omoush et al. (2025) characterize as mimetic institutional pressure – rather than because of a clear understanding of what problem it should solve tend to achieve operational improvements instead of true SCI. The realization of AI's full potential therefore depends not only on the technology deployed but on the strategic intent behind its adoption.

Equally important is the human dimension. Jarrahi (2018) makes the case that the most productive relationship between AI and humans is one of partnership and not competition, where machines take on the data-heavy analytical work and people focus on the things they do best, like judgment, creativity, and making sense of complex situations. Cohen et al. (2026) reinforce this, stating that "AI's role is not to replace people in supply chains but to augment them" (p. 694). Cannas et al. (2024) ground this in empirical reality: despite AI's clear potential, many organizations are still far from realizing it in practice, held back by the absence of a clear strategy, insufficient infrastructure, and limited commitment from leadership.

2.3 Research Gaps and Analytical Framework

2.3.1 Research Gaps

Despite the growing body of literature on AI in SCM, significant gaps remain in understanding how AI drives innovation specifically. Richey et al. (2023) note that existing research regarding AI and SCM remains limited when compared to the pace of technological developments, while Mariani et al. (2023) note that the innovation literature has largely overlooked how AI systems can assist businesses in achieving their broader innovation goals. This is evident when talking about BMI, where studies investigating the direct impact of AI remain scarce (Lee et al., 2019) and where the literature remains unclear on how organizations need to reconfigure their business models to create and capture value from AI adoption (Jorzik et al., 2024). Additionally, certain AI application types, such as prescriptive analytics, remain considerably underexplored compared to predictive and descriptive AI, despite their transformative potential in supply chain operations (Smyth et al., 2024).

At the organizational level, a gap exists between the documented potential of AI and managers' capacity to realize it in practice. Grover et al. (2022) note that many managers still do not know how to put AI to work effectively across their operations. Jorzik et al. (2024) add to this, mentioning that most organizations have not yet built the internal capabilities needed to move AI beyond the experimental phase into meaningful operational use.

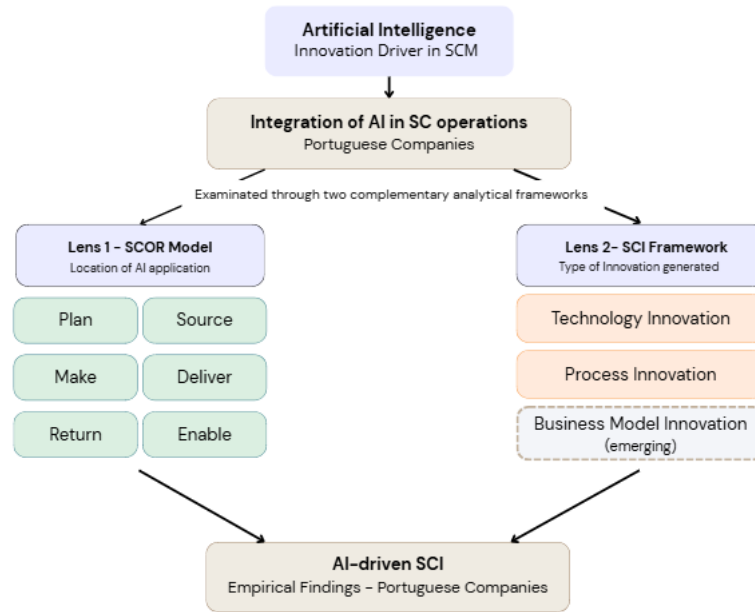
The most significant gap concerns the geographic concentration of existing research and the limited empirical evidence available from non-American contexts. Wong and Ngai (2019) note that close to half of all SCI studies are based on American samples, and that manufacturing firms dominate the studies – a concentration that raises serious questions about how widely these findings can be applied across different business environments and national contexts. Besides this geographic gap there is a structural one: existing research has been predominantly conducted in large organizational contexts, leaving SME-dominated business landscapes, where financial and capability constraints shape how AI is adopted and what innovation it generates, largely unexplored (Richey et al., 2023; Teixeira et al., 2025). This gap is critical in the Portuguese context. Recent data from INE (2025) indicates that only 11.5 percent of Portuguese companies currently use AI technologies, while an exploratory survey of Portuguese supply chains found that this figure drops to just 8.8 percent within supply chain operations specifically (Oliveira et al., 2024). Therefore, studying Portuguese companies offers an opportunity to extend the geographic scope of SCI research, contributing empirical evidence from a European SME-dominated context that remains largely absent from existing literature and challenging the generalizations drawn predominantly from American samples.

2.3.2 Analytical Framework

The literature reviewed points to two analytical structures that complement each other and are suited to examine AI-driven SCI. The extended SCOR model, with the Plan, Source, Make, Deliver, Return, and Enable phases (APICS, 2017), is the most widely adopted reference framework for supply chain analysis and provides a structured way of mapping where across supply chain operations AI is being applied, making it well suited to addressing the first research objective of identifying and characterizing AI implementation in Portuguese companies. The SCI framework, based on the technology and process innovation dimensions established by Kwak et al. (2018) and the emerging BMI dimension identified by Jorzik et al. (2024) and Foss & Saebi (2017), provides the

categories through which the type of innovation AI is generating can be identified and classified, directly addressing the second research objective of exploring how organizations experience and interpret the impact of AI on their supply chain processes. Figure 1, presented below, illustrates this conceptual framework elaborated by the author and its application to the empirical analysis conducted in Chapter 4.

Figure 1. Analytical Framework: AI-Driven Supply Chain Innovation in Portuguese Companies



Source: Author's own elaboration

CHAPTER 3: METHODOLOGY

3.1 Research Design and Justification

The objective of this study is to understand how AI is driving innovation in Portuguese companies' supply chains. To this end, the research employs a qualitative and exploratory design, implemented through a multiple case study approach (Yin, 2018). As the research questions focus on 'how' and 'why', this methodological choice is well-suited to investigating an under-explored phenomenon in the Portuguese context (Yin, 2018). This is particularly pertinent when we consider that, according to Oliveira et al. (2024), only 8.8 percent of Portuguese companies currently utilize AI in their supply chain operations. Furthermore, Wong et al. (2019) highlight that existing research on this topic largely focuses on samples from the U.S. and the manufacturing sector.

A qualitative approach was selected to capture rich, context-specific insights into participants' experiences, perceptions and interpretations (Flick, 2014; Saunders et al., 2023). Additionally, the multiple case study design allows for cross-case comparisons

across various companies, sectors, and supply chain functions, providing a more comprehensive understanding of the practical applications of AI-enabled innovation (Yin, 2018). The study adopts a cross-sectional time horizon, collecting data at a single point in time. This provides a snapshot of the phenomenon as it exists at the time of investigation (Braun & Clarke, 2006; Saunders et al., 2023).

3.2 Analytical Framework

The empirical analysis is guided by two complementary frameworks developed in Chapter 2. The extended SCOR Model (APICS, 2017) provides the operational structure for the analysis, in which interview data was examined against each of its six phases to identify where AI is being applied. The SCI framework, drawing on Kwak et al. (2018), Wong and Ngai (2022), and Zhou et al. (2026), provides the classification structure. Interview data was coded against its three dimensions to determine what type of innovation AI is generating: technology, process, or emerging BMI.

3.3 Sample Selection

The companies and professionals included in this study were selected using purposive sampling, a non-probability sampling approach in which the participants are deliberately chosen regarding the relevance they pose for the defined RQs, ensuring depth and pertinence of the data collected (Teddlie & Yu, 2007; Yin, 2018). The target population comprised Portuguese organizations that had adopted AI in one or more supply chain functions, as well as professionals with direct knowledge and experience of these AI applications. To ensure informed insights, participants were required to hold managerial or specialist roles with responsibilities related to AI implementation or supply chain decision-making.

The selection of participants followed two complementary criteria. The first targeted managers at consulting firms who deal with first-hand implementation of AI solutions in clients' supply chains, providing a broad and realistic cross-sectoral perspective on which industries are pursuing AI adoption, in which supply chain phases implementation is happening most commonly and what barriers and challenges are the most frequent. The second targeted managers/directors at companies that have already adopted AI tools in their supply chain operations – or are actively identifying opportunities to do so, which allows understanding of concrete examples of AI application and perceived outcomes, whether already observed or anticipated, that come from their own experience. This dual

approach was deliberately chosen to balance both the realistic vision that consulting professionals bring - which is shaped by the exposure to multiple implementation scenarios across different sectors and maturity levels, with the specific, grounded evidence companies can offer. Given that companies may have a more optimistic view of AI's potential while consultants offer a more measured assessment, supported by repeated implementation experience, combining both perspectives will provide a more complete picture of AI driven supply chain innovation in the Portuguese context.

3.4 Data Collection and Analysis Techniques

The primary data collection was obtained through 7 semi-structured interviews of approximately 30 to 45 minutes which, according to DiCicco-Bloom and Crabtree (2006), is the expected duration of this type of interview. According to Hennink and Kaiser (2022), this sample size can be considered methodologically adequate, given that saturation in qualitative research can be achieved with few interviews, depending on the study context. Furthermore, in this study, close saturation was facilitated by the seniority of the participants, their involvement in AI adoption within supply chain operations and their extensive professional experience – all factors that increase information power and support thematic saturation with a smaller number of interviews (Malterud et al., 2016).

The semi-structured format adopted combines structure with adaptability, allowing the interviewer to delve deeper into certain topics and complementing the base questions in order to gather more detailed and nuanced knowledge (Yin, 2018; Saunders et al., 2023).

The participants were managers, specialists and directors responsible for operations, innovation, digital transformation or consulting functions. All interviews were conducted one-on-one, fully online using Microsoft Teams and recorded with consent for further and complete analysis of information. To comply with confidentiality requirements expressed by the participants, both individual identities and organizational names have been anonymized throughout this study. Participants are identified using a code system, C or E and respective interview number, in which C refers to participants of consulting organizations and E denotes enterprise organizations. Additionally, company names have been replaced with aliases, based on the military alphabet code system (NATO Phonetic Alphabet). Table II, presented in Appendix A, provides the identification associated with each company and more information about the participating professionals.

The interview guides, one for each type of professional (consultant or part of an organization), available in Appendix B, were organized having in consideration the RQs presented, with themes revolving around AI adoption, results of innovation, barriers and future outcomes.

Data was then analyzed using a thematic approach. This approach enables the identification and interpretation of patterns across the collected data (Braun & Clarke, 2006; Saunders et al., 2023). By utilizing this technique, the interview recordings were first compiled, the main and most relevant quotations transcribed and sorted. The data collected was then coded based on the conceptual framework adopted – the SCI framework serving as the primary coding structure and the SCOR Model phases providing the operational organizing principle, allowing each quote to be systematically associated with a specific innovation type and supply chain phase. Following Miles and Huberman's iterative approach (1984), the initial codes were grouped into broader categories aligned with the RQs, constantly moving between the base data and the categories created until consistent patterns were identified for each presented case. After analyzing each case individually, a cross analysis of all the subjects of the study was conducted to compare findings, identify common patterns and divergences. This approach allows conclusions to be drawn beyond the context of a single organization and support the generalization of the observations (Yin, 2018).

CHAPTER 4 – FINDINGS AND DISCUSSION

This chapter presents the findings of the empirical research conducted through seven semi-structure interviews with professionals from six Portuguese companies. The analysis is organized in order to give response to the central research question “*How is AI driving innovation in the supply chains of Portuguese companies?*”. The main topics to be approached follow a continuous thread in order to give a clear answer to the question, starting by defining the current state of AI adoption in Portuguese supply chains, the nature of the SCI being generated and the conditions that have shaped how innovation manifests itself. The discussion will provide academic context to real-world findings that can be associated with the experience of the interviews.

4.1 Findings

4.1.1 AI Adoption in Portuguese Supply Chains

- **AI implementation across supply chain phases**

As mentioned by interviewee C2, a study conducted by Delta in the previous year, surveying CEOs on AI adoption within their organizations, found that more than 50% of respondents still described AI at a very idealistic and trial-based stage. Organizations were aware of AI's potential, and recognized its strategic importance, but remained far from meaningful integration into their core operations. Interviewee C2 further noted that, based on what he and his team assess, and on the implementation projects they have been involved in the period following the study, this picture had not changed significantly. This contextualizes the current state of AI implementation observed across the six organizations studied.

The **Plan** phase presents the strongest and most consistent evidence of AI adoption across the sample. Interviewee C3 confirms that predictive analytics applied to stock and procurement management represents one of the most frequent AI applications encountered across Portuguese companies, alongside the improvement of operational data analysis that used to rely on manual efforts. Interviewee C2 references a large Portuguese retailer that has deployed AI-powered algorithms for demand planning, stock optimization, inventory management, and replenishment. At the company level, Tango is actively developing an AI-based forecasting system specifically designed to strengthen predictive capacity in planning, purchasing, and supply management, described by interviewee E3a as the organization's most advanced and strategically significant AI initiative at the time of data collection.

Hotel provides pharmaceutical companies with market data intelligence solutions that enable them to anticipate consumption needs and support more informed supply planning decisions, as described by interviewee E1. Interviewee E1 also explains that pharmaceutical clients use these intelligence solutions not only to anticipate consumption patterns but also to manage inventory levels more effectively, reducing both excess stock and supply gaps across their distribution networks.

Interviewee E2 describes how Lima deployed a robot for visual monitoring of stockouts across the store floor that collects real-time shelf availability data that feeds directly into replenishment planning decisions. In another example given by Interviewee E2 leading Portuguese supermarket chains operate AI-powered replenishment systems that continuously process data on sales rhythms, seasonality, temperature, and transport conditions to generate optimized replenishment plans.

Within the **Source** phase, no dedicated AI applications were explicitly identified across the organizations studied, though interviewee C3 references procurement management as an area benefiting indirectly from broader predictive analytics and administrative automation initiatives. This comment aligns with what Daios et al. (2025) have documented regarding AI's ability to streamline routine procurement tasks, freeing up resources and reducing manual effort. However, the more strategic dimension of AI in sourcing, i.e., its potential to fundamentally change how organizations select and manage suppliers, moving from reactive to more anticipatory and intelligence-driven approaches (Richey et al., 2023; Samuels, 2025) remains largely absent from the Portuguese cases studied, pointing to a gap between what the literature envisions for this phase and what is currently being realized in practice.

The examples mentioned in the **Make** phase, such as a computer vision solution for accident prediction in a manufacturing facility and an AI-based system for detecting errors in automotive component production, were referenced by interviewee C2. However, those were examples of international companies operating in Portugal rather than national Portuguese organizations. This distinction is important. While the literature points to intelligent manufacturing as an emerging field globally (Zhong et al., 2017), the applications it describes, such as quality control and real-time production monitoring to predictive maintenance that prevents unplanned equipment stops (Daios et al., 2025; Dash et al., 2019) are already being implemented in Portugal, but exclusively through multinational companies. This suggests that even the earliest waves of AI adoption in manufacturing are reaching Portugal through foreign investment rather than domestic initiative, pointing to structural differences in the capacity and resources available to international versus national organizations when it comes to more complex and capital-intensive AI applications.

Within the **Deliver** phase, interviewee C2 describes a Portuguese logistics and distribution company using AI for delivery window prediction and route optimization across its distribution network. While this represents the only direct evidence gathered for this phase (a problem resulting from the composition of the sample and not from the absence of adoption in the sector) it confirms what the literature documents as one of AI's capacities to make logistics operations more dynamic and responsive, moving away from fixed pre-planned routes toward systems that continuously adapt to real-time conditions

and are able to consider multiple variables in order to improve efficiency and service levels (Richey et al., 2023; Teixeira et al., 2025).

Regarding the **Return** phase, Tango has initiated an early-stage pilot for the management of claims and defective products. This initiative is still in the requirements definition and conceptual phase at the time of data collection, as noted by interviewee E3b. This is the phase with less mentions across the sample, which mirrors what the literature acknowledges as a globally underdeveloped area. Reverse logistics has attracted significantly less research and technological investment than forward logistics, and AI applications here remain at an earlier stage of maturity. That Tango is already exploring this possibility, even at a conceptual level, is a good sign especially considering that regulatory pressure around circular economy practices within the European market is growing, pushing companies to develop new strategies and technologies to better manage the end of the lifecycle of their products (Teixeira et al., 2025).

The **Enable** phase showcases the most diverse evidence of AI adoption across the sample, approaching supplier risk monitoring, commercial risk management, knowledge management, administrative automation, and customer service. Interviewee C3 describes a growing application of AI in supplier risk monitoring that analyzes patterns of delivery delay, detects early signs of instability in the supply base, and generates automatic alerts that used to require extensive manual analysis. Tango is developing a Commercial Erosion initiative for proactive risk monitoring, enabling the early identification of commercial risk signals before they become significant operational or financial problems, as described by interviewee E3a. However, the fact that these applications are concentrated in organizations with more advanced digital infrastructure suggests this shift is still limited and not widespread in Portugal. Interviewee C3 confirms this, noting that supplier risk monitoring and similar advanced AI applications remain viable only in organizations that already have structured data and solid technological foundations, which is something that most Portuguese companies, particularly SMEs, have not yet achieved. Tango is also developing a Commercial Knowledge Hub designed to bring together dispersed organizational knowledge into structured, accessible information that different teams can use to make faster and better informed decisions, while reducing time spent searching for and interpreting relevant data, as outlined by interviewees E3a and E3b. Interviewee C3 identifies administrative process automation as a frequent Enable phase application across Portuguese companies, covering data entry, reporting, and operational

analysis that previously demanded significant manual effort. Interviewee C2 references a logistics and distribution company that deployed an AI-powered virtual assistant to handle customer service operations, managing client queries and complaints through automated interaction – a practice that is growing across multiple sectors in the Portuguese context. This gap between how many Enable phase functions AI is touching and how deeply it is being used reveals where Portugal currently stands: AI is present in many areas, but organizations are still building the foundations needed to make it work effectively (Teixeira et al., 2025).

When mapped against the extended SCOR model, the findings reveal a concentration of AI adoption in the Plan and Enable phases, partial presence in the Deliver phase, and limited evidence in the Make, Source, and Return phases. Nonetheless, evidence of AI applications was indeed found across all six phases. This extensive but uneven presence suggests that, even at an early stage of adoption, AI is already reaching different parts of the supply chain in Portugal, which is consistent with what recent literature has documented across different industries and contexts (Daiois et al., 2025; Richey et al., 2023; Teixeira et al., 2025).

Table IV, presented in Appendix A, summarizes the findings across the SCOR Model phases, indicating the organizations or clients of the consulting firms in which AI applications were found and the current stage of implementation.

- **Drivers of adoption**

Across the organizations studied, the motivations driving AI implementation in Portuguese supply chains reveal that the adoption is mostly reactive. Interviewee C3 characterizes the adoption directly: *"adoption is mostly reactive. Most of the Portuguese companies I see adopting AI do so because they felt external pressure: a competitor already using it, a news story, or the sales team of a software vendor. It rarely stems from their own strategic decision about which problem they want to solve"* (C3). Interviewee C2 describes a client that was fully satisfied with an ongoing implementation project but requested the addition of AI solely because, in the client's words, *"we have to start following the market"* (C2). Interviewee E2 reinforces this from a company perspective, noting that even organizations that are not prepared for AI adoption feel compelled to pursue it because if a competitor gains efficiency advantages through AI, others must follow regardless of their readiness. This pattern of adoption by pressure raises an

important question about the nature of the innovation that is being generated in Portuguese companies. When adoption is driven by the fear of falling behind rather than by a clear will and understanding of what problems should AI be solving, or at least helping with, the outcomes tend to reflect that lack of intentional implementation. As both Al-Omoush et al. (2025) and Richey et al. (2023) suggest, adoption based on external factors tends to produce operational improvements rather than genuine innovation, since organizations are optimizing existing ways of working instead of rethinking them.

Interviewee C3 mentions that most Portuguese companies are not building their own solutions or choosing tools strategically, but consuming whatever comes integrated within the software ecosystems they already use. Additionally, when asked to quantify the return on the AI already adopted, most managers approached by interviewee C3 cannot provide an answer. This inability to measure results presents a critical point: if organizations are not able to demonstrate the value of AI, they have already implemented, it becomes difficult to justify going further or investing more strategically (Daios et al., 2025). Interviewee C2 observes that clients are more focused on what competitors may be doing than on identifying specific problems AI could solve within their own organizations. Interviewee C1 similarly notes that Portuguese companies have used AI rather timidly in general. What stands out in these observations is that exists not a resistance to AI, but more of a genuine uncertainty on how to use it well – a gap identified between the promise of AI and the practical expertise required to convert that understanding into strategic action (Grover et al., 2022). This feeling of unpreparedness is not exclusive to Portugal; in fact, most organizations globally struggle to move AI beyond early pilots into something that genuinely transforms their operations (Jorzik et al., 2024), suggesting that what is observed here reflects a wider challenge rather than a specifically Portuguese limitation.

Not all adoption within the sample follows this pattern. Hotel underwent a significant strategic repositioning in 2025, driven by a change in ownership and a deliberate decision to reposition themselves as a Health Tech company, with interviewee E1 describing this as a proactive internal driver of AI adoption. Tango also demonstrates an intentional approach, with interviewee E3a describing a phased strategy designed to control risk, validate data, involve users and ensure AI initiatives respond to concrete and well-defined problems, essentially “*building the conditions for a more robust adoption in the future*” (E3a). These cases suggest that when organizations have a clear internal motivation for

adopting AI the approach to implementation tends to be more structured and deliberate, in contrast to the reactive pattern observed across the rest of the sample.

4.1.2 The Nature of AI-Driven Supply Chain Innovation

The findings presented in this section are analyzed through the Supply Chain Innovation framework, established in the methodology chapter, which identifies three dimensions of SCI: technology innovation, process innovation, and BMI.

- **Technology innovation**

Across the organizations studied, AI adoption has introduced new technological capabilities into supply chain operations. When mapped against the SCI framework, these capabilities align consistently with what Kwak et al. (2018) define as technology innovation – the enhancement of integrated information systems, real-time tracking capabilities, and logistics infrastructure, and the findings reflect all three of these dimensions in the Portuguese context.

The most prevalent evidence relates to the introduction of AI-powered information and analytics systems. Predictive analytics has long been recognized as one of the most established AI applications in SCM, precisely because the data it needs already exists in most organizations and the results it delivers are immediate and measurable (Oyewole et al., 2024; Toorajipour et al., 2021).

Hotel developed a platform that allows pharmaceutical clients to interact dynamically with market data, as described by interviewee E1: *“[our clients] moved away from the classic dashboard, the pre-defined analysis that needed monthly updating, to create their own dashboards and liveboards. The client can instantly create, share within their organization, ask questions through a chatbot to obtain more insights, conduct on-demand market analyses and do forecasting. This made companies stop being so reactive in their information analysis and decision-making, and start being more proactive.”* (E1).

The academic literature points in a similar direction, noting that the most recent advances in AI, particularly Gen-AI capabilities, are enabling organizations to move beyond static forecasting models toward dynamic, interactive systems that improve the accuracy and responsiveness of demand and supply planning (Jackson et al., 2024; Richey et al., 2023) and Hotel's platform appears to be an early but concrete expression of this evolution in the Portuguese context.

Tango is developing a Commercial Knowledge Hub designed to transform dispersed organizational knowledge into structured and accessible information for cross-functional teams, as outlined by interviewees E3a and E3b. The examples of both companies, Hotel and Tango, reflect something that goes beyond tool adoption, since these organizations are building internal technological capabilities that did not exist. This finding is consistent with what Wong and Ngai (2022) identify as a primary driver of supply chain innovation: the development of internal technology resources that enable new ways of creating and delivering value. Tango's Knowledge Hub is particularly notable in this aspect: by creating a shared intelligence layer that different functions can access and query, it represents an early attempt to achieve what the literature identifies as one of AI's more structural contributions: connecting previously isolated parts of the organization through shared data and intelligence, enabling more coordinated and responsive ways of working (Teixeira et al., 2025).

Additionally, the productivity consequences of system enhancements are measurable. Interviewee C3 mentions a system integration project for data processing that generated a return on investment of 160% in the first year, while interviewee E1 describes faster information processing at lower cost through AI-driven optimization. Together these cases illustrate what technology innovation means in practice: not just new tools, but a fundamental change in what organizations can do with their data and how quickly they can do it – which translates directly into the kind of productivity gains and expanded value proposition that Kwak et al. (2018) associate with technology innovation in supply chains.

Real-time tracking and monitoring capabilities represent a second area where technology innovation is clearly evidenced. Interviewee E2 describes how Lima deployed a robot for autonomous visual monitoring of stockouts, generating continuous shelf availability data that replaced periodic manual stock counting. Tango's Commercial Erosion initiative similarly moves from periodic manual risk assessment to continuous automated monitoring of commercial risk signals, as described by interviewee E3a. Both cases point toward what academics have increasingly documented, that is, AI giving organizations the ability to anticipate and prepare for supply chain disruptions rather than simply reacting to them (Daios et al., 2025; Richey et al., 2023). Academics have increasingly highlighted this shift as crucial to building more resilient and adaptive supply networks (Teixeira et al., 2025)

Evidence of technology innovation in logistics infrastructure is present across the sample. Interviewee C2 references a logistics company that deployed AI for delivery window prediction and dynamic route optimization. Interviewee C2 further references the deployment of computer vision systems for quality control and safety monitoring in manufacturing environments that can detect production errors and predict accident probability in real time. What these examples reveal is a shift from planning that happens once and then gets executed, to planning that happens continuously as conditions change. This kind of operational responsiveness was not possible before AI and reflects what the literature describes as one of its most significant contributions to supply chain operations: the ability to continuously learn from complicated data collected from various sources in order to rethink how decisions are made (Jackson et al., 2024).

- **Process innovation**

AI adoption is generating significant changes in how supply chain activities are carried out. Looking at these changes through the SCI framework lens, what emerges is a clear pattern of process innovation. Not radical transformation, but in the sense that Kwak et al. (2018) describe as the redesign and re-engineering of operational activities to enhance management practices, improve service quality, and deliver greater efficiency across supply chain functions.

The automation of repetitive and time-intensive tasks represents the most consistent process change observed across all participants. Interviewee C3 describes the automation of administrative tasks and the improvement of operational data analysis as among the most common process changes across Portuguese companies, replacing manual work with AI-driven processing that delivers results faster and at lower cost. C3 also shared a concrete example of a content production automation project that reduced editorial costs by 60% and generated a return on investment of 66% in the first year. Interviewee E1 describes Hotel's own experience: *"From an internal perspective, the tools brought more speed to information processing and at lower cost. We were able to identify processes with duplicated information that were eliminated through AI-driven process optimization. We got faster information processing with less effort, making information management cheaper."* (E1). Interviewee C2 describes clients whose demand planning, stock management, and replenishment processes shifted from manual spreadsheet-based approaches to AI-powered automated systems. Interviewee E2 reinforces this from a retail

perspective, describing how AI-powered replenishment systems replaced periodic manual ordering with continuous automated optimization across leading Portuguese supermarket chains, a process redesign that improved both efficiency and responsiveness to changing demand conditions. Interviewee C2 also references the deployment of an AI-powered virtual assistant by a logistics and distribution company, capable of handling client queries, complaints, and delivery-related questions through automated interaction – that lead to the replacement of a previously human-operated customer service process. What these cases collectively illustrate is something that goes beyond efficiency gains. They show organizations beginning to question and redesign the fundamental logic of how routine supply chain tasks are performed, which is what distinguishes process innovation from simple digitization. As Kwak et al. (2018) note, process innovation is not about doing the same things faster but about rethinking how activities are structured to deliver better service at lower cost. The examples gathered here suggest this shift is underway, even if still at an early stage (Kwak et al., 2018). The fact that it is happening first in administrative and operational tasks is not coincidental, since these are the areas where the gap between what humans can process manually and what AI can handle automatically is most immediately visible, and where the case for change is easiest to make (Daivos et al., 2025).

The shift from reactive to predictive management represents a second significant process change across the sample. Interviewee E3a describes Tango's ongoing transition: *"The organization is preparing to move from a more reactive logic based on manual analysis to a more predictive, structured, and data-supported logic [to planning and supply management]."* (E3a). At Hotel, their clients similarly moved from periodic static reporting to real-time on-demand analysis, as described by interviewee E1, a shift that significantly improved decision-making responsiveness. Interviewee C2 references a logistics company that replaced fixed routing plans with dynamic AI-powered route optimization, enabling real-time responses to changing delivery conditions. Interviewee E2 further describes how Lima's stockout monitoring robot transformed stock management from a periodic manual process into a continuous automated one, enabling faster and more accurate replenishment responses. Taken together, these findings suggest that Portuguese organizations are beginning to realize what the literature describes as AI's core contribution to supply chain planning: the capacity to turn data into actionable intelligence that improves forecast accuracy, reduces inventory inefficiencies, and enables

faster and more informed operational decisions (Belhadi et al., 2024; Jackson et al., 2024; Oyewole et al., 2024). What makes this shift analytically significant is not just that things are being done faster, it is that the underlying logic of how decisions are made is changing. This is where, as Kwak et al. (2018) argue, process innovation tends to generate its greatest value for customers and supply chain partners. Richey et al. (2023) take this further, noting that when AI enables this kind of cross-functional process redesign, encompassing planning, logistics, and commercial management simultaneously, it starts to generate dynamic capabilities that go beyond individual efficiency gains toward a more fundamental change in how the supply chain operates as a whole.

A significant finding across the sample is that the majority of the process innovation being generated is of incremental nature. Interviewee C3 is direct on this point: *"process innovation dominates, and it is almost always incremental"* (C3). Interviewee E3a similarly characterizes Tango's current position as one of incremental innovation in development, with potential for transformation if cases are successfully integrated and scaled. Interviewee E1 describes Hotel's innovations as mostly incremental improvements, attributing this partly to resistance to change and distrust of some tools regarding data confidentiality.

Interviewee C2 notes that companies will progressively start using AI without realizing it as it becomes embedded in the ERP, WMS, and planning tools they already use. Interviewee E2 builds on this and captures the subtle nature of this process change: *"It is invisible. It is everywhere and it is a change that users, employees, and customers end up dealing with. In organizations it will make life easier, allow working on other matters where we are more effective, and we can allocate more resources and eliminate what is not so relevant."* (E2). What the findings consistently show is that Portuguese companies are operating at the incremental end of the innovation range, using AI to optimize what already exists rather than to create something completely new. As Arlbjørn et al. (2011) argue, SCI ranges from incremental optimization of current practices all the way to radical change that sets entirely new rules within an application area; the gap between Portugal's current position and that radical end of the spectrum is substantial. In a way, this finding is not surprising, since process improvement has historically been the dominant form of SCI, long before AI entered the picture (Hahn, 2020). What is impressive is that even with the technology opening more doors for ambitious transformation, most Portuguese organizations are not chasing it yet. This is not due to AI not being capable of doing so,

but because the strategic intent and foundational conditions needed to go further are still missing in most cases. As one AI consultant captures directly: *"much of what is done in Portugal with AI in supply chains is catching up: automating what European competitors were already doing years ago with other tools. Calling that 'innovation' is inaccurate, and that inaccuracy has real consequences: for companies, because they overestimate what they have achieved; and for academic research, because it can create an image of the Portuguese market as more advanced than it actually is. Real innovation exists, but it is still the exception."* (C3).

- **Emerging Business Model Innovation**

BMI is the dimension of the SCI framework that is least pointed out across the conducted interviews, but the most strategically important. Unlike technology and process innovation, which are present across all six organizations, BMI is an exception rather than a rule in the Portuguese context. This is an expected outcome since that, of the three SCI dimensions, BMI is the hardest one to pursue and leverage, requiring organizations not just to adopt new tools or redesign existing processes but to fundamentally rethink how they create and capture value – something that most organizations find difficult to do even when the technology makes it possible (Jorzik et al., 2024; Kahn & Cook, 2026). Interviewee C3 is clear on this point, stating that *"Portuguese companies are using AI to do better what they already did, not to create radically different business models"* (C3). This observation points to something important about the current state of AI adoption in Portugal: organizations are engaging with the technology, but they are not utilizing it to the most extent possible. The literature suggests that companies which genuinely leverage AI's potential are capable of creating disruptive innovation through entirely new business models and value propositions (Lee et al., 2019). Yet, what the evidence gathered in this study reveals that most Portuguese organizations lack either the ambition and/or conditions needed to translate AI adoption into genuine business model transformation.

Nonetheless, the clearest and most explicit evidence of BMI is found at Hotel. Interviewee E1 describes how a change in ownership structure in 2025 triggered a deliberate strategic decision to reposition Hotel as a Health Tech company, a fundamental reconfiguration of how the organization defines its business, the value it offers to clients, and the markets it competes in. This repositioning was directly enabled by AI capabilities that expanded what Hotel could offer beyond traditional market research into technology-driven health

intelligence services. What Hotel's case reveals is something that the literature has begun to emphasize: realizing AI's potential for BMI requires more than just deploying new technology. It requires a deliberate organizational decision to redefine in what business to operate and the willingness to build the capabilities needed to compete in that new space. As Jorzik et al. (2024) argue, successfully leveraging AI's potential at this level requires firms to actively engage in BMI alongside technological adoption, and Hotel appears to be one of the few Portuguese organizations in this study that has taken that step.

A second form of emerging BMI is observed at Tango, where the development of the Commercial Knowledge Hub points toward a new organizational model based on shared, structured knowledge accessible across functions. Interviewee E3a describes how this initiative is shifting value creation within the organization: *"The way of creating value is shifting towards forecasting capabilities, anticipation, structured knowledge, and decision support."* (E3a). Interviewee E3b further notes: *"this initiative could fundamentally change how knowledge is managed and shared across the organization, representing a structural shift in how Tango operates internally."* (E3b). What is interesting about Tango's case is that BMI is not coming from a repositioning, as in Hotel's case, but from a gradual structural change in how the organization manages and shares knowledge internally, suggesting that BMI can take different forms and does not always require a top-down strategic renovation to begin (Zhou et al., 2026).

A third form of emerging BMI is observed through the broader market dynamics described by interviewee E2. Interviewee E2 notes that many consulting firms are working alongside organizations to redefine their business models, since AI introduces capabilities such as predictability, traceability, and data-driven decision-making that challenge the existing ways of work and force organizations to change, not only the business models but also organizationally and culturally. This observation shows, in the Portuguese context, that the pressure to rethink how organizations operate is not limited to those already pursuing BMI, i.e., AI is changing the competitive landscape enough that even organizations standing on the sidelines are being pushed toward it. This aligns with what Zhou et al. (2026) identify as one of the less visible but important dimensions of supply chain innovation: the relational and cultural pressures that force organizations to evolve how they operate, not just what tools they use.

Interviewee C3 identifies sustainability and ESG traceability as an additional emerging area where AI is beginning to generate new organizational capabilities, particularly in exporting companies responding to European buyer requirements for embedded carbon measurement and verifiable sourcing data. While this does not constitute fully realized BMI, it points toward a trajectory that the literature has increasingly highlighted: AI's capacity to contribute to supply chain transparency, responsible sourcing, and environmental performance in ways that go beyond operational efficiency and begin to reshape how organizations position themselves in their markets (Daivos et al., 2025; Teixeira et al., 2025).

Table V identifies the innovations that were found in the organizations, and their perceived results, against the SCI Dimensions (Technology, Processes and Business Model Innovations), providing a detailed summary of the findings described.

4.1.3 Conditions Shaping AI-Driven Supply Chain Innovation in Portugal

Beyond identifying what AI is being used for and what innovation it is generating, the interviews revealed a set of conditions that significantly shape how AI-driven supply chain innovation manifests in the Portuguese context. These conditions help explain the picture generated in the previous sections: why adoption tends to be reactive, why innovation stays incremental, and why the gap between what AI could enable and what organizations are actually achieving remains significant. Three conditions stood out consistently across the sample: data quality and governance, human and organizational readiness, and structural and financial constraints.

- **Data quality and governance**

Data quality and governance emerge as the most consistent condition shaping AI adoption and its outcomes across organizations, being the only finding that is unanimously confirmed regardless of sector, organization type or stage of AI implementation. When organizations as different as a health data company, a specialized retail multinational, a distribution company, and three consulting firms all point to the same bottleneck it stops being a coincidence and starts being a structural characteristic of the Portuguese business landscape. The literature also has identified data quality as a prerequisite for effective AI adoption, particularly among SMEs that tend to lack the infrastructure and governance models needed to make data usable (Richey et al., 2023; Teixeira et al., 2025).

Interviewee C3 makes the most precise characterization of this condition: *"the real bottleneck in Portuguese companies is earlier: they do not have a data strategy. They have data, often in abundance, but fragmented, inconsistent, and without an architecture that makes it usable by AI systems. Investing in AI without first resolving data quality and structure is like buying a high-performance car and driving it on a dirt road"* (C3). This metaphor is analytic and reveals the nature of the problem – Portuguese companies do not lack data, but the strategic and architectural thinking needed to turn that data into something AI can work with. This condition constrains the capacity for real AI-driven supply chain innovation regardless of investment in technology, meaning that the solution is not simply more data, but rather a change in the relationship with data as an organizational asset.

Interviewee C2 identifies data quality alongside cost as the two primary barriers to AI adoption in Portugal, noting that poor data quality prevents not only correct interpretation by AI tools but also constitutes an obstacle to implementing any system at all. Interviewee E3a states that AI can only generate value if it starts from reliable, well-structured data contextualized with clear business rules. Otherwise, there is a risk of producing forecasts and recommendations that appear technically sophisticated but are not useful for decision-making. Both observations reflect what Richey et al. (2023) document as one of the most consequential data-related risks in AI adoption: gaps and inconsistencies in data do not just limit AI's effectiveness but can make it counterproductive, generating outputs that mislead rather than inform. In other words, bad data does not produce no result, it produces the wrong result, which can be worse than having no AI at all.

Interviewee E1 describes data governance as an organizational challenge at Hotel company. Defining who can access what data, what belongs to the company and what can be shared externally were problems mentioned, also noting that AI opens enormous amounts of information but requires clear governance frameworks to organize access and protect sensitive data. This points to a dimension of the data challenge that goes beyond technical data quality into organizational policy and culture, which is consistent with what Daios et al. (2025) identify as the need for organizations to develop digital maturity and governance structures before AI can deliver its intended value.

Interviewee C1 reinforces this from a broader perspective, noting that AI still requires much review and validation before actions can be taken, reflecting the reality that data

quality issues create a need for human oversight that slows the realization of AI's potential benefits. Interviewee C3 further notes that most Portuguese companies are not yet aware of this bottleneck since the conversation in the market is dominated by tool adoption rather than by the data foundations that make those tools effective. This is one of the most concerning aspects of the data quality finding – not that the problem exists, but that most organizations have not yet recognized as a priority to be dealt with.

- **Organizational and human readiness**

Alongside data quality, human and organizational readiness emerges as a significant condition shaping AI adoption and its outcomes across the organizations studied. The evidence gathered points to two distinct but interrelated dimensions: the barriers created by human and cultural resistance to AI adoption, and the consistent positioning of AI as a complement to human decision-making rather than a replacement for it.

Regarding human and cultural resistance, interviewee C3 describes this as a fundamentally different type of barrier from technical ones: *“middle managers who resist because AI exposes inefficiencies that were previously invisible, and operators who perceive the tool as a threat to their jobs”* (C3). Interviewee C3 emphasizes that this is a human barrier, not a technological one, and that it cannot be resolved through technical training alone. Interviewee E1 describes change management as a long road that must be directed: *“Is a long road and must be targeted. People, being caught up in their daily work, are overloaded, and it is difficult to find a moment to stop and explore the tools a little. The strategy we followed consisted of the demonstration of a specific benefit, or use cases, so that it stays in employees' minds and they begin to use AI tools more and more”* (E1). Interviewee E2 identifies the behavioral and cultural side of organizations as the biggest brake on AI adoption, even among organizations that are enthusiastic about its potential. Interviewee C1 identifies lack of understanding, lack of familiarity with technology, difficulty of use, the age of those involved, and lack of specific training as the main human barriers to AI adoption. What emerges across these observations is that human resistance to AI is rarely about the technology itself and more about what the technology reveals and what it demands. AI exposes inefficiencies, challenges established roles and requires people to change habits that have been built up over years, and no amount of technical investment resolves those tensions without deliberate and sustained organizational work alongside it. This is consistent with what the literature has

documented as one of the most persistent barriers to AI adoption and the need for organizations to redefine roles, processes, and culture before the technology can deliver its intended value (Daios et al., 2025; Samuels, 2025).

In what concerns human-AI complementarity, a consistent theme across all organizations is the positioning of AI as decision support rather than a replacement for human judgment. Interviewee E1 describes this through a direct comparison: *"AI will not replace people. A robot helps the nurse who takes measurements but does not replace the nurse. It is a more precise machine that can even correct human errors, but it comes to complement - not replace"* (E1). Interviewee E3a states that AI must supplement human decision-making, not replace it automatically, describing the correct organizational message as one of augmentation rather than substitution. Interviewee C2 similarly describes future AI adoption as a process where humans and AI agents work together under human supervision rather than autonomously. Interviewee E2 describes AI adoption as making organizational life easier and allowing people to focus on matters where they are more effective, reallocating human resources toward higher value activities rather than eliminating human roles entirely.

These remarks are present across all the organizations of this study, and they are not a defensive narrative about job protection but a genuine organizational understanding of where AI adds value and where human judgment remains essential. Jarrahi (2018) mentions this, arguing that the most effective human-AI relationships are not about replacement but about complementarity, with AI handling the analytical and data-intensive dimensions of decision-making while humans contribute with the judgment, creativity, and contextual understanding that machines cannot replicate. The findings suggest that Portuguese organizations, even at an early stage of AI adoption, are positioning AI as a complement rather than a replacement for human judgement. This positioning may itself be one of the conditions that makes more sustainable and meaningful AI-driven innovation possible over time.

- **Structural and financial constraints**

The structural characteristics of the Portuguese business landscape represent a third condition shaping AI adoption and its outcomes across the organizations studied. Unlike data quality and human readiness, which are conditions that organizations can address through internal investment and strategic decisions, structural and financial constraints

reflect broader contextual realities of the Portuguese economy that individual companies have limited capacity to overcome in the short term.

Interviewee C2 provides the most comprehensive characterization of this condition, identifying cost and data quality as the two primary structural barriers to AI adoption in Portugal, noting that the Portuguese business fabric is composed predominantly of SMEs, with approximately 90% of companies lacking the capital to access frontier technologies. This percentage is not just a business statistic, but also an explanation for why AI implementation in Portugal looks the way it does. When the vast majority of organizations simply cannot afford to build their own solutions or invest in the latest technology, adoption inevitably becomes reactive and through convenience (i.e., through whatever tools are available, even if they are not suited to the organization's problems) rather than strategic. The literature acknowledges implementation costs as a significant barrier, noting that integrating AI into existing supply chain systems requires substantial investment in technology, infrastructure, and human expertise that is frequently underestimated (Daio et al., 2025). In the Portuguese landscape this challenge is concerning, precisely because the predominance of SME creates a ceiling that limits what most organizations can even attempt. This is reflected in the numbers, since 8.8% of Portuguese companies currently use AI in supply chain operations, and only 11.5% overall (Oliveira et al., 2024; INE, 2025). These numbers point to a gap between AI's documented potential and its organizational reality in Portugal that goes beyond adoption willingness into structural capacity.

Interviewee C2 further describes the planning infrastructure of most Portuguese companies as fundamentally underdeveloped, with planning processes still supported by spreadsheets and very few organizations having dedicated planning tools, characterizing these as foundational gaps that make meaningful AI adoption considerably more challenging. Interviewee C3 reinforces this structural picture, noting that most Portuguese companies are not building their own AI solutions but consuming whatever comes integrated within existing software ecosystems – reflecting financial and capability constraints that limit strategic AI investment. Interviewee C3 further notes that when asked to quantify the return on AI already adopted, most managers cannot provide an answer, a reflection not only of limited strategic intentionality but also of the absence of the measurement infrastructure needed to assess AI investments. These observations

point to something the literature has begun to identify as a critical gap: most organizations lack the capabilities for successful AI implementation beyond early conceptual stages, and without the financial and infrastructural foundations to go further, this gap is likely to persist (Jorzik et al., 2024).

Despite these constraints, the consulting participants offer a forward-looking perspective on how the structural landscape is evolving. Interviewee C3 anticipates that AI will progressively become embedded in the ERP, WMS, and procurement platforms that companies already use, making the adoption decision less relevant as AI becomes a standard feature of existing tools; additionally states that *“what will distinguish companies is not whether or not they have AI, but the quality of the data that feeds these systems. The companies that invest today in structuring their data are building the most valuable asset for the next phase”* (C3). Interviewee C2 similarly anticipates a future where AI agents work continuously under human supervision, executing processes autonomously and scaling across operational topics that go beyond human capacity to manage manually. Interviewee E2 expresses optimism about Portugal's potential, noting that the country's cultural flexibility and adaptability position it well to benefit from AI adoption as the technology matures and becomes more accessible. This forward-looking perspective is consistent with what the literature anticipates as AI becomes increasingly embedded in the systems organizations already use, reducing the financial and capability barriers that currently constrain adoption and gradually making AI's benefits accessible to a broader range of organizations (Richey et al., 2023; Teixeira et al., 2025).

What the three conditions documented across this section have in common is that none of them are about AI itself. Data quality, human and organizational readiness, and structural and financial constraints were present in Portuguese organizations long before AI arrived. AI has made the issues more visible and more consequential. Organizations that could manage with fragmented data, resistant workforces, and limited investment when operating manually are discovering that those same conditions become critical obstacles the moment they try to deploy AI at any meaningful scale. The image that appears is that genuine AI-driven supply chain innovation in Portugal is not primarily constrained by a lack of technology or awareness. What is missing, for most organizations, are the foundational conditions that allow that potential to be realized.

4.2. Discussion

The empirical evidence gathered across this study in most part confirms what the existing literature anticipated about AI adoption in SCM, while adding contextual specificity that the literature has not yet fully examined. The concentration of AI applications in planning and governance functions is consistent with what Jackson et al. (2024) and Toorajipour et al. (2021) identify as the most accessible entry points for AI in SCM, where structured data already exists and results are measurable. This study confirms that pattern in the Portuguese context but adds a nuance the literature does not fully capture: the concentration is not only a matter of technological accessibility but also reflects where organizations feel the operational consequences of not having AI intensely. Planning and governance are the phases where the gap between manual capacity and AI capability translates directly into margin and competitiveness.

More significant is what the evidence reveals about why organizations are adopting AI. For most organizations in the sample, adoption is driven by the fear of falling behind competition rather than by a strategic diagnosis of where AI can create value – and this is important considering adoption motivation shapes innovation outcomes. This confirms what Al-Omouh et al. (2025) characterize as mimetic institutional pressure and builds on it by showing its consequences empirically: when organizations adopt in a reactive way, the innovation they create tends to be related to operational improvements rather than value creation that real SCI requires, which is consistent with what Richey et al. (2023) observe about traditional AI applications being inclined toward optimization rather than innovation. Much of what is being called AI-driven innovation in Portugal is, in practice, catching up — automating processes that more advanced competitors were already conducting years ago with other tools. That progress is real and should not be dismissed, but it is important to name it accurately. Sullivan and Wamba (2024) show that AI delivers its greatest innovation value when organizations use it to actively sense and respond to market opportunities, a form of adoption that remains an exception among Portuguese organizations. The two companies in the sample that approached AI with strategic intent produce noticeably different innovation outcomes, offering within-sample evidence of what becomes possible when adoption motivation shifts from reactive to deliberate.

When examined through the SCI framework, the findings both confirm and extend what the literature anticipated. Technology and process innovation are clearly evidenced across

the sample, consistent with Kwak et al.'s (2018) dimensional classification and with Kahn and Cook's (2026) observation that technology is the most consistently documented dimension across SCI definitions. The efficiency gains, responsiveness improvements, and decision-making quality enhancements reported across the sample are real and measurable: significant returns on investment, shift from static periodic reporting to dynamic real-time intelligence and the redesign of manual processes into automated ones. These findings confirm what the literature describes as AI's core contribution to supply chain operations: the capacity to turn data into actionable intelligence and enable faster and informed decisions (Belhadi et al., 2024; Jackson et al., 2024). What the study expands is the understanding of what these gains represent in terms of genuine innovation. Arlbjørn et al. (2011) establish that supply chain innovation can range from the gradual optimization of existing practices to transformations that fundamentally redefine how activities are organized and conducted. The evidence places Portuguese organizations at the incremental optimization end of that range, not because the technology is incapable of enabling more, but because the adoption context is not yet creating the conditions for it. This finding adds empirical grounding to what Cannas et al. (2024) identify as a broader organizational pattern in which companies struggle to move AI beyond early operational applications and contextualize it within an SME-dominated early-adoption landscape that the existing literature has not yet examined.

The most analytically consequential contribution of this study is the distinction it establishes between optimization and genuine SCI, a distinction the literature acknowledges but has not yet examined in the specific conditions of the Portuguese context. Organizations in the sample are improving efficiency, reducing costs, and making better-informed decisions, and these are meaningful gains. But as Arlbjørn et al. (2011) argue, genuine SCI requires the creation of something new – new ways of competing, new value for stakeholders, new structures for delivering that value, rather than the improvement of what already exists. By that standard, much of what is occurring in Portuguese supply chains is more accurately described as AI-enabled “catching up” than as AI-driven innovation. The SCI that the literature describes, with new technologies, redesigned processes, and reconfigured business models, is beginning to emerge in Portugal, but it remains concentrated in a small number of organizations that have approached AI with a clear purpose that most have not yet found.

This significantly nuances the existing literature: research on AI-driven SCI has predominantly examined what AI generates under favorable conditions, e.g., in large organizations, technologically mature markets, with strategic adoption intent. The Portuguese case shows what the relationship between AI and SCI looks like when those conditions are not yet in place, suggesting that it is not the technology but the conditions surrounding its adoption that determine whether the outcome is optimization or genuine innovation.

The conditions documented across the findings: data quality, human and organizational readiness and structural and financial constraints, provide the explanatory thread that connects adoption patterns to innovation outcomes, and each finds grounding in the existing literature. The universal identification of data quality as a precondition across the entire sample is consistent with what Richey et al. (2023) and Teixeira et al. (2025) identify as one of the most significant barriers to effective AI adoption, but extends their argument by showing that in Portugal the challenge is not simply about data accuracy, but about absence of a data strategy, governance model, and infrastructure that would make data usable by AI systems at scale.

Human and organizational readiness confirms what Daios et al. (2025) and Samuels (2025) argue about the need to manage cultural and organizational change alongside technological adoption, while adding the finding that Portuguese organizations are already positioning AI as a complement to human judgment rather than a replacement for it – a point Jarrahi (2018) and Cohen et al. (2026) identify as a precondition for AI to drive genuine rather than superficial innovation. The finding that this complementarity is already emerging intuitively across Portuguese organizations, even at an early adoption stage, represents a positive signal for the longer-term trajectory of AI-driven SCI in Portugal.

Structural and financial constraints, given by the predominance of SMEs across the Portuguese business landscape, explain why the gap between AI's documented potential and its organizational reality is more severe in Portugal than the existing literature anticipated. Together these three conditions do not merely explain the current state of AI-driven SCI in Portugal, but they define what needs to change for the next stage of that innovation to become possible.

Taken together, the findings position the Portuguese case as a grounded empirical contribution to a gap in the existing literature on AI-driven SCI. Wong and Ngai (2019) found that close to half of all SCI studies draw on American samples, and existing research is heavily concentrated in large organizational and manufacturing contexts. This study contributes evidence from a European, SME-dominated, early-adoption context, where AI use in supply chain operations remains below 9% (Oliveira et al., 2024) and that is structurally and contextually different from the environments in which most existing research has been conducted. What the Portuguese case reveals is that the relationship between AI adoption and SCI is not automatic, it is mediated by a set of organizational and structural conditions that determine whether adoption produces optimization or genuine innovation.

CHAPTER 5 – CONCLUSION

This study set out to understand how AI is driving innovation in the supply chains of Portuguese companies, a question that, as the findings reveal, does not have a straightforward answer. AI is present, it is being adopted, and it is generating real change. But the picture that emerges from six organizations across different sectors and roles is one of a phenomenon still in its early stages, where the gap between what AI could enable and what is actually happening remains significant.

What the findings reveal most clearly is that the nature of AI-driven SCI in Portugal is predominantly incremental, shaped by an adoption context that is reactive rather than strategic for most organizations, and constrained by conditions that most have not yet fully addressed. The SCI that the literature describes, with new technologies, redesigned processes, and reconfigured business models, is beginning to emerge, but it remains concentrated in a small number of organizations that have approached AI with a clear purpose that most companies have not yet found. The gap between optimization and genuine innovation is the most substantial distinction this study presents and closing it does not require more technology but better foundations.

Despite these constraints, the potential for more transformative AI-driven SCI is clearly present. The organizations in this study that have approached AI with strategic intent provide an early signal of what becomes possible when the right foundations are in place. The evidence gathered suggests a future where AI becomes progressively embedded in the planning, warehouse management, and procurement systems that organizations

already use, making adoption less of a deliberate decision and more of a natural evolution. The gap between where most Portuguese companies currently are and where genuine AI-driven SCI becomes a reality is significant, but it is not permanent. Awareness is growing, technology is becoming more accessible, and the foundations are starting to be built. What this study suggests is that the organizations that will benefit most from AI are not necessarily those that adopted first, but those that adopted with purpose and treat AI as a long-term capability rather than a short-term trend.

5.1 Theoretical Implications

This study contributes to academic literature on AI-driven SCI in three specific ways.

From an empirical point of view this study provides grounded evidence of how AI-driven SCI manifests in an SME-dominated, early-adoption context that is absent from existing literature. As noted in the research gaps identified in the literature review, studies on AI in SCM have been concentrated in larger organizations, more technologically mature markets, and manufacturing environments, such as the U.S.A. (Wong & Ngai, 2019; Richey et al., 2023). By contributing evidence from a European, SME-dominated context where AI adoption in supply chain operations remains below 9%, this study broadens the empirical base of the field and challenges the generalizability of findings drawn from more advanced adoption environments.

The findings also contribute to the ongoing development of the SCI framework applied in this study. The three dimensions of technology innovation, process innovation, and BMI were useful in organizing and classifying the empirical evidence. However, the study reveals that in practice, technology and process innovation are deeply intertwined and difficult to separate since the introduction of a new AI system almost always involves a simultaneous redesign of the processes it supports. While the framework treats these as distinct dimensions, the empirical evidence suggests they function as a single integrated capability in practice, with implications for how future studies operationalize and measure SCI dimensions. Future theoretical development may benefit from exploring this relationship more explicitly,

Finally, the study also adds contextual specificity to the incremental/radical distinction established by Arlbjørn et al. (2011). The finding that AI-driven SCI in Portugal is almost entirely incremental is not simply a reflection of technology maturity but a direct consequence of adoption motivation and organizational conditions. This suggests that

where organizations sit on the incremental-radical spectrum is shaped as much by how and why they adopt as by what the technology itself could enable. Organizations that adopt reactively, without strategic intent and without the foundational conditions in place, are structurally predisposed to generate incremental rather than radical innovation, regardless of what the technology itself could enable.

5.2 Managerial Implications

The findings of this study point to several practical implications for managers and organizations operating in or entering the Portuguese supply chain context.

The most immediate implication concerns data. Before investing in AI tools, organizations should invest in their data, ensuring it is clean, structured, accessible, and governed by clear policies about who can use it and for what purpose. The evidence gathered across this study is straight on this point: AI cannot deliver reliable value without a solid data foundation, and organizations that skip this step risk generating outputs that create more harm than good decision making. Building that foundation is the prerequisite for everything else.

The second implication concerns adoption motivation. Organizations that adopt AI because competitors are doing so, without a clear understanding of what problem they want AI to solve, tend to generate operational improvements at best and wasted investment at worst. Before adopting, managers should ask a simple question: what specific problem are we trying to solve, and is AI the right tool to solve it? Starting from that question rather than from the technology leads to more focused, more measurable, and ultimately more valuable implementations. Cohen et al. (2026) reinforce this point, recommending that organizations begin with targeted, complementary applications rather than pursuing full automation from the beginning. This is an approach that allows organizations to build evidence, confidence, and capability progressively.

Closely related is the importance of measurement. Organizations should define clear metrics and KPIs before implementing AI, not after, so that they can track what is changing, quantify the value being generated, and compare it against implementation costs. This enables organizations to identify which AI applications are genuinely delivering value and concentrate investment there, and it builds the internal evidence base needed to justify deeper adoption over time. Investing in everything at once, without measurement, is how organizations end up unable to explain what AI has done for them.

Additionally, change management should be treated as a core component of any AI implementation, not an afterthought. Human resistance to AI is rarely about the technology itself but about what the technology reveals, what it demands, and what it changes about how people work and are valued. Organizations that invest as seriously in managing that transition as they do in the technology itself are more likely to achieve sustainable adoption and lasting results. Critically, organizations should communicate AI as a tool that augments human judgment, not a replacement for it – framing adoption as an opportunity to focus human effort on higher-value activities rather than as a threat to existing roles. Jarrahi (2018) and Cohen et al. (2026) identify this complementarity as a precondition for AI to drive genuine innovation rather than superficial automation, and the evidence gathered in this study confirms that organizations already embracing this framing tend to achieve more sustainable and meaningful adoption outcomes.

Finally, for organizations (particularly SMEs) that face financial constraints limiting their ability to build their own AI solutions, the most practical path forward may be through the AI capabilities already embedded in the platforms and tools they already use. ERP systems, WMS platforms, and planning tools are increasingly incorporating AI features that do not require significant additional investment to access. By starting here companies can reduce risk, lower the barrier to entry, and build experience and confidence before pursuing more ambitious implementations.

5.3 Limitations and Future Research

Like any research, this study has limitations that should be acknowledged when interpreting its findings.

The sample size, while appropriate for a qualitative exploratory study, limits the range of sectors and company sizes represented. Despite efforts to include organizations from across all SCOR phases, it was not possible to secure participation from manufacturing companies, a sector widely represented in the existing literature, which limits the study's coverage of the Make phase and its ability to speak to AI-driven innovation in production environments. Some professionals approached during data collection were unable to participate due to confidentiality agreements with their organizations, preventing them from sharing processes or future projects for fear of exposing competitive information.

The geographic concentration on Portugal, while justified by the research gap identified in the literature review, means that the conclusions drawn may not be directly applicable

to other national or cultural contexts. Portugal's low AI adoption rate and SME-dominated business landscape create a specific set of conditions that may differ significantly from other European or global markets. Comparative studies across different European markets with varying AI adoption rates and business landscape characteristics would help establish whether the conditions identified in this study are specific to the Portuguese context or generalizable across early-adoption environments more broadly.

The reliance on self-reporting also carries an inherent risk of overstatement. Managers and specialists may describe AI's impact in a more positive way than what the evidence suggests, particularly at an early stage of adoption where results are not yet fully measured or quantified. This concern was partially mitigated by the inclusion of consulting participants, who offered a more grounded and cross-sectoral perspective on what AI is actually delivering in Portuguese organizations, and by the use of specific, evidence-based interview questions rather than general opinion questions. However, it cannot be fully eliminated. Future research using objective performance metrics alongside self-reported data would provide stronger and more reliable evidence of the relationship between AI adoption and supply chain innovation outcomes.

Finally, the cross-sectional nature of the study, that captures a snapshot of AI adoption at a specific point in time, is a limitation given how rapidly technology and its organizational applications are evolving. Findings that accurately describe the Portuguese landscape today may look different within a few years as adoption matures and new capabilities become accessible. Longitudinal research following the same organizations over time would capture how AI-driven SCI evolves as foundations are built and adoption deepens.

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APPENDIX

Appendix A – Tables

Table I - Summary of the main types of AI Models

AI Model	Definition	Key Capabilities	Relevance to SCM	Key References
Predictive Analytics	Application of machine learning, statistical algorithms, and data mining techniques to analyze historical and current data and generate forecasts about future outcomes or trends	Demand forecasting, pattern recognition, anomaly detection, regression analysis, text and image processing	Anticipates customer demand, adjusts inventory levels, improves production planning, and supports strategic decision-making	Oyewole et al. (2024); Toorajipour et al. (2021); Jackson et al. (2024)
Prescriptive Analytics	The most advanced form of analytics, building on predictive outputs to generate automated, adaptive, and optimized recommendations for action	Scenario simulation, optimization algorithms, real-time decision support, proactive and reactive planning	Enables informed and prompt decision-making in complex, dynamic supply chain environments by moving beyond forecasting toward actionable guidance	Lepeniotti et al. (2020); Smyth et al. (2024)
Generative AI	AI systems integrating machine learning and deep learning to generate new content — including text, images, documents, simulations, and audio — based on patterns learned from large datasets	Content generation, scenario modeling, natural language interaction, creative problem-solving, autonomous decision support	Supports risk mitigation, sourcing evaluation, procurement forecasting, logistics coordination, sustainability practices, and customer engagement across the supply chain	Jackson et al. (2024); Fosso Wamba et al. (2024); Richey et al. (2023); Teixeira et al. (2025)

Source: Author's own elaboration based on reviewed literature.

Table II - Summary of AI Applications Across the Extended SCOR Model Phases

SCOR Phase	Main AI Applications	Key Outcomes	Key References
Plan	Demand forecasting, inventory optimization, scenario simulation	Increased forecast accuracy, reduced stockouts, leaner inventory management, waste reduction	Jackson et al. (2024); Richey et al. (2023); Belhadi et al. (2024)
Source	Supplier selection, procurement automation, contract management	Optimal supplier portfolios, reduced procurement costs, improved sourcing decisions	Richey et al. (2023); Daios et al. (2025); Samuels (2025)

Make	Predictive maintenance, quality control, robotics, intelligent manufacturing	Reduced defects, minimized downtime, increased productivity, adaptive production systems	Dash et al. (2019); Zhong et al. (2017); Daios et al. (2025)
Deliver	Route optimization, warehouse automation, distribution planning	Reduced logistics costs, improved delivery efficiency, dynamic real-time routing	Richey et al. (2023); Samuels (2025); Belhadi et al. (2024); Teixeira et al. (2025)
Return	Reverse logistics, closed-loop supply chains, resource recovery	Waste reduction, improved resource recovery, support for circular economy objectives	Teixeira et al. (2025)
Enable	Risk management, resilience, sustainability, governance	Enhanced disruption anticipation, ESG compliance, transparency, ethical sourcing	Richey et al. (2023); Daios et al. (2025); Teixeira et al. (2025)

Note: AI applications in the Return phase remain less developed in the current literature compared to other phases. Source: Author's own elaboration based on reviewed literature

Table III - Overview of Case Study Companies and Interview Participants

Code	Company Alias	Sector	Organization Type	Role regarding AI adoption	Role of the interviewee
C1	Charlie	Business Services – IT	Consulting	Implementer	SCRUM Master
C2	Delta	Business Services – Supply Chain/Logistics	Consulting	Implementer	Manager
E1	Hotel	Health Data and Analytics / Health Tech	Company	Adopter	Director – Technology and AI
E2	Lima	Retail	Company	Adopter/ expanding implementation	Director
C3	Sierra	Business Services - AI	Consulting	Implementer	CEO / Consultant
E3a	Tango*	Logistics / Food Services	Company	Early adopter/ In implementation	Director of Organization, Processes and Projects
E3b					Executive in Charge of Logistics

C – Consulting firm; E – Enterprise | *Two interviews were conducted in this company

Source: Author's own elaboration based on interview data.

Table IV - AI Applications in Portuguese Supply Chains Mapped Against the Extended SCOR Model (Framework 1)

SCOR Phase	AI Application	Description	Organization	Stage of Implementation
Plan	Demand forecasting and planning system	AI-powered algorithms deployed for demand planning, stock optimization, inventory management, and replenishment	Lima, Tango, Delta client (retail)	Operational / In development

	Real-time market data intelligence platform	AI-powered platform enabling pharmaceutical clients to generate real-time market analyses, forecasting, and insights through chatbot interfaces	Hotel	Operational
	Predictive stock and procurement analytics	Predictive analytics applied to stock and procurement management, improving operational data analysis previously conducted manually	Sierra clients	Observed across multiple clients
	Stockout monitoring and replenishment	Robot deployed for autonomous visual monitoring of stockouts, feeding real-time data into replenishment planning decisions	Lima	Operational
Source	Procurement analytics	Procurement management benefiting indirectly from broader predictive analytics and administrative automation initiatives	Sierra clients	Indirect / Emerging
Make	Computer vision for quality and safety	Computer vision solution for accident prediction in manufacturing and AI-based error detection in automotive component production	Delta clients (international)	Operational - international companies with operations in Portugal
Deliver	Route optimization and delivery prediction	AI deployed for delivery window prediction and dynamic route optimization across distribution networks	Delta client (logistics)	Operational
Return	Claims and defective products management	Early-stage pilot for AI-assisted management of claims and defective products across food services operations	Tango	Early-stage pilot
Enable	Administrative process automation	Automation of repetitive administrative tasks including data entry, reporting, and operational analysis	Sierra clients	Operational
	Commercial risk monitoring	AI initiative for proactive identification of commercial risk signals before they materialize into operational or financial impact	Tango	In development
	Knowledge management platform	AI-powered platform transforming dispersed organizational knowledge into structured, accessible, and contextualized information for cross-functional teams	Tango	In development
	Virtual assistant for customer service	AI-powered virtual assistant supporting customer service operations, responding to client queries in logistics and distribution contexts	Delta client (logistics)	Operational
	Supplier risk monitoring	AI systems analyzing patterns of delivery delay and supply base instability, generating automatic alerts for risk management	Sierra clients	Emerging

Note: Applications attributed to Sierra clients and Delta clients were identified through consulting participants describing AI implementations observed across their client organizations.

Source: Author's own elaboration based on interview data.

**Table V - Innovations Identified and Perceived Results Mapped Against SCI Dimensions
(Framework 2)**

SCI Dimension	Innovation Identified	What Changed	Perceived Results	Organization
Technology innovation	AI-powered demand forecasting and planning system	Manual planning replaced by AI-powered predictive algorithms	n.a.*	Tango, Delta client (retail)
	Real-time market data intelligence platform	Static periodic reports replaced by dynamic real-time analytics	Companies shifted from reactive to proactive information management and decision-making	Hotel
	Stockout monitoring robot	Manual stock counting replaced by autonomous shelf monitoring	More accurate and timely replenishment decisions	Lima
	AI-powered replenishment systems	Periodic manual ordering replaced by continuous automated optimization	n.a.*	Lima, Delta clients
	Supplier risk monitoring system	Manual supplier monitoring replaced by automated pattern analysis and alerts	Reduced manual analysis effort and faster identification of supply base instability	Sierra clients
	Commercial Knowledge Hub	Dispersed knowledge transformed into structured accessible intelligence	Reduced time spent searching for and interpreting relevant information	Tango
	Commercial risk monitoring	Manual risk analysis replaced by continuous automated signal detection	n.a.*	Tango
	Route optimization and delivery prediction	Static routing replaced by dynamic real-time logistics management	n.a.*	Delta client (logistics)
	Computer vision for quality and safety	Human inspection replaced by real-time automated error and risk detection	n.a.*	Delta clients (international with operations in Portugal)
Process innovation	Automation of administrative and operational tasks	Manual repetitive tasks replaced by AI-driven automated processing	60% reduction in editorial costs, 66% ROI in first	Sierra clients, Hotel, Delta clients

			year; faster information processing at lower cost	
	Redesign of planning and replenishment processes	Reactive manual planning replaced by predictive data-supported management	n.a.*	Tango, Delta client (retail), Lima
	Shift from reactive to predictive management	Periodic reactive decision-making replaced by continuous proactive intelligence	More informed and faster decision-making; improved responsiveness to market changes	Tango, Hotel, Delta client (logistics), Lima
	Virtual assistant for customer service	Human-operated customer service replaced by AI-powered automated interaction	n.a.*	Delta client (logistics)
Business model innovation	Strategic repositioning as Health Tech company	Traditional market research business redefined as technology-driven health intelligence	New market positioning and expanded service offering	Hotel
	Knowledge-based cross-functional collaboration model	Siloed organizational knowledge replaced by shared structured intelligence layer	n.a.*	Tango

Note: Applications attributed to Sierra clients and Delta clients were identified through consulting participants describing AI implementations observed across their client organizations.

*n.a. - No perceived results were explicitly mentioned by interviewees in relation to this innovation at the time of data collection.

Source: Author's own elaboration based on interview data.

Appendix B – Interview Guides

Note: Both interview guides were translated from Portuguese to English, given that the interviews were conducted only to Portuguese firms.

Interview Guide – Applied to Companies

First of all, thank you very much for your availability and interest in participating in this study. The central objective is to understand how Artificial Intelligence has contributed to the creation of innovation in the supply chains of Portuguese companies, namely at the level of products, processes, business models, or other forms of innovation, at any stage of the supply chain (production, logistics, distribution, procurement, customer support, among others).

All data collected will be treated in strictly confidential terms and used exclusively for academic purposes. Both your identity and that of the organization will be kept anonymous, unless you indicate otherwise.

Background of the interviewee and the company

1. What is your current role, your experience in the supply chain, and your involvement in AI projects at the organization?
2. How would you classify the company's digital maturity — initial, intermediate, or advanced?

AI adoption in the supply chain

3. Where does the organization currently use AI in the supply chain? (demand forecasting; suppliers and procurement; production; logistics and distribution; governance and risk management)
4. How long have you been using it, and what phase are you in — pilot, partial adoption, or full integration?
5. Was adoption driven by internal factors (efficiency, costs, innovation) or external ones (competition, customers, sector)? What are the main drivers?

AI's contribution to the supply chain

6. Which areas or processes benefit, or could benefit, most from AI, and why? (examples: demand/sales forecasting; suppliers and procurement; inventory and warehousing; risk and resilience; sustainability; process management and automation; supply chain integration; network design; predictive maintenance; logistics and distribution (transport, routes, reverse logistics); production/manufacturing; quality; cost forecasting.)

Factors perceived as drivers of AI implementation

7. What benefits did you expect from AI and what concrete improvements have you already observed?

Perceived limitations or barriers to AI implementation

8. What obstacles and risks have you faced, or do you foresee, in implementing AI?
9. How was AI accepted within the organization, particularly by the workforce?
10. Has European AI legislation influenced your organization's approach to the adoption and use of these technologies? If so, in what way?

Innovation outcomes

11. What changes have you observed in the way your supply chain operates since the introduction of artificial intelligence technologies? Could you give concrete examples of processes created, transformed, or optimized?
12. How were these changes reflected in operational performance (efficiency, responsiveness, costs, quality)? Did the adoption of AI bring about changes in the internal organizational structure or in the way your company coordinates with other supply chain participants, such as suppliers, logistics partners, or customers?
13. Have new products or services, or new forms of collaboration (digital platforms, data sharing, systems integration), emerged?
14. How has the way of creating and capturing value along the chain changed (for example, through personalization, new digital services, data-based models)? Considering the set of changes introduced, how would you characterize the effect of AI on your supply chain?
15. Overall, has AI added mainly incremental improvements or deep transformations that have altered the supply chain? Can you give examples?

Future perspectives

16. Do you believe AI will be a competitive advantage? Where will it take your supply chain in the coming years?

Interview Guide – Applied to Consulting Firms

First of all, thank you very much for your availability and interest in participating in this study. The central objective is to understand how Artificial Intelligence has contributed to the creation of innovation in the supply chains of Portuguese companies, namely at the level of products, processes, business models, or other forms of innovation, at any stage of the supply chain (production, logistics, distribution, procurement, customer support, among others).

All data collected will be treated in strictly confidential terms and used exclusively for academic purposes. Both your identity and that of the organization will be kept anonymous, unless you indicate otherwise.

Background and experience

1. Could you briefly describe your current role and the main focus of your work in the area of AI and supply chain management?

AI adoption in Portuguese supply chains

2. How do you perceive the adoption of AI/AI tools by Portuguese companies? In your opinion, what are the reasons behind this adoption?
3. How do you perceive the evolution of AI adoption in the supply chains of Portuguese companies? In your opinion, what were the factors that most drove or accelerated that evolution?
4. At which point in the supply chain (for example, planning, procurement, production, or logistics) do you consider AI adoption to be most significant among Portuguese companies?

Innovation outcomes in the Portuguese context

5. Based on your research or experience, what types of innovation are Portuguese companies generating through the adoption of AI in their supply chains — for example, process improvements, new products or services, organizational changes, or new business models?
6. Would you say that AI is driving incremental innovation in Portuguese supply chains, such as gradual improvements to existing practices, or a more radical transformation in the way companies operate?
7. Are there specific examples of Portuguese companies or sectors that you consider particularly illustrative of AI-driven supply chain innovation?
8. In your opinion, are Portuguese companies that adopt AI in their supply chains gaining a measurable competitive advantage over those that do not?
9. What are the main barriers preventing wider adoption of AI in Portuguese supply chains?
10. How do you assess Portugal's potential to leverage AI as a driver of supply chain innovation in the coming years, given the current level of adoption?

Research gaps and future perspectives

11. In your opinion, where is the relationship between AI and supply chain management in Portugal heading over the next five years? (optional)
12. Is there any aspect you consider particularly important about this topic that has not yet been addressed? (optional)