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The Key Opportunities and Barriers to AI Adoption in Sustainable Supply Chain Management

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Abstract

As sustainability becomes a strategic imperative in global supply chains, artificial intelligence (AI) is increasingly viewed as a tool that can support not only efficiency but also environmental and social objectives. Yet, the extent to which AI directly contributes to sustainable supply chain management (SSCM) remains underexplored. This thesis investigates the key opportunities and barriers to AI adoption in SSCM, focusing on Swedish industries including automotive, chemicals, electronics, logistics, and consumer goods. Guided by the supply chain operations reference (SCOR) model and the technology–organization–environment–human (TOEH) framework, the study adopts a qualitative abductive approach based on 16 semi-structured interviews with professionals across different supply chain functions. The findings show that AI offers clear benefits for forecasting, sourcing, production, delivery, and return processes—particularly through waste reduction, emissions control, and improved efficiency. However, most companies prioritize economic gains, while environmental and especially social dimensions of sustainability receive less attention. The study also highlights persistent challenges such as poor data quality, limited organizational readiness, regulatory uncertainty, and human resistance. This research contributes to a more holistic understanding of AI in SSCM and provides practical insights for firms aiming to integrate sustainability more meaningfully into supply chain operations.

Keywords: Artificial Intelligence, Sustainable Supply Chain Management, SCOR, TOEH, Sweden, Sustainability, Qualitative Research

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List of Abbreviations

Abbreviation	**Full Term**
AI	Artificial Intelligence
CE	Circular Economy
DL	Deep Learning
Fuzzy-AHP	Fuzzy-Analytical Hierarchy Process
IoT	Internet of Things
GDPR	General Data Protection Regulation
GenAI	Generative Artificial Intelligence
LLMs	Large Language Models
MCMSS	Multi-Criteria Material Supplier Selection
ML	Machine Learning
P1–P16	Participant 1 to Participant 16 (Interviewee IDs)
R&D	Research and Development
ROI	Return on Investment
SCM	Supply Chain Management
SCOR	Supply Chain Operations Reference
SSCM	Sustainable Supply Chain Management
TBL	Triple Bottom Line
TOEH	Technology–Organization–Environment–Human

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1.0 Introduction

This section provides the background and motivation for the study, outlines the research problem and questions, and defines the thesis structure and scope.

1.1 Background

Sustainability has become a defining priority in global supply chain management (SCM). As environmental issues such as climate change and resource depletion intensify, and concerns about labor rights and ethical sourcing grow, businesses are under increasing pressure to align their operations with broader social and environmental goals (Carter & Easton, 2011). Supply chains—once judged primarily on cost and speed—are now expected to minimize carbon footprints, reduce material waste, and ensure fair working conditions. In response, the concept of SSCM has emerged, advocating for the integration of environmental, social, and economic goals across all supply chain activities (Elkington, 1994; Carter & Rogers, 2008). SSCM emphasizes not only operational efficiency but long-term responsibility and resilience.

To meet these expectations, many companies are exploring the use of advanced technologies. Among them, AI has received growing attention. AI refers to computer systems that can analyze data, recognize patterns, and support complex decision-making, often through methods such as machine learning (ML), deep learning (DL), and generative artificial intelligence (GenAI). In the context of supply chains, AI has been successfully applied to enhance forecasting accuracy, automate inventory management, optimize delivery routes, and improve production scheduling (Wamba & Queiroz, 2021). These functions offer clear operational benefits such as cost reduction, speed, and process standardization.

However, the sustainability potential of AI—especially in supporting environmental and social objectives—remains significantly underexplored. Existing literature tends to focus on the efficiency and economic advantages of AI adoption, often treating sustainability as a peripheral or indirect benefit rather than a strategic driver (Divya et al., 2024; Qu & Kim, 2024). For instance, while AI may help reduce emissions through better route planning or predictive maintenance, these outcomes are rarely the primary motivation behind adoption. This imbalance limits our understanding of how AI could be harnessed more deliberately to address sustainability goals in SSCM.

The gap between what AI can offer and how it is used reflects a broader issue: sustainability is still not fully embedded in the digital transformation strategies of many firms. AI is often introduced to optimize performance, not to solve sustainability challenges. In particular, there is limited research on how AI is used across different supply chain functions, such as planning, sourcing, production, delivery, and return, to directly address sustainability targets. In many cases, organizations implement AI in isolated pilots rather than as part of a holistic SSCM approach.

The urgency of this research is further heightened by recent developments. Regulatory pressure is growing, with governments in the European Union and globally introducing stricter sustainability disclosure and due diligence requirements. At the same time, companies are facing rising stakeholder expectations—from investors to customers—regarding their environmental impact and supply chain transparency. Meanwhile, AI technologies are maturing rapidly, and many organizations are still in the early stages of exploring their use. This creates a narrow but important window to shape AI implementation in ways that serve sustainability objectives from the outset, rather than retrofitting them later.

The empirical scope of this research includes Swedish companies from a range of sectors with complex, global supply chains. These include automotive manufacturing, chemicals, consumer electronics, logistics services, and branded consumer goods such as outdoor apparel and photography equipment. Although these industries differ in their specific supply chain configurations, they share a common challenge: balancing operational performance with sustainability targets under increasing external pressure. For example, automotive firms must reduce emissions and shift toward electric mobility; electronics companies face scrutiny over material sourcing and lifecycle waste; and logistics providers are expected to improve energy efficiency across their transport networks.

Despite growing interest, the path to effective AI adoption in SSCM remains fraught with barriers. On a technical level, firms struggle with legacy systems, poor data quality, and the opaque logic of many AI models. Organizationally, challenges include a lack of digital readiness, budget constraints, unclear return on investment (ROI), and a shortage of AI talent. Human-related barriers are equally significant—employees may fear job loss, managers may distrust automated decisions, and sustainability professionals may lack input into digital transformation efforts (Hangl et al., 2023).

Sweden was chosen as the setting for this research because it has a strong record in both sustainability and digital innovation. It ranks second worldwide in progress toward the United Nations Sustainable Development Goals (Sachs et al., 2023) and 14th in global AI readiness, which reflects its advanced infrastructure, policy support, and digital capabilities (Oxford Insights, 2024). These strengths make Sweden an ideal place to study how AI can support the development of more sustainable supply chains.

Taken together, these challenges underscore the need for a deeper understanding of how AI is currently being adopted to support SSCM goals, not just economically, but environmentally and socially as well. By focusing on how Swedish companies across key industries apply AI in their real-world supply chain functions, this study aims to offer insights into both the opportunities and limitations of AI in driving sustainable transformation.

1.2 Research Problem and Gap

While AI has received growing attention in supply chain research, most existing studies focus primarily on its ability to improve operational performance, such as reducing costs, increasing efficiency, and accelerating decision-making. However, the extent to which AI contributes to sustainability, especially in environmental and social terms-remains significantly underexplored (Divya et al., 2024; Qu & Kim, 2024). In many cases, AI is introduced with economic goals in mind, and any sustainability benefits are seen as a secondary outcome rather than a core objective.

In addition, current research often focuses on isolated use cases like predictive maintenance or route optimization, without examining how AI can be applied across different supply chain functions to achieve sustainability objectives (Naz et al., 2022; Qu & Kim, 2024). There is a lack of comprehensive, process-oriented analysis that links AI applications to the core activities of supply chains, such as planning, sourcing, production, delivery, and returns, from a sustainability perspective.

Another issue is that much of the literature is conceptual or technically driven, with limited insight into how organizations actually experience the challenges of adopting AI in real-world settings. There is a clear gap in research that combines theoretical models with the perspectives of practitioners who work directly with AI and sustainability in supply chain operations.

To address these gaps, this thesis investigates:

- How AI contributes to not only economic, but also environmental and social goals within SSCM;
- What barriers companies face during the adoption of AI;
- And how structured models like SCOR and TOEH can be used to organize this investigation across different supply chain functions.

By focusing on real-world examples from Swedish manufacturing-related sectors, the study aims to bridge the gap between academic theory and business practice, offering a clear understanding of AI adoption in SSCM.

1.3 Research Aim and Questions

This study aims to explore how AI is applied in SSCM and to identify the main opportunities and challenges that organizations encounter during this process. The research focuses on understanding how AI supports environmental, social, and economic sustainability goals in real-world supply chain operations, rather than limiting its role to efficiency improvements or cost savings.

By combining existing theoretical literature with insights from industry professionals, this study seeks to offer a structured analysis that integrates both academic and practical perspectives. It aims to uncover the actual contributions of AI in driving supply chain sustainability, as well as the limitations and barriers faced in practice.

To achieve this objective, the study is guided by the following two research questions:

- RQ1: What are the key opportunities that AI offers for SSCM?
- RQ2: What are the main challenges that organizations face when adopting AI in SSCM?

The research adopts the SCOR model as its analytical framework and examines five core supply chain functions: planning, sourcing, production, delivery, and return. In addition to SCOR, the TOEH framework is utilized to reveal barriers from various perspectives, including technological, organizational, environmental, and human. The ultimate goal is to provide actionable insights for both researchers and practitioners, helping organizations develop supply chains that are not only smarter but also more sustainable.

1.4 Significance of the Study

This study contributes to the growing body of research at the intersection of AI and SSCM. While much of the existing literature has focused on the technical capabilities of AI, such as improving accuracy, speed, or cost-efficiency, this thesis shifts attention toward its potential role in supporting environmental and social goals. By doing so, it addresses a notable gap in both theory and practice.

From an academic perspective, this research extends current understanding by combining structured theoretical frameworks with real-world insights from professionals. It explores how AI is used across supply chain functions—not just in isolated use cases—and links these applications to sustainability outcomes. This approach provides a more comprehensive view of AI’s role in SSCM and offers a foundation for future studies aiming to integrate digital innovation with sustainable development goals.

From a practical standpoint, the study offers valuable insights for companies that are considering or already implementing AI tools in their supply chains. By highlighting both the opportunities and the barriers involved, it can help decision-makers understand where AI adds the most value, what risks to anticipate, and how to align AI initiatives with broader sustainability strategies.

In the context of Sweden, a country recognized for its leadership in both sustainability and digital readiness, this study offers relevant, context-specific findings that may also be useful for policymakers, technology providers, and supply chain managers across similar industrialized economies.

1.5 Scope and Limitations

This study focuses specifically on how AI is adopted within SSCM, with an emphasis on the environmental, social, and economic dimensions of sustainability. The research is grounded in the SCOR model and examines five key supply chain functions: planning, sourcing, production, delivery, and return. Empirical data are drawn from Swedish companies operating primarily in the manufacturing, automotive, chemical, logistics, electronics, and branded consumer goods sectors.

To ensure a clear and manageable research scope, this study deliberately ruled out hybrid digital systems that integrate AI with other technologies, such as Robotic Internet of Things

(IoT), Blockchain, and Big Data Analytics. While these technologies are important in broader discussions of digital transformation, their technical complexity and overlapping applications fall outside the boundaries of this thesis. The focus here remains on standalone AI applications and their contribution to sustainability within supply chain operations.

Additionally, the study is limited by its geographical focus on Sweden, which, while relevant due to the country's advanced digital infrastructure and sustainability leadership, may restrict the generalizability of findings to other regions. The research also relies on qualitative interviews, meaning the insights are shaped by the perceptions and experiences of a specific group of professionals. Although this approach allows for rich, context-specific understanding, it does not capture a statistically representative sample.

Finally, this study concentrates on the current state of AI adoption rather than long-term impacts or post-implementation outcomes. It provides a snapshot of how companies are using AI in practice and what challenges they encounter but does not track the evolution of these practices over time.

2.0 Literature review

The following section reviews existing literature on SSCM, AI, and outlines the theoretical frameworks that guide this study's analysis of AI adoption in SSCM.

2.1 Sustainable Supply Chain Management

SCM has evolved significantly over the past few decades, transitioning from a relatively simple logistical function to a comprehensive, strategic discipline that integrates multiple business operations (Carter & Easton, 2011). The foundations of SCM were laid in the 1980s (Oliver and Webber, 1982), when the concept first emerged to describe the dependencies between different nodes of the supply chain, from the point of origin—typically suppliers and manufacturers—to the point of consumption, which includes customers and end-users (Svensson, 2007). As Krumme (2019) outlined, early supply chains were largely focused on logistics and distribution, ensuring that products moved efficiently through networks of wholesalers, retailers, and distributors. However, these systems operated in a fragmented manner, with limited integration between companies and their partners.

In the 1990s, SCM began to gain importance as companies recognized the need for greater coordination across their supply chain, aiming to optimize supply and demand (Bowersox and Closs, 1996; Cooper et al., 1997). At this stage, SCM was increasingly seen as a management philosophy, encouraging businesses to manage dependencies between supply chain nodes (Svensson, 2007). According to Svensson (2002), these dependencies are categorized into three fundamental types, namely, time, relational, and functional dependencies, as well as additional subcategories based on directionality, hierarchy, and interaction. This period is regarded as a shift from individual logistics and procurement to a broader focus on system-wide integration.

By the early 2000s, industrialization had evolved into Industry 4.0, also known as the Fourth Industrial Revolution, driven by the rapid advancement of digital technologies (Ghobakhloo, 2018). As companies navigate this new era, the role of data-driven analytics, digital tools such as AI, IoT, and Blockchain has become a backbone to achieving process optimization and profitability in the ever-evolving global market (Ivanova, 2023; Rossini et al., 2023; Nozari, 2024). This transformation has shifted traditional SCM toward Lean practices, emphasizing highly interconnected and efficient systems that maximize customer value while minimizing resource usage (Rossini et al., 2023). Suppliers have become more intelligent, factories operate autonomously, products are equipped with smart capabilities, and customers expect seamless and personalized experiences (Tortorella & Fettermann, 2018).

Furthermore, Industry 5.0 represents the next evolution, focusing on a more human-centric, sustainable, and resilient industrial landscape (Leng et al., 2022). Unlike its predecessor, which prioritized automation and efficiency, Industry 5.0 aims to harmonize technology with human collaboration, ensuring that advancements serve both people and the planet while earning profit (Frederico, 2021). Elkington's (1994) Triple Bottom Line (TBL) framework played a pivotal role in this shift by emphasizing that businesses should account for environmental and social impacts alongside economic performance. Foundational work by Carter and Rogers (2008) further highlighted the significance of sustainability in supply chains by developing a framework that incorporated corporate sustainability, economic value, and governance.

In this regard, SSCM became a dominant focus in both academic research and industry practice (Carter & Easton, 2011; Min et al., 2019; Frederico, 2021). The relevance of SSCM is anchored in its ability to address critical global challenges (Krumme, 2019). Climate change, resource depletion, and ethical labor practices are no longer peripheral concerns but core business imperatives. Businesses began embedding sustainability strategies into their supply chain operations, with greater emphasis on green logistics, circular economy (CE) models, and closed-loop supply chains (Leng et al., 2022). Therefore, SSCM is defined as the strategic integration of environmental, social, and economic considerations into the management of supply chain processes, from sourcing raw materials to product delivery and end-of-life disposal (Elkington, 1994; Krumme, 2019; Frederico, 2021; Leng et al., 2022).

2.2 AI in SSCM

Although its roots trace back to ancient Greece, the modern history of AI began in the 1950s, with early pioneers like Alan Turing (Turing, 1950) laying the groundwork and John McCarthy coining the term "Artificial Intelligence" in 1956 (Collins et al., 2021). During this period, AI emerged as an academic discipline, driven by the ambition to create machines that could mimic human intelligence, learn from experience, and solve complex problems (Souza et al., 2021). In the 1980s and 1990s, AI experienced a resurgence as researchers refined algorithms and explored new systems, which mimicked human decision-making in specific domains, making progress in neural networks (Topraklı, 2024). Despite these developments, researchers didn't reach agreement on the specific definition of AI (Harrir & Triqui Sari, 2024). At the basic level, AI refers to the imitation or reproduction of human intelligence in machines (Stewart et al., 2020). As Stewart et al. (2020) noted, one of the hindrances to defining AI is its rapid developments, which make previous definitions outdated. Since AI continuously develops new capabilities, scholars Harrir and Triqui Sari (2024) argue that its definition should be broad enough to encompass all its characteristics without being restricted by functional or temporal limitations. Besides, Caluori (2024) identified five key dimensions of AI, including learning ability, human likeness, state of 'mind', complexity of the problem, and success. The author also highlighted the lack of evidence on which of these criteria are essential for the definition or how they should be applied. Another concern is the broad scope of AI, which encompasses a wide range of applications and tools, from basic algorithms to advanced automation, such as self-driving cars and robots (Stewart et al.,2020; Harrir and Triqui Sari, 2024). Given that different contexts serve distinct purposes and audiences, AI should be defined according to the framework of its intended distribution and objectives (Caluori, 2024).

Regarding the above consideration, our focus is exclusively on AI applications designed and utilized in SSCM. Our study excludes AI-integrated technologies such as Robotic IoT, Blockchain, and Big Data Analytics, as these systems encompass a broader spectrum of applications that extend beyond the scope of our research. Including these technologies would introduce additional layers of complexity, making it challenging to isolate the specific impact of AI in SSCM. Therefore, to maintain a focused and manageable analysis, this study narrows its scope to AI applications, which play a direct role in decision-making, optimization, and predictive analytics within SSCM. These applications can be categorized into three main areas: ML, DL, and GenAI. Their definitions and capabilities in SCM are illustrated in Figure 2.1.

AI appears to play a crucial role in SSCM, drawing significant interest from academics (Ivanova, 2023; Nozari, 2024; Harrir & Triqui Sari, 2024; Qu & Kim, 2024). It brings the ability to process vast amounts of data in real time, recognize patterns, and recommend optimized decisions across the supply chain (Qu & Kim, 2024). In the context of sustainability, these capabilities help businesses identify inefficiencies, reduce waste, lower emissions, and design more circular and resilient systems. For instance, AI-powered demand forecasting helps prevent overproduction, reducing both excess inventory and the associated environmental footprint. Similarly, AI-driven route optimization minimizes fuel consumption in transportation, contributing directly to carbon reduction targets.

Companies at the forefront of digital transformation illustrate how AI can serve both operational and environmental objectives (Towler, 2024). For example, as Towler (2024) states, Honeywell Inc. has integrated intelligent technologies into its industrial operations to enhance energy efficiency and minimize emissions. By deploying AI algorithms in combination with sensor data and environmental monitoring tools, Honeywell can detect and quantify greenhouse gas leaks, such as methane or fluorinated gases—at industrial sites. These tools not only reduce environmental harm but also prevent costly losses and improve regulatory compliance. Honeywell has further applied AI in smart energy systems like microgrids, enabling decentralized, low-carbon energy generation that supports both operational continuity and emissions reduction (Towler, 2024).

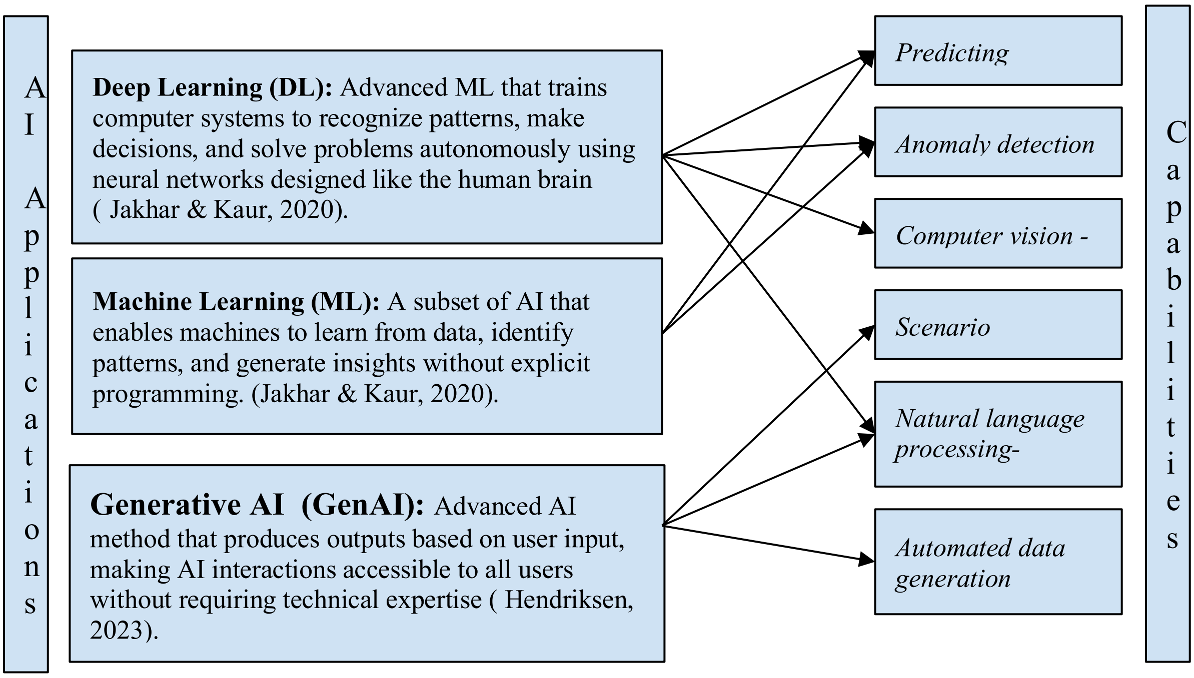
Similarly, retail firms such as Unilever use AI to improve demand sensing, reducing product spoilage and inventory waste (Gielens, 2024). These companies' digital transformation efforts include AI-driven insights for responsible sourcing and production planning that align with sustainability goals. Therefore, Gielens (2024) illustrate how AI is no longer just a tool for efficiency—it is a strategic enabler of sustainable value creation across the supply chain.

Thus, AI is not merely a technological upgrade—it is becoming a foundational pillar in the transition to more sustainable, agile, and intelligent supply chains. Its application is critical in helping companies navigate uncertainty, meet stakeholder expectations, and achieve long-term environmental and economic performance.

However, researchers debate whether AI should be considered essential for sustainability, given that digital tools themselves consume energy (Alzoubi & Mishra, 2024). Additionally, concerns have been raised about job displacement, potential unemployment, and the widening knowledge gap in society. Acemoglu and Johnson (2024) have argued that while digital technologies were expected to boost productivity, employment, and wages, their actual impact has been more complex, often exacerbating inequality and reducing real wages for less-educated workers, particularly since the 1980s. Moreover, AI methods are often expensive to implement and do not always guarantee successful outcomes, raising further economic concerns.

As a result of these controversial points, current research is shifting toward a holistic perspective on how AI adoption can support SSCM and what barriers may arise during the adoption process (Qu & Kim, 2024). For example, Min et al. (2019) questioned whether integrating those intelligent technologies into SCM genuinely creates value for customers. Building on this discussion, our study aims to explore both the opportunities and challenges of AI adoption in SSCM. By assessing its benefits and potential barriers, this research seeks to offer valuable insights for academics and practitioners, guiding strategic decision-making in operational SSCM.

Figure 2.1: *AI applications and capabilities*



2.3 AI applications to the supply chain operations reference - SCOR

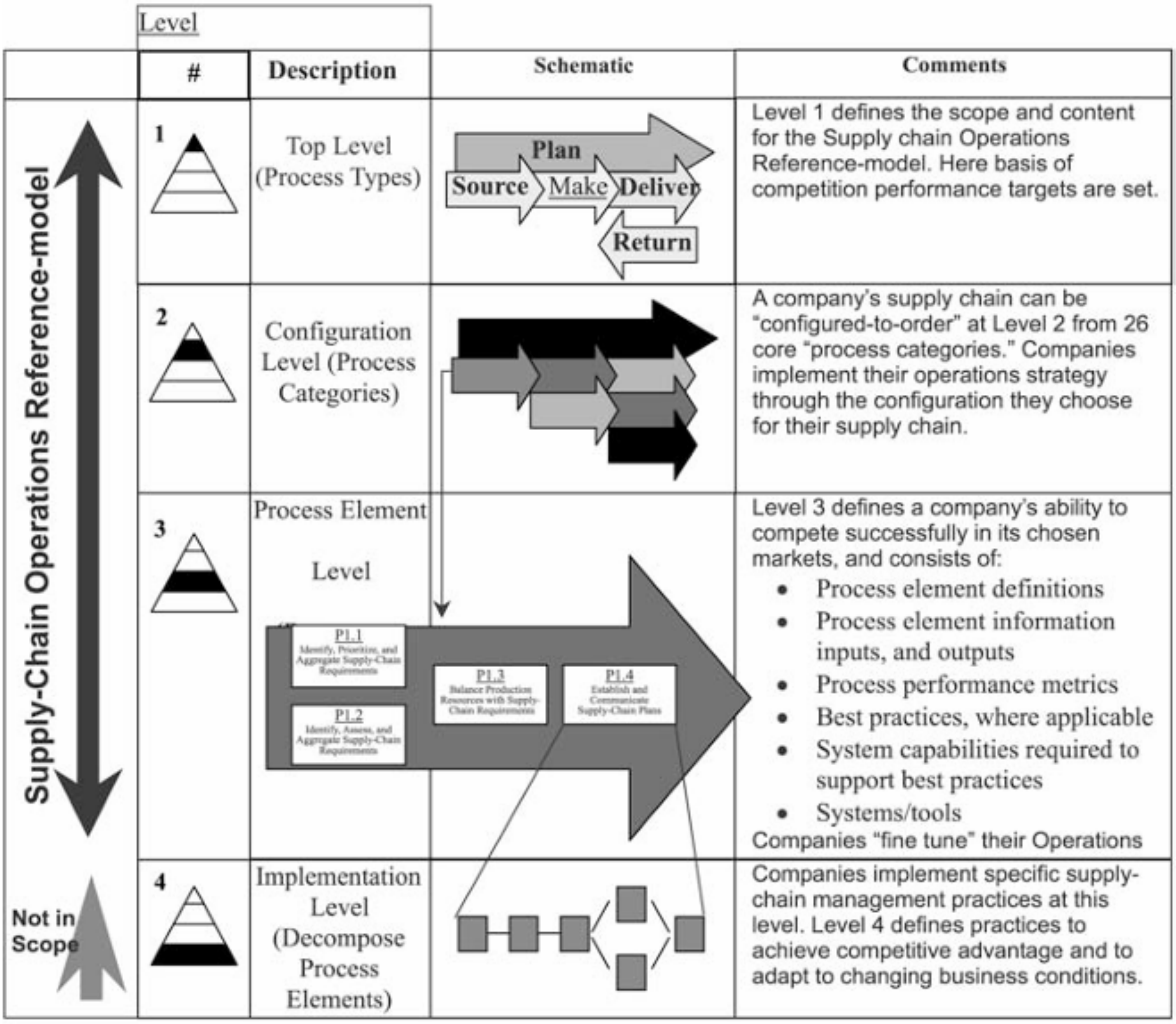
Since its first development in 1996, the SCOR model has become the backbone of operational SCM at both academic and practical levels (Nguyen, 2024). The key attribute of this model is its process-based approach, which enables the integration of supply chain activities into market conditions (Chehbi-Gamoura, 2020). This makes the SCOR model highly suitable for studying the opportunities and potential barriers of AI adoption in SSCM as it has evolved to incorporate end-to-end supply chain thinking with sustainability metrics in response to market shifts toward sustainability (Ebrahimi et al., 2021; Muslim et al., 2024). Previous studies, such as Chehbi-Gamoura et al. (2020) and Cannas et al. (2024), have successfully applied SCOR for the comprehensive examination of what digital tools could offer in SCM. Just as SCOR has been used in prior research papers, so too can it serve as a valuable framework for studying opportunities for AI adoption. Another strength of SCOR is its functional structure, which would allow us to make a systematic analysis across different process levels, ensuring a detailed investigation of AI applications at various stages of SSCM (Huan et al., 2004; Harrir & Triqui, 2024). In addition to the above motivations, scholars have validated the SCOR model's applicability across various industries, recognizing it as a standard framework in SCM (Huan et al., 2004; Cannas et al., 2024; Nguyen, 2024; APICS, 2025). Based on these rationales, our study is grounded in the SCOR model.

As for the brief about the SCOR model depicted in Table 2.1, it provides a structured way to analyze and improve supply chain processes, breaking them down into three levels (Stewart, 1997). At the top, Level 1 defines the overall scope and strategic focus of SCM. It sets the foundation for core processes such as balancing supply and demand, ensuring that sourcing, production, and delivery align with business objectives. This level is broad, outlining key decision areas without going into operational details. Furthermore, Level 2 categorizes core management processes into more specific process types—planning, execution, and enabling. This level is essential for structuring supply chain operations, ensuring that planning processes exist for sourcing, making, delivering, and returning products. It provides a framework for companies to develop systematic approaches to managing their supply chain efficiently while maintaining a balance between demand and supply. At the most detailed, Level 3 breaks down each Level 2 category into specific process elements. It captures the inputs, outputs, workflows, and execution details of supply chain operations, providing a step-by-step view of how processes function in best practices. Lastly, level 4 refers to the implementation of a certain SCM that fits the firm's unique competitive advantages and specific market conditions. Since the objective of the SCOR model is to describe operational processes, analyse the integration as well and evaluate SCM across industries, level 4 remains out of the current scope (Lockamy & McCormack, 2004).

When analysing the role of AI in SSCM, Level 1 appears to be suitable because it focuses on the overall scope, strategy, and high-level decision-making processes within the supply chain. At this level, companies define their core management processes, such as balancing supply and demand, optimizing sourcing strategies, and ensuring sustainability goals are integrated into supply chain operations. AI plays a critical role in shaping these strategic decisions by enabling predictive analytics, enhancing demand forecasting, optimizing supply chain networks, and supporting data-driven decision-making. By examining AI at Level 1, organizations can assess how AI applications align with their overarching SSCM objectives, such as reducing carbon footprints, improving resource efficiency, and thus enhancing supply chain sustainability. Additionally, since Level 1 outlines key decision areas across sourcing, production, and delivery, it provides a broad framework for analyzing AI's impact on multiple aspects of SSCM, from supplier selection and procurement automation to smart logistics and sustainable production planning.

Traditional SCOR processes, shown in Table 2.2, include 5 fundamental components, namely, plan, source, make, deliver, and return (Huan et al., 2004). Each stage is further broken down into multiple supply chain activities to analyze, control, and evaluate complex supply chain processes (Chehbi-Gamoura et al., 2020).

Table 2.1: *Hierarchical levels of the SCOR model*



	Level #	Description	Schematic	Comments
Supply-Chain Operations Reference-model	1	Top Level (Process Types)	Plan; Source, Make, Deliver, Return	Level 1 defines the scope and content for the Supply chain Operations Reference-model. Here basis of competition performance targets are set.
	2	Configuration Level (Process Categories)		A company's supply chain can be "configured-to-order" at Level 2 from 26 core "process categories." Companies implement their operations strategy through the configuration they choose for their supply chain.
	3	Process Element Level	P1.1 Identify, Prioritize, and Aggregate Supply-Chain Requirements; P1.2 Identify, Assess, and Aggregate Supply-Chain Requirements; P1.3 Balance Production Resources with Supply-Chain Requirements; P1.4 Establish and Communicate Supply-Chain Plans	Level 3 defines a company's ability to compete successfully in its chosen markets, and consists of: • Process element definitions • Process element information inputs, and outputs • Process performance metrics • Best practices, where applicable • System capabilities required to support best practices • Systems/tools Companies "fine tune" their Operations
Not in Scope	4	Implementation Level (Decompose Process Elements)		Companies implement specific supply-chain management practices at this level. Level 4 defines practices to achieve competitive advantage and to adapt to changing business conditions.

Source: Stewart, G. (1997). SCOR: the first cross-industry framework for integrated supply-chain management. Journal of Enterprise Information Management, 10(2), p62.

Based on this hierarchical structure, the following sections describe the five core SCOR processes—Plan, Source, Make, Deliver, and Return—with a focus on their relevance to sustainable SCM and AI applications.

2.3.1 Plan

AI is important in supply chain planning because it can handle complex, nonlinear, and ambiguous demand data, which traditional forecasting methods may struggle to interpret (Sohrabpour et al., 2021; Kochakkashani et al., 2024).

In their literature review, Harrir and Triqui (2024) discovered that AI-based tools are extensively utilized in the planning process, highlighting their significance in optimizing inventory management and improving operational efficiency. Previous studies further emphasized AI contributions in SCM planning in the context of resource allocations (Jackson et al., 2024) and demand optimization (de Mattos et al., 2024). Common AI algorithms used in planning SCM involve Artificial Neural Networks, data mining, and fuzzy models. help identify consumption patterns and refine demand predictions. AI-driven sentiment analysis, which is an ML method, for instance, extracts insights from social media to tackle customer preferences and new opportunities. Large Language Models (LLMs) further enhance predictions by processing and interpreting vast amounts of both structured and unstructured data, making demand forecasting more precise and adaptive in dynamic market conditions (Daios et al., 2025).

By leveraging ML techniques, like reinforcement learning and anomaly detection, AI improves forecasting accuracy, ensuring better decision-making and enhancing the overall efficiency and reliability of supply chain operations (Jackson et al., 2024; de Mattos et al., 2024). This is especially critical in economic aspects while contributing to social and environmental benefits indirectly. For instance, the AI-based model designed by Kochakkashani et al (2024) delivers both economic and social value by minimising total system costs, enhancing inventory control, and ensuring equitable distribution during disruptions. Fu & Chien (2019) proposed the UNISON data-driven analytics framework, which enhances efficiency and profitability in the electronics supply chain by improving demand forecasting for intermittent components. Through real-data analysis, the model has demonstrated economic benefits by minimizing operational losses caused by information asymmetry (Fu & Chien, 2019). Optimizing demand helps prevent excessive stocking, reducing wast,e and contributing to environmental sustainability. The implementation of genetic programming—an AI model inspired by biological evolution— has also led to similar results (Sohrabpour et al. 2021).

2.3.2 Source

Research in this area primarily focuses on supplier selection (Qu & Kim, 2024), supplier control (Brintrup et al., 2024), and procurement management (Daios et al., 2025).

Current literature highlights the role of AI in enhancing supplier selection by providing intelligent, data-driven decision support (Bigaud et al., 2016; Sudarsanam et al., 2022). For example, Bigaud et al. (2016) developed a tool using AI predictive models, such as genetic algorithms and neuro-fuzzy systems, to assess whether suppliers' capabilities align with firms' demands from a TBL perspective. Additionally, Sudarsanam et al. (2022) demonstrated how AI's optimization power, when extended to Fuzzy-Analytical Hierarchy Process (Fuzzy-AHP), effectively handles uncertainty and vagueness in expert evaluations, leading to more robust and reliable supplier selection decisions. Furthermore, the AI-powered multi-criteria material supplier selection (MCMSS) model enhances SSCM in the lithium-ion batteries industry by providing comprehensive assessments and rankings of material suppliers based on their sustainability practices (Wang et al., 2024). These studies emphasize how AI-driven approaches improve the accuracy, reliability, and sustainability of supplier selection, ultimately strengthening the sourcing process in the complex nature of SSCM.

2.3.3 Make

As industries strive to reduce their environmental footprint, ML has emerged as a powerful tool for optimizing processes, enhancing operational efficiency, and driving sustainable manufacturing. AI applications in production not only improve efficiency but also enable smarter resource management, contributing significantly to sustainability goals (Govindan et al., 2022). Through predictive maintenance, AI also helps extend the lifespan of machinery, reducing unnecessary replacements and promoting sustainable manufacturing practices (Daios et al., 2025). Danach et al (2024) noted that manufacturing firms can cut their unplanned downtimes by 25% by using predictive analytics. This achievement significantly reduces waste, lowers operational costs, and minimizes the environmental footprint.

Several researchers have pointed out that AI technologies facilitate the automated configuration of production components while enabling real-time monitoring and control of manufacturing operations and production processes (Akhshik et al., 2022; Govindan et al., 2022; Hussain et al., 2025).

Despite constraints in data availability, Akhshik et al. (2022) revealed how ML contributes to automotive lightweighting by predicting emissions reductions, highlighting AI's potential to drive eco-friendly manufacturing. Authors discovered that the neural network model is a reliable one compared to other AI applications for their study purposes. When it comes to production, AI mostly contributes to CO2 emissions reduction and energy optimization (Danach et al., 2024; Hussain et al., 2025).

2.3.4 Delivery

AI plays a transformative role in optimizing delivery systems by providing more advanced and adaptive solutions (Danach et al., 2024; Qu & Kim, 2024). Methods such as genetic algorithms, ant colony optimization, and reinforcement learning, enhance vehicle routing by continuously analyzing real-time and historical data (Daios et al., 2025). These methods help minimize fuel consumption, reduce delivery times, and improve overall efficiency, contributing to sustainability goals (Danach et al., 2024; Qu & Kim, 2024).

Moreover, scholars Daios et al (2025) have emphasized the power of GenAI in the prevention of disruptions caused by traffic congestion, extreme weather conditions, or unexpected supply chain disturbances. By proactively suggesting alternative routes or adjusting delivery schedules, AI can be adopted to reduce the environmental footprint, thus enhancing reliability and resilience in logistics operations. Another study by Danach et al (2024) suggested that advanced technologies, driven by AI, could optimize order fulfillment, minimizing manual labor and enhancing order accuracy, leading to effective warehouse management.

2.3.5 Return

The Return process encompasses all activities related to the reverse flow of goods, also known as reverse logistics (Cannas et al., 2024). In this context, AI enhances not only the economic viability of reverse logistics but also strengthens environmental sustainability by supporting CE practices based on the principles of reduction, reuse, and recycling (Wilson et al., 2022).

Network analysis by Bhowmik et al. (2024) reveals that past research has predominantly utilized supervised and unsupervised ML applications to address challenges in reverse logistics. However, there has been a notable shift toward DL in recent years, driven by its ability to process large datasets efficiently and handle complex environments (Bhowmik et al., 2024). AI's advanced computational capabilities enable organizations to enhance material recovery, minimize waste, and reduce environmental impact, further aligning reverse logistics with CE principles (Wilson et al., 2022; Bhowmik et al., 2024).

As discussed above, the SCOR model organizes supply chain operations into five key functions. Table 2.2 summarizes these top-level process types for clarity and reference.

Table 2.2: *Top-Level SCOR Process Types*

SCOR main processes	Description
Plan	Since planning is the base for all businesses, this process covers all the other parts of the supply chain – plan sourcing, making, delivery, and returning (Huan et al., 2004).
Source	The source details the activities related to procurement, ordering, scheduling, delivery, receipt, and the transfer of products and services (APICS, 2025).
Make	This process refers to the transformation of raw materials, components, or resources into finished products or services to fulfill planned and actual orders (Huan et al., 2004; APICS, 2025).
Deliver	Delivery covers order management, warehousing, transportation, and distribution to fulfill customer requirements efficiently and reliably (APICS, 2025).
Return	Return includes the handling of defective, surplus, or end-of-life items, facilitating repair, recycling, refurbishment, or responsible disposal (APICS, 2025).

Source: Adapted from Stewart, G. (1997, p. 62)

In summary, the integration of AI into supply chain operations offers a range of sustainability benefits across the SCOR functions—from improved demand forecasting and predictive maintenance to supplier selection and reverse logistics. These applications not only contribute to operational efficiency but also support environmental and social objectives, such as reducing emissions, minimizing waste, and enhancing fairness in resource distribution.

Table 2.3 consolidates these insights by mapping key AI applications to their sustainability contributions across each SCOR process, categorized by environmental, social, and economic dimensions.

Table 2.3: *Opportunities of AI adoption in SCOR functions regarding SSCM*

SCOR Functions	AI applications	Environmental opportunity	Social opportunity	Economic opportunity	References
Plan	*ML*	Reduced waste	Distribution equity	Cost efficiency Inventory control Improve agility Resource allocation	Kochakkashani et al (2024), Fu and Chien (2019), Jackson, et al (2024), de Mattos et al (2024).
Source	*DL* *ML*	Sustainable supplier selection			Brintrup et al (2024), Bigaud et al (2016), Sudarsanam et al., (2022) Wang et al., 2024.

Make	ML Simulation tools based on DL	Lower material usage Energy efficiency Lower emissions		Cost efficiency	Akhshik et al., 2022; Govindan et al., 2022; Danach et al., 2024; Hussain et al., 2025.
Deliver	ML DL GenAI	Lower emissions		Cost efficiency Agile warehouse management	Danach et a,l 2024; Daios et al., 2025; Qu & Kim, 2024.
Return	ML DL	Waste reduction Lower emissions		Cost efficiency	Wilson et al., 2022; Bhowmik et al., 2024

Overall, the findings from previous literature suggest that AI not only enhances operational efficiency but also drives the transition toward sustainable supply chains. While AI adoption has shown a significant impact on environmental and economic sustainability, its role in social sustainability remains underexplored. The prevailing trend indicates that the primary economic benefit of AI adoption lies in cost efficiency, while its strongest contributions to sustainability are in waste reduction, emissions control, and resource optimization.

2.4 Barriers of AI adoption in SSCM from the TOEH perspective

The adoption of AI in SSCM presents significant challenges across multiple dimensions (Shrivastav, 2022), which can be effectively analysed using the TOEH framework. The TOEH framework has gained increasing recognition in recent years for its ability to offer a holistic view of digital transformation challenges, especially in complex and human-influenced environments such as supply chains. This model extends the widely used Technology-Organization-Environment (TOE) framework by incorporating the human dimension, offering a more comprehensive perspective on the interplay of factors influencing SCM (Dora et al., 2022).

The technology dimension focuses on the inherent attributes of technology itself, including its functionality, complexity, compatibility with existing infrastructure, and ease of use, while the organization dimension examines the role of internal resources, structural dynamics, and strategic objectives. The environmental dimension considers external constraints such as industry regulations, market dynamics, and economic factors. The key advancement of the TOEH framework is the inclusion of the human parameter, which addresses the roles, behaviors, skills, motivation, and interactions of stakeholders (Dora et al., 2022). By integrating this human element, the TOEH model provides deeper insights into how individual and collective actions influence digital transformation in SCM, making it a valuable tool for analyzing AI adoption barriers.

2.4.1 Technological barriers

From a technological perspective, AI's integration into SSCM is hindered by several key obstacles. One of the primary challenges in applying AI applications is the lack of sufficient data. During the selection of suppliers, many organizations do not have access to historical records on contractor performance, making it difficult to develop reliable predictive algorithms (Bigaud et al., 2016). Without comprehensive datasets, AI models struggle to generate accurate insights and forecasts, limiting their practical utility (Renigier-Biłozor & Janowski, 2024). Moreover, AI models often suffer from a lack of transparency, which is known as the opacity of AI algorithms—many models operate as "black boxes," meaning their decision-making processes are not easily interpretable (Renigier-Biłozor & Janowski, 2024). Another challenge lies in the implementation and integration of AI solutions, which require sophisticated IT infrastructure—something many companies struggle with (Daios et al., 2025). Additionally, biases within AI models may lead to unfair or inaccurate predictions, creating further resistance to AI applications. Another critical technical limitation is the oversimplification of supply chain problems in highly volatile and uncertain markets. AI models often struggle to account for rapidly changing variables, lowering the effectiveness in dynamic environments (Walacik & Chmielewska, 2024; Renigier-Biłozor & Janowski, 2024).

2.4.2 Organizational challenges

On an organizational level, digital readiness is a prerequisite for AI adoption, yet many firms are not fully prepared to embrace AI-driven transformation (Naheed et al., 2025).

A lack of change management and traditional structure leads to misaligned objectives across departments, making it difficult to adopt innovative technology such as AI (Shrivastav, 2022). Budget constraints further hinder adoption, as high upfront costs and long-term ROI uncertainty make securing investments challenging (Daios et al., 2025). Additionally, a shortage of AI-skilled professionals limits effective implementation, preventing businesses from leveraging AI-driven insights (Topraklı, 2024; Shrivastav, 2022). Leadership hesitation also plays a critical role, as uncertainty around AI's benefits and resistance to change slows adoption (Shrivastav, 2022; Daios et al., 2025). Furthermore, data privacy and security concerns remain critical, as supply chain operations involve handling sensitive information that is vulnerable to cyber threats (Daios et al., 2025).

2.4.3 Environmental barriers

The adoption of AI faces significant environmental barriers, primarily due to regulatory uncertainty and external constraints (Dogru & Keskin, 2020). Currently, AI operates in a weak legal area, where regulations have not yet caught up with the rapid pace of technological advancement (Dogru & Keskin, 2020). Without well-defined legal guidelines, companies may unknowingly expose consumers to risks, leading to ethical and practical concerns.

Also, geopolitical risks pose significant environmental barriers to AI adoption in SCM (Shrivastav, 2022). Political tensions, trade disputes, and economic sanctions introduce uncertainty and disrupt supply chain operations. These events alter the distribution of data used for AI training, leading to inaccuracies and reducing model effectiveness.

2.4.4 Human barriers

Beyond technical and operational hurdles, human factors play a crucial role in AI adoption. Many managers remain sceptical about AI's impact on decision-making, influenced by past technological trends that failed to meet high expectations (Daios et al., 2025).

Based on 12 interviews across various industries, Hangl et al. (2023) identified key human-related barriers to AI adoption in SCM. One major challenge is resistance to change, especially in traditional industries, where stakeholders may be hesitant to embrace new technologies.

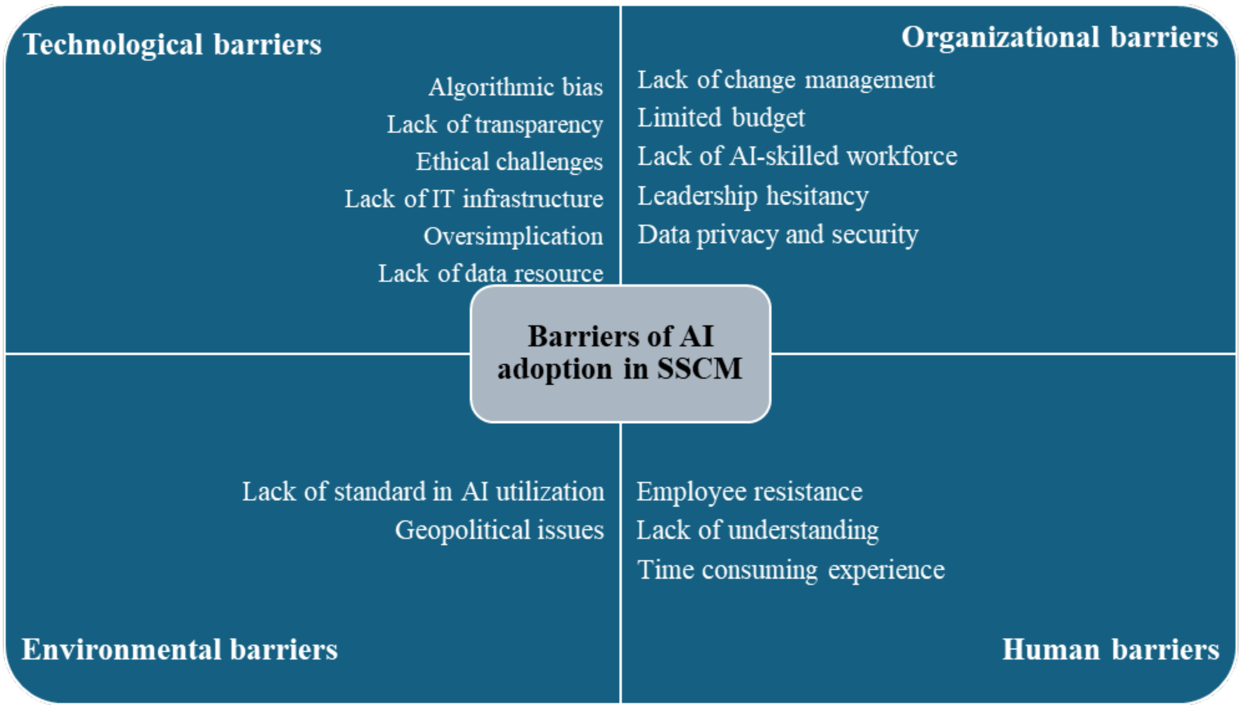
Another significant barrier is the lack of understanding and trust in AI—many professionals remain unfamiliar with how AI functions in SCM, leading to skepticism and reluctance.

Additionally, integrating AI into existing workflows is a complex and time-consuming process. For AI solutions to be successfully implemented, they must seamlessly align with current operations without causing disruption. Addressing these human-centric challenges is crucial for organizations to fully realize AI's potential in SCM.

The analysis above identified a wide range of challenges associated with the adoption of AI in SSCM, categorized under four dimensions: technological, organizational, environmental, and human (TOEH framework). While these barriers are discussed in detail across individual SCOR functions, such as lack of data quality in planning or employee resistance in returns, there is value in summarizing how these challenges align across the broader supply chain.

To enhance clarity, Figure 2.2 presents a visual overview that integrates these insights into a single framework. It maps each type of barrier to the corresponding SCOR process (Plan, Source, Make, Deliver, Return), illustrating where in the supply chain these challenges tend to emerge. This figure serves as both a synthesis of the findings and a practical tool for identifying function-specific intervention points in future AI implementation strategies.

Figure 2.2: *Barriers of AI adoption in SSCM*

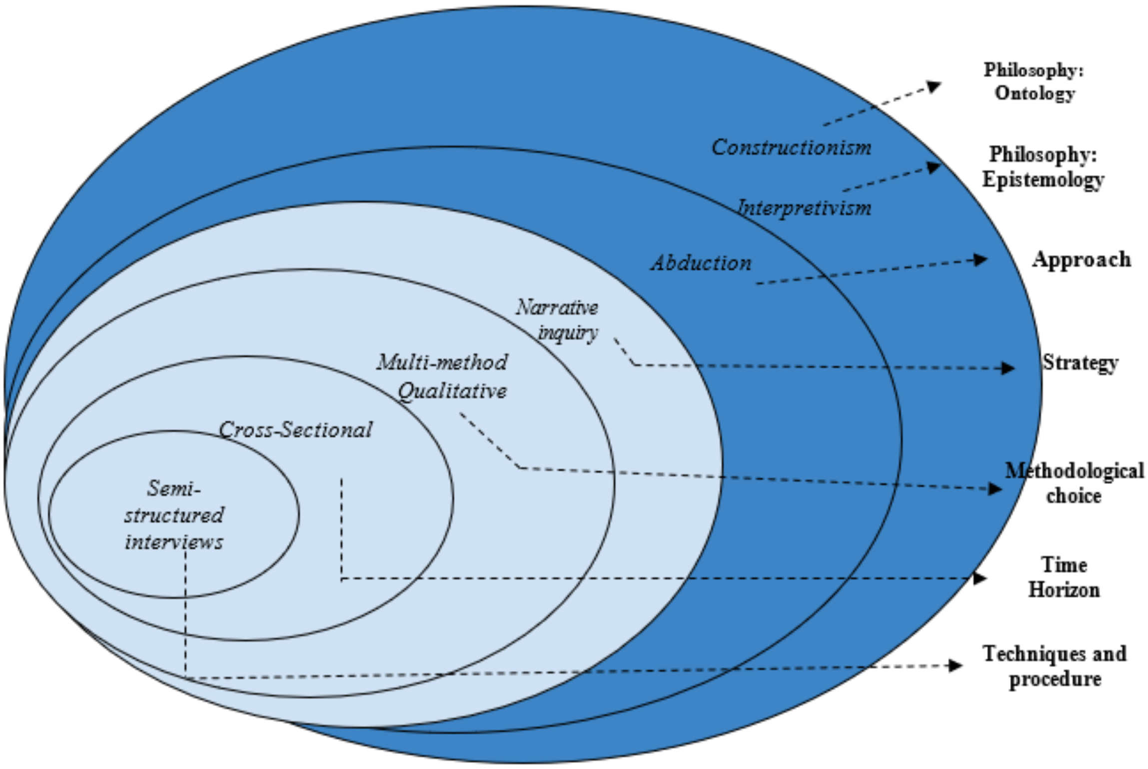


3.0 Methodology

This chapter outlines the methodological framework used to examine the adoption of AI in SSCM. It introduces the philosophical foundations, research approach, strategy and design, data collection, data analysis, and ethical considerations of the study.

The structure of this chapter follows the "research onion" model developed by Saunders et al. (2019), which ensures alignment between the research philosophy, methodological choices, and practical implementation. This structured approach supports the development of a coherent and valid qualitative study grounded in both theory and empirical insight.

Figure 3.1: *Methodology choices adopted in this study based on the "Research Onion" model (Saunders et al., 2019, p. 108)*



3.1 Research philosophy

The philosophical foundation of this study is based on a constructionist ontology and an interpretivist epistemology. Together, they shape the way knowledge is approached and understood throughout the research process.

Ontology concerns the nature of reality (Bell et al., 2019). This study adopts a constructionist ontological position, which assumes that reality is not objective and fixed, but rather formed through social interaction and shared understanding (Pretorius, 2024). In the context of AI adoption in SSCM, this means that the meaning of "AI adoption," its perceived benefits, and its challenges are shaped by the people involved, such as managers, engineers, and sustainability professionals. These meanings can evolve over time as practices change, technologies develop, and new regulations or social expectations emerge (Bell et al., 2019). This ontological stance supports a flexible, experience-based investigation, particularly suited for understanding how different professionals perceive and define the role of AI in their organizations.

Epistemology deals with how knowledge is acquired and validated (Bell et al., 2019). This research follows an interpretivist epistemology, which views knowledge as being developed through understanding people's subjective experiences and interpretations. In contrast to a positivist approach, which seeks to explain behavior through measurable variables, interpretivism focuses on how individuals make sense of their actions and environments (Pretorius, 2024). This is especially relevant when studying technologies like AI, whose meaning and value are still under discussion and vary widely across industries and roles. Rather than aiming to produce general laws, this research seeks to develop rich, context-specific insights that reflect how people engage with AI in the pursuit of sustainable practices.

The combination of constructionism and interpretivism supports the use of qualitative methods (Bell et al., 2019). It allows the study to capture detailed narratives and explore the diverse perspectives of professionals involved in AI implementation across supply chain functions. This foundation ensures that the chosen methods are aligned with the nature of the research topic and the type of knowledge being sought.

3.2 Research Approach

This study adopts an abductive research approach, which combines both inductive and deductive reasoning (Bell et al., 2019). The process began with an initial review of existing literature on AI and SSCM, which helped identify key theories, assumptions, and research gaps. However, instead of testing predefined hypotheses, the research moved toward exploring new patterns and insights drawn from empirical data.

The abductive approach was selected because it allows for flexibility when working with complex and evolving topics such as AI adoption. It supports an iterative process, where data from interviews is used to refine or challenge the initial understanding drawn from the literature. In this way, the study remains open to unexpected findings while staying connected to existing theory.

This approach is especially valuable when the aim is not to confirm universal laws but to build context-specific understanding (Alturki & Usman, 2021). It is well-suited for qualitative research, where the goal is to generate new insights from the lived experiences of professionals. By going back and forth between theory and data, this study develops a deeper and more grounded understanding of the opportunities and challenges associated with AI in SSCM.

3.3 Research Strategy and Design

A qualitative research strategy was adopted to explore how professionals perceive and experience AI adoption in sustainable SCM. Given the socially constructed and context-specific nature of this topic, qualitative inquiry offers the depth and flexibility required to understand individual perspectives and organizational realities.

Narrative inquiry was chosen as the core strategy. This approach allows participants to share their experiences in their own words, revealing how they interpret opportunities, challenges, and decisions related to AI in supply chains. It is particularly effective when studying emerging phenomena influenced by human judgment, organizational context, and changing technologies (Saunders et al., 2019).

The overall design of the study was inspired by grounded theory principles (Bell et al., 2019), with the goal of developing theory from empirical data rather than testing a predefined model. To support a structured and transparent analysis, the Gioia methodology was used. This involved three levels of coding: identifying first-order concepts from interview data, grouping them into second-order themes based on emerging patterns, and synthesizing them into aggregate dimensions that reflect broader insights (Magnani & Gioia, 2023).

Details of the interviewees, including their industry, position, and interview duration, are presented in Table 3.1 in the next section.

3.4 Methodological Choice

This study adopts a qualitative multi-method approach, combining a theoretical literature review with semi-structured interviews. This choice aligns with the interpretivist and constructivist philosophical stance, emphasizing meaning-making through human experiences and perspectives.

While quantitative research is suitable for measuring patterns across large datasets, it often lacks the contextual depth required to understand complex social phenomena (Bell et al., 2019). In contrast, qualitative methods are well-suited to exploring how individuals define, interpret, and act upon concepts such as sustainability and AI in practice.

The research design followed two stages:

- Stage One involved a literature review to establish theoretical foundations, identify relevant frameworks (such as SCOR and TOEH), and map out existing knowledge on AI in SSCM.
- Stage Two consisted of conducting semi-structured interviews with professionals engaged in AI or sustainability-related supply chain work. This allowed for the collection of firsthand insights that reflect real-world conditions.

Together, this methodological structure enabled the study to combine academic theory with empirical evidence, offering a richer and more grounded understanding of AI's role in sustainable SCM.

3.5 Time Horizon

This study adopts a cross-sectional time horizon, focusing on participants' perspectives at a single point in time (Alturki & Usman, 2021). The aim is to capture current insights, experiences, and challenges related to AI adoption in sustainable SCM, rather than tracking changes over a longer period.

A cross-sectional approach is appropriate given the exploratory nature of the research and the practical constraints of conducting interviews within a limited timeframe. While this design does not account for long-term developments, it offers a timely snapshot of how professionals perceive AI's opportunities and barriers in the present landscape.

3.6 Data Collection

This study employed a two-phase data collection process, combining both secondary and primary data sources. The first phase consisted of a literature review to establish a theoretical foundation, while the second phase involved semi-structured interviews with professionals engaged in SCM, sustainability, or AI.

Phase One: Literature Review

Relevant peer-reviewed academic literature was identified using scholarly databases. Selection criteria focused on theoretical relevance, empirical contribution, and alignment with the research questions. A snowballing technique was also used to trace additional references from key articles to ensure comprehensive coverage.

Phase Two: Semi-Structured Interviews

Primary data was collected through 16 semi-structured interviews conducted with professionals across various industries. Participants were selected by snowball sampling methods and purposefully sampled to ensure a diverse range of perspectives. Among them, nine participants had over ten years of domain experience, while four had between five and six years, and the remaining three had one to three years of professional experience. While extensive industry experience was considered valuable for understanding historical and strategic developments in SSCM, we intentionally included early-career professionals as well. The rationale for this lies in the emerging nature of AI technologies. Given the recency of AI adoption in supply chain practices, newer professionals, particularly digital natives or those educated in the era of rapid AI development, often bring fresh insights, higher digital fluency, and a greater openness to emerging tools and innovations. Their firsthand engagement with AI in day-to-day tasks provides practical and contemporary perspectives that complement the strategic and long-term viewpoints offered by more experienced participants. This mix enabled us to capture a holistic and multi-generational understanding of AI's current and potential impact on SSCM.

To guide the interviews, a semi-structured interview guide was developed based on themes derived from the literature review and the TOEH framework (Technology, Organization, Environment, Human). The guide was divided into four sections: background and role, AI in

SSCM – adoption and opportunities, barriers to AI adoption, and future outlook. A full version of this guide is included in Appendix A.

Participants were assigned according to their functional roles in the SCOR model—planning, sourcing, making, delivery, and return—ensuring comprehensive representation of supply chain processes.

Table 3.1 presents an overview of all interviewees, including their professional roles, years of experience, and interview duration.

Table 3.1: *Interviewees' details*

Participants	Position	Years of experience	Company	Interview duration
P1	Delivery & Return Logistic manager	+10 years	Logistics company	30:10 min
P2	Sourcing Supply chain manager	13 years	Car manufacturer	27:45 min
P3	Making Quality engineer	+10 years	Car manufacturer	24:45 min
P4	Planning Supply chain manager	+ 10 years	Chemical company	Refused to record
P5	Sourcing Procurement manager	6 years	Distributor	32:18 min
P6	Delivery & Return Global operations team	5 years	Car manufacturer	37:40 min
P7	Planning Supply chain analytics	3 years	Car manufacturer	40:22 min
P8	Delivery & Return Logistic manager	+5 years	Temporarily unemployed	35:30 min

P9	Planning SC Transformation Leader	10 years	Car manufacturer	41:34 min
P10	Making Research and Development (R&D) team - AI consultant	5 years	Equipment Manufacturer	30:25 min
P11	Making & Delivery Supply chain manager	10 years	Camera Manufacturer	31:00 min
P12	Plan R&D team - Demand planning	1 year	Equipment Manufacturer	30:43 min
P13	Delivery & Return Digital driver	2 years	Car manufacturing	43:20 min
P14	Whole supply chain Sustainability consultant	10 years	Consultant agency	37:05 min
P15	Plan AI and statistics expert	+10 years	Energy and automation industry	45:30 min
P16	Whole supply chain Sustainability manager	15 years	Car manufacturer	36:30 min

3.7 Data Analysis

To analyze the interview data, this study adopted the Gioia methodology, a systematic qualitative approach well suited for inductive theory development (Magnani & Gioia, 2023). The Gioia methodology, combined with grounded theory (shown in Appendix B), enables a structured process of moving from raw qualitative data to abstract theoretical insights, making it ideal for exploring emerging phenomena such as AI adoption in sustainable SCM.

The analysis process was conducted using ATLAS.ti, a qualitative data analysis software that facilitated efficient management and coding of the interview transcripts. The software enabled clear traceability from raw data to emerging concepts, themes, and aggregate dimensions, thereby enhancing transparency and analytical rigor.

Following the Gioia method, the analysis progressed through three main stages:

1. First-order coding and Concept Formation

   In the initial stage, first-order codes were created by identifying key phrases and expressions directly from interview transcripts. These codes closely reflected participants' language and perspectives. Multiple codes with similar meanings were then grouped together into first-order concepts, which represented broader ideas articulated by the interviewees while remaining grounded in their lived experiences.

2. Development of Second-order Themes

   The first-order concepts were then re-examined from a more abstract, theory-informed perspective. At this stage, second-order themes were developed by interpreting patterns across the data and aligning them with the existing literature on AI and sustainable SCM. The process reflected a shift from an informant-centric to a researcher-centric interpretation of the data.

3. Synthesis into Aggregate Dimensions

   Finally, the second-order themes were further distilled into aggregate dimensions. These dimensions captured the overarching insights and directly addressed the two research questions:

   (1) What are the key opportunities that AI offers for SSCM?

   (2) What are the main barriers organizations face in adopting AI in SSCM?

A full visualization of this three-level data structure - codes → concepts → themes → dimensions - is provided in Appendix B. Additionally, representative quotes are presented in the findings chapter to illustrate the identified themes and validate the analysis with participants' original voices.

3.8 Research Quality and Trustworthiness

To ensure the rigor of this study, we adopted widely recognized criteria for evaluating qualitative research quality: credibility, transferability, dependability, and confirmability (Lincoln & Guba, 1985). Each of these dimensions was addressed through deliberate methodological decisions.

To ensure credibility, we selected interviewees from diverse professional backgrounds—including sustainability experts, AI professionals, and supply chain managers—to enable triangulation and enrich the perspectives gathered. The use of semi-structured interviews allowed for in-depth exploration of lived experiences. Additionally, member checking was applied in several cases to verify the accuracy of the interview summaries.

Transferability was supported by providing detailed descriptions of the research context, participant roles, and organizational backgrounds. These contextual details allow readers to assess the applicability of the findings in other settings or sectors.

Dependability was strengthened through transparent documentation of the research design, sampling strategy, data collection procedures, and thematic analysis process. A consistent interview guide was used across all interviews to maintain comparability while allowing flexibility.

Confirmability was ensured through systematic data coding using the Gioia methodology. All themes and interpretations were backed by verbatim participant quotes and cross-validated during analysis discussions.

By addressing these four criteria systematically, this study maintains a high level of trustworthiness and offers robust, grounded insights into AI adoption in SSCM.

3.9 Ethical Considerations

All interviews were conducted in accordance with the University of Gothenburg's ethical research guidelines and the General Data Protection Regulation (GDPR). Verbal informed consent was obtained from all participants prior to the interviews, and they were informed of their right to withdraw at any time without consequence. To ensure anonymity and confidentiality, all names, company identifiers, and sensitive details were removed from the transcripts. In the final report, participants were referred to using anonymized codes such as P1 to P16, based on their interview order and function. Recordings were stored securely and used solely for the purpose of transcription and analysis.

4.0 Findings

This chapter presents the main empirical findings from the interviews conducted with professionals in Swedish manufacturing-related industries. Drawing on the SCOR model and TOEH framework, the findings are categorized into two core areas: the opportunities that AI offers for achieving sustainability in supply chain functions, and the barriers that organizations face in adopting these technologies. The results are structured according to the five key supply chain processes—Plan, Source, Make, Deliver, and Return—and are supported by direct quotes from the interviewees to illustrate practical perspectives.

4.1 Current adoption of AI in SSCM

Our findings reveal that companies are at varying stages in their adoption of AI within SSCM. While some organizations view AI as a strategic enabler with transformative potential, others have only recently begun exploring its applications, often as a reactive move to broader industry trends. Most of the reported use cases involved ML applications, LLMs being the most common tools within the broader category of GenAI. In fact, interviewees did not disclose specific AI applications by name, likely due to confidentiality concerns and the fact that many managers possess only a general understanding of AI rather than detailed technical expertise.

A number of participants emphasized that AI adoption is increasingly perceived as necessary to remain competitive in a rapidly evolving market. P11 highlighted this sentiment, stating:

> *"Any company, if they don't do it. They will lose the competition in the long run. The big change, the big opportunity to adopt AI, is to keep the competition. And keep the advantages and the competitiveness of the company in the long run. being competitive."*
> This proactive stance aligns with a broader recognition that AI is no longer optional, but essential to long-term viability.

Similarly, P13 reflected the urgency of AI engagement due to external pressures, noting:

"When you see your competitors growing in this direction and the whole world going in this direction, it's not normal to be. playing, playing out of the group, you have to be in this area or you're gonna be out of the market."

These responses illustrate a common narrative: companies are motivated not only by internal strategic goals but also by the fear of being left behind.

Nevertheless, not all firms have embraced AI with the same level of integration. For example, P4 described a more reactive approach, explaining that his team has only recently started considering AI applications, primarily in response to the growing trend rather than as part of a long-term digital strategy. This suggests that, for some, AI exploration is still in its early, experimental stages.

In terms of practical application, AI is not yet universally embedded in sustainability efforts within supply chains. P6 acknowledged this gap, stating:

"AI is not yet a core component of the sustainability roadmap, but it has the potential to support it, for example, improving forecasting accuracy for materials used to build cars, logistics, and reducing inefficiencies in energy use or emissions tracking. It's not fully incorporated yet."

This perspective reinforces the notion that while AI holds significant promise, its current use in SSCM remains limited and often confined to pilot projects or specific functions.

Interestingly, our data also surfaced mixed views on the cost of AI adoption. While high initial investment was cited as a key barrier by many, others pointed to the increasing availability of affordable AI solutions. P9 suggested that

"AI solutions could actually be cheaper than you think. Nowadays, companies can use outsourcing or build AI models based on ready infrastructure or some shelf products," indicating that cost may no longer be a prohibitive factor in every case.

Similarly, P15 emphasized the role of enterprise platforms in reducing costs:

"SAP has made things cheaper for companies, for example, they offer AI-enabled planning tools that are ready to go, and for many companies, that's a faster and more affordable path."

When it comes to sustainability dimensions, a recurring theme emerged: many participants strongly associated AI with economic sustainability. Several interviewees emphasized that among the three dimensions of sustainability—economic, environmental, and social—the economic aspect often takes precedence in practical implementation. As P5 candidly explained:

"*It's not this sustainability. It means making money, to be honest with you, the concept, sustainability is how to make sustainability more profitable. For us, this is. When we talk about corporate work, this is sustainability, and of course it's about reducing the emissions and environmental aspect, as and social. The main thing. It's the economic aspect in my opinion, because if you have you want to implement it to sustainability and it is costly, and if you can make a profit from it, it's hard to continue with sustainable practices.*"

In comparison to the economic and environmental dimensions, interviewees generally demonstrated limited awareness of AI's role in advancing social sustainability. Many participants perceived social sustainability as outside their core responsibilities or misunderstood it as being synonymous with corporate social responsibility. For instance, P9 shared:

"*In my role, there is no need to be concerned about social sustainability. In my understanding, it is a social responsibility, right? So, of course, our business complies with all the regulations, and we have a special department that works for social responsibility. In the AI case, I don't see any direct link with social sustainability.*"

Interestingly, P16, a sustainability manager, expressed a similar view. This sentiment was echoed by other participants who primarily associated AI with operational or environmental benefits rather than social ones. As P10 explained:

> "*AI is currently used for automation and better optimization, and helps us make more sophisticated decisions for business. This can lead to environmental benefits, but it is hard to look at it from a social sustainability perspective*."

Despite this general lack of emphasis, several interviewees acknowledged AI's potential contribution to social sustainability, particularly in areas such as job transformation, employee development, and workplace safety.

AI can support workforce development by enabling reskilling and upskilling, allowing employees to shift from repetitive tasks to higher-value roles. P12 captured this transition clearly:

> "*If you approach AI as something that can increase your productivity, you can learn it and stuff. It will contribute a lot to your social sustainability. But if you are against it, and you want to keep doing the automated work, it will block your future career, if you understand what I mean. So it's, it is how you approach it. It's definitely taking some work, but it is opening something else.*"

This insight suggests that AI can serve as a catalyst for empowering individuals, particularly if accompanied by a culture of learning and effective change management.

In addition to job development, AI is also enhancing workplace safety, which is a vital yet often overlooked aspect of social sustainability. P1 illustrated this with a concrete example:

> "*If the employee lifts up a little bit too heavy in the wrong way. If the camera detects that one is then it will update this, it will inform the system how he's doing, what mistakes. Doing everything. And it will notify the employee, the employee who is making mistakes will get special training instructions, and everything it will. In the case of social sustainability, it reduces accidents.*"

This kind of real-time monitoring and feedback not only helps prevent workplace injuries but also fosters a culture of care and continuous improvement.

Interviewees generally shared consistent views on the positive contributions of AI to environmental sustainability. A key opportunity lies in cost reduction and inventory optimization, which allow companies to avoid overproduction and overstocking—thereby minimizing waste and related emissions. For instance, P7 stated:

“*If we can reduce how much we use, we will reduce CO_2 and other emissions, and also reduce costs. It's more in that sense*.”

Similarly, P1 highlighted the environmental benefits of operational optimization:

“*I think a tool can be positive. It has both positive and negative aspects, but in my case, it can support sustainability. As I said, route optimization, from my experience, helped us avoid releasing extra emissions.*”

P16 emphasized the role of predictive analytics in reducing inefficiencies:

“*It can help optimize these processes and reduce waste. In waste reduction, predictive analytics play a key role, helping to minimize inefficiencies in your supply chain and improve overall performance*.”

Another opportunity lies in energy efficiency through environmental control. AI-powered monitoring systems help maintain ideal conditions for sensitive materials, thus ensuring production quality and reducing unnecessary energy use. As P5 explained:

“*We face many issues on the shop floor, but AI-based temperature monitoring helps in some cases. These materials require very specific environmental conditions. If those conditions aren't met, the production becomes inefficient, leading to significant energy loss, which is a fundamental concern*.”

4.2 AI in SCOR

4.2.1 Plan

The findings of this study indicate that AI plays a major role in enhancing the Plan process within the SCOR framework. Across interviews, participants consistently emphasized that the predictive capabilities of AI allow for more accurate demand forecasting, inventory optimization, maintenance scheduling, and overall planning efficiency, leading to both economic and environmental benefits.

Several participants highlighted that AI is actively used in various aspects of planning, including demand forecasting, supply planning, inventory optimization, and predictive maintenance. P1 emphasized the central role of AI in logistics planning, noting its contribution to scheduling:

"*We are using one tool that analyzes the priority of orders and makes the schedule for the delivery.*"

P12 further supported this by illustrating the benefits of AI in handling large data volumes:

"*For example, now we are five people analyzing the data, and it's a huge amount of data. This is gonna be fast, and sometimes we miss some stuff if we analyze it by hand. Sometimes we miss some information, which is acceptable because we are human and we make errors sometimes. But with AI, it is gonna be way less likely to miss important points. And the plan is gonna be more accurate. Your forecast is gonna make more sense once you see the logic of ML models. Your cells and your warehouse and your inventory level are gonna be more efficient, and your customers, they don't need to face any backlog or any out of stock.*"

Moreover, P15 stressed AI's contribution to the CE through better planning:

"*In terms of circular economy, AI can again help in better planning, through its ability to forecast the demand, through its ability to increase the yield of what we produce, and reduce the waste.*"

Similarly, P14 highlighted that,

"*Some companies use AI for better demand forecasting, reducing waste, and improving resource efficiency.*"

Participants also pointed out the broader sustainability impact achieved through efficient planning. P9 stated:

"*Where that one talks about widely about reducing waste as environmental sustainability, but in general, by planning better, there's one-on-one on inventory optimization — we're keeping what inventory at what location.*"

P8 further noted:

"*If you have a more efficient supply chain, then you will reduce the* CO_2 *impact and also reduce the cost. It's real. That is a successful way of working, combine money with sustainability.*"

Finally, P6 added that operational efficiency, even in small forms such as reduced computational resource use, has environmental benefits:

"*It's helpful because if we do the work more efficiently, it can also reduce environmental impact. It’s not a direct link, but if we use fewer computers, for example, that’s better for the environment.*"

4.2.2 Source

The findings indicate that companies are increasingly utilizing AI to enhance sustainability efforts within the Sourcing stage of the SCOR model. A key application of AI in this stage is supplier selection. Many companies have introduced AI-enabled scoring systems to evaluate suppliers specifically on their sustainability performance. As one participant (P2) explained,

“*With AI, we can even evaluate supplier sustainability scores using external data.*”

This demonstrates the growing reliance on AI to incorporate diverse external datasets into supplier evaluation processes, allowing companies to identify partners that align with their sustainability goals.

Risk analysis also emerged as an important area where AI supports sustainable sourcing. P11 stated that

“*We can analyze the supplier and the environmental risks,*” reflecting the use of AI in identifying and mitigating potential environmental liabilities within the supply chain.

AI applications further support sustainable sourcing through contract management and digitalization. P14 highlighted the shift toward environmentally friendly alternatives to traditional paper-based processes:

“*We have AI solutions in supply chain, such as known as paper digitalization. One of our clients wanted to turn all the paper-based work in their supply chain to be more environmentally friendly. So we offered a digital solution that improves supply chain visibility with paperless trade documents. Another solution is around compliance or contract AI. All these manufacturing companies, the folks with raw materials. They all have contracts with one another. And these contracts are getting renewed in a certain period. So AI applications could help them with contract compliance.*”

The role of AI in automation was also noted. P6 shared:

"*We use AI to review bugs and for automation. For example, in contract renewal, suppliers' data and order amount in some areas are automatically populated, so we don't need to retype them — it's for efficiency.*" This use of AI not only improves efficiency but also supports sustainability by reducing redundant work and potential errors in data entry.

A broader digital transformation was described by a P15, who emphasized the value of centralized platforms:

"*So AI can lead to a shared platform, and that shared platform is to provide a single source of true data flowing from all points in the supply chain up to the point of sale in real time, which is key to remediating supply chain issues before they arise and ensuring maximum products sell through. It can also prevent waste by controlling overstocking.*" This points to the potential of AI to foster system-wide transparency and reduce environmental impact through better coordination and data visibility.

4.2.3 Make

The findings revealed that AI plays a critical role in enhancing sustainability and operational efficiency in the "Make" stage of the SCOR model. This stage, which encompasses production activities such as manufacturing, assembling, and packaging, has seen growing integration of AI technologies aimed at reducing resource use, emissions, and inefficiencies.

One significant application of AI in this stage is predictive maintenance. P6 emphasized this use case, stating:

"*AI used in predictive maintenance — helping schedule maintenance more efficiently, which reduces gas emissions and improves sustainability*." This illustrates how AI-driven monitoring of equipment conditions not only minimizes downtime but also contributes to environmental goals by reducing unnecessary energy use and associated emissions.

Another theme that emerged was resource efficiency during manufacturing operations. P4 underscored the importance of optimizing resource consumption as part of their sustainability strategy. While specific implementation details were not provided, the emphasis supports the broader trend of using AI to refine manufacturing processes and reduce waste.

AI also contributes to packaging optimization, which is a key activity in the Make phase. P15 noted:

"*We use AI to simulate what kind of packaging is needed, how much can go into a truck stuff like that…. AI can actually even help optimize your packing, and we use it. In fact our firm has a certain number of standard packaging size,s and that's actually optimized using AI.*" This shows how AI simulations help reduce material usage, improve space utilization, and potentially decrease transportation-related emissions through better packaging decisions.

The application of AI in design and production simulation was another area of innovation. P10 highlighted AI's broad applicability across departments, especially in product and process design:

"*AI Can be used in any department for engineering or customer team's or designers that can design based on their customer needs. What I know from my understanding here, there's a lot of innovation going on in AI. One of the greatest features of AI is its visualization power. We can see and gain experience by using an AI simulation to evaluate innovative ideas or designs in the production line. It may even further lead to the next innovation.*" This reflects the role of AI in enabling agile and customer-centric manufacturing processes, where digital twin simulations and design optimization can accelerate development and support sustainability goals by reducing physical prototyping and material waste.

Despite the wide range of AI applications in the "Make" process, the findings suggest that the use of AI in engineering quality control remains limited or approached with caution. Notably, even participants in technical roles expressed skepticism about overreliance on AI for quality-related decisions. As P3, a quality engineer, stated:

"*We don't like to totally rely on AI is just use it as an assistant right now…… just because there is this AI trend, I think the company can't, like, yeah, choose a software or something, just for the sake of it. In fact, quality control is a delicate process that requires careful handling.*" This perspective reflects a broader hesitation to delegate critical quality assurance tasks entirely to AI, highlighting the ongoing need for human oversight in production environments where safety, precision, and compliance are paramount.

4.2.4 Deliver

The findings of this study reveal that AI significantly enhances various activities within the delivery part of the SCOR model, particularly in the domains of transportation management, warehouse operations, inventory control, and delivery scheduling.

A primary area of AI application is transportation route optimization, which is a central function in the delivery process. Multiple participants emphasized the transformative role of AI in this regard. As P8 cited:

"In my experience, in the transportation area, we should have some AI with IoT to optimize the routing or some job." This perspective is reinforced by Susan Huang, who stated that "it's more first, it can help to. optimize the root, the root planning of the transportation, the logistics, which will save a lot of carbon emissions."

P10 also noted that:

"*AI improved the route optimization, I would say. An application, which, based on the conditions, several conditions, you could say is the shortest path or the optimal time to deliver products.*"

Moreover, P14 echoed this benefit, explaining that "*Some also use data analytics platforms to help optimize transportation routes from their distribution facilities, right to the stores themselves, further reducing fuel consumption and emissions.*"

Similarly, P1 emphasized, "*It optimizes the transportation routes for the delivery. It analyzes the traffic and our delivery schedules where we have to reduce deliveries, and it analyzes all this data and makes plans for us, and we are delivering according to that plan. It saves time. It reduces the carbon footprint, time, and helps us avoid traffic.*"

Beyond routing, AI also supports inventory management and distribution decisions within delivery operations. P15 explained, "*We use AI to decide how much safety stock to hold in which location. Again, considering all the variability in the market and the issues that are not foreseen.*"

P5 similarly shared that "*optimization of inventory, for example, making sure that you have enough inventory and not holding inventory a lot, which means we'll be holding less money. That played a key role, knowing that we could be able to maintain our stock levels at that level.*"

In relation to delivery scheduling, AI was found to support prioritization and planning functions. P1 described this application, stating, "*We are using one tool. Which analyzes the priority of orders and makes the schedule for the delivery.*" This function supports more responsive and efficient delivery processes, aligned with customer needs and operational constraints.

AI is also playing an increasingly important role in warehouse management, which is critical in the delivery phase. P10 reported that

"*We use an AI system that predicts the demand. that we don't need to overstock the products. Given a system that can predict the expiry date. And alert the various stakeholders in the company that they can give the products before expiring and give them to people at our discount rate that which can avoid wastages*." This insight reflects how AI aids in reducing inventory waste and aligning stock levels with real-time demand.

Additionally, P1 explained how AI is used to automate physical operations:

"*We are using AI-based software for sorting, and machines would learn the items' size and weight, then make the decision of the package. It all shows on a screen*."

P9 added to this by describing the impact of AI on workload prediction and cross-warehouse logistics:

"*We use AI for workload prediction in our warehouses. We use it for distribution, there's a manual process where I get the order proposal. Should I ship 10 pieces from or should I move 10 pieces from this warehouse to this warehouse? We reached almost 90% of the automation level by having an AI supporting us. With that, we'll also take AI decisions on how to package our. Our spare parts. Should we or should we not? Which type of acting material should we use for each spare part? We also do it for customs clearance.*"

Finally, in sectors such as food retail, AI is contributing to sustainability by improving monitoring systems. As P15 explained,

"*Some food retailers use AI to monitor the conditions of their perishable food, thus reducing food waste.*"

4.2.5 Return

AI's primary contribution within the return process lies in demand optimization, which helps reduce resource use, particularly labour resources, by automating tasks that would otherwise require manual intervention. As P6 emphasized,

"*The first benefit is operational efficiency. It really cuts time on manual work. Automation and smart analytics help detect problems before they happen*." This highlights how AI not only streamlines workflows but also enables predictive capabilities that can prevent inefficiencies and disruptions before they escalate.

This operational efficiency translates into cost savings and waste reduction, two key pillars of SSCM. P12 reinforced this by stating:

"*I would say I will connect it more for the economic perspective that because your work is gonna be a bit more efficient, it's gonna be way faster. It's gonna be. From my work, if I'm gonna talk about my area.*" The increased speed and reduced effort brought by AI directly support economic sustainability by lowering operational costs and enabling quicker turnaround times for returned goods.

Furthermore, the environmental benefits, although sometimes indirect, are evident. P6 noted,

"*It's helpful because if we do the work more efficiently, it can also reduce environmental impact. It's not a direct link, but if we use fewer computers, for example, that's better for the environment.*" This comment underlines how efficiency gains can lead to reduced energy consumption and equipment use, contributing to environmental sustainability, even if the connection is not always immediately apparent.

P13 expanded on this by pointing to AI's potential in enabling network-wide optimizations: "*It opens a very big opportunity for us to identify where in our network we can do optimization or automation, and whatever it is that we can do for the environment, let's say this part contributes to the sustainability*." Here, AI is portrayed not just as a tool for automation but also as a strategic enabler that helps firms identify areas for environmental improvement across the supply chain.

Finally, P8 encapsulated the dual benefits of AI integration within the return process by stating: "*If you have a more efficient supply chain, then you will reduce the CO2 impact and* *also reduce the cost. It's real. That is a successful way of working, combining money with sustainability. Then you can be more successful.*" His statement reinforces the idea that economic and environmental goals are not mutually exclusive, and that AI provides a tangible bridge between them.

4.3 Barriers of AI adoption

4.3.1 Technological barriers

One of the key barriers identified is the energy consumption of AI technologies, which paradoxically challenges the sustainability goals they are meant to support. As P6 stated,

> *"AI may require significant computing power, which can increase energy usage unless paired with green tech solutions."*

This concern was also echoed by P12, who remarked,

> *"These computers and servers are producing a lot of energy and a lot of emissions at the same time. We call it intangible emission because you don't see it directly."*

P4 also pointed out the energy consumption as a big issue unless the company uses green energy. P15 summarized this point succinctly by saying,

> *"In terms of sustainability, AI consumes quite a lot of energy. So it is dirty that way."*

Another technological concern relates to digital waste, which often goes unnoticed in sustainability assessments. P13 highlighted,

> *"A lot of people don't think about, which is the digital waste as well. But because it's it is kind of not visible to people. So they think it's free to refresh, it's free to use those automation, so that stuff, if you're not aware of it. It can create a lot of ways that are not the physical ways that you see."*

Similarly, P14 explained,

> *"Some part of it belongs to dark data, which means it is not gonna be used again, but still consumes energy because it is online."*

Participants also emphasized the interpretability challenge of AI outputs. P7 said, *"You have a black box model. That takes decisions, makes decisions, and then what if it? It can be difficult to understand how it reaches that conclusion."* P2 added, *"Many supply chain professionals don't fully trust black-box AI. If the system says, 'Don't buy from supplier X next quarter,' you need to explain why. Explainability is a big issue."*

Data quality is another critical issue. P11 emphasized,

"We need to feed AI with clean, real-time data to make sure the results is reliable."

P3 added concerns over data access and sensitivity:

"There is a lot of, like, confidential information and so on, so those things, how do you tackle that? Because they need better data, the results will be better. So, training data on confidential information could be challenging."

4.3.2 Organization

From the organizational perspective, cost and investment emerged as significant barriers. P13 remarked,

"It's from a cost perspective. It is, it is costly, like we always talk about that. So, I mean, we need, we need a lot of time, workspaces, environments, blah, blah, blah, to do our stuff. So we always like it to be costly, but will it bring value?"

P6 pointed out that,

"AI is currently more suitable for large companies because implementation can be expensive. The return on investment isn't immediate, so it may be a financial constraint."

P5 added,

"it takes roughly a few billion dollars to construct your own to construct some of these tools."

The technical limitations of existing systems were also raised. P7 observed, *"Many supply chain companies they are having very old systems, including Volvo. Having the data there, that's a technical thing. Being able to integrate it's also technical, but then being able to show the value of it."*

Organizational culture and structural rigidity were recurring concerns. P12 expressed,

"It's super large, and when you work with a large company will establish that company flexibility is not our strength. I would say we are not flexible. We are slow in the process. We are taking decision in a very slow pace."

P9 highlighted leadership-related hurdles:

"The biggest issue might be a leadership where we need to escalate everything higher and higher to make decisions. The decisions need to be decentralized, we need to think differently from leadership."

Talent deficiency was highlighted as another organizational barrier. P9 acknowledged,

"For such an old company like us, we don't have that many people who know AI from the beginning, so we need to make an effort to get to know more."

4.3.3 Environment Barriers

Supply chain complexity and a lack of clear guidance emerged as major concerns hindering AI adoption in SSCM.

Regulatory uncertainty complicates adoption. P12 explained,

"This fast pace of developing AI and the regulation is not going hand in hand. I think it's the development and implementation of AI is going very fast, and we are still struggling with putting regulations."

P6 confirmed this by saying,

"AI is new, and there may not be clear regulations yet."

Furthermore, **s**upply chain complexity in a globalized environment was seen as a contextual challenge for AI tools. P5 remarked, *"Supply Chain is international. It's global, and it's interconnected. And there are a lot of aspects of the supply chain that make it more complicated. Let's say, the example of the suppliers, suppliers, customers, customers, if they make an entire map, and an entire supply chain is super complex. So I think AI, I think can help, but it is not really efficient to reduce that complexity at this stage."*

4.3.4 Human

The human dimension revealed several crucial concerns. One major theme was fear of job loss and knowledge displacement.

P1 stated,

"Not everyone is brilliant. Not everyone is educated. Not everyone is in this process the including this it or other common people. They will suffer for a salary because it reduces the opportunity for them."

P10 added,

"They have some fear of AI. Will lose their job or something. I think it will be the future. That is why some people are hesitant to learn and explore."

P9 shared that,

"It is the leaders that are scared of this change because they have accumulated all this knowledge and the status and the whatnot during their twenty-year career, and they have reached this point."

Another concern was the lack of understanding of AI. P13 mentioned,

"A lot of push or a barrier for management is, to be honest, because there is a lack of understanding of AI. So also for you as a manager, and this is what my company was, was was trying to do, was to include workshops or trainings for managers as well. So it's not just the employees who have to understand you, for you as a manager, you should understand the value."

Lack of trust was also mentioned by several interviewees, as P2 emphasized:

"*More importantly, the mindset in supply chain teams was still quite traditional. In many organizations, especially in manufacturing, the focus was on cost reduction, delivery precision, and compliance. AI isn't seen as necessary or even trustworthy. You could say people were comfortable doing things the way they had always done—Excel, emails, meetings.*"

Overall, our findings reveal that companies are at different stages of AI adoption within SSCM, ranging from early experimentation to strategic integration. While AI is widely seen as essential for maintaining competitiveness, practical use remains limited, often focused on ML and LLMs. Economic sustainability is prioritized over environmental and social dimensions, with cost reduction and efficiency being key motivators. Despite concerns about high implementation costs and slow ROI, some participants noted the growing affordability of AI solutions. Social sustainability is the least emphasized, though AI's potential in workforce development and safety was acknowledged.

Furthermore, AI significantly enhances sustainability and efficiency across all five SCOR processes—Plan, Source, Make, Deliver, and Return. In the plan phase, AI improves forecasting accuracy, inventory optimization, and scheduling, contributing to both economic and environmental gains. In sourcing, AI supports sustainable supplier selection, risk analysis, and digitalization, enhancing transparency and reducing waste. Within the make stage, AI enables predictive maintenance, resource and packaging optimization, and sustainable design through simulation, though its role in quality control remains limited. In delivery, AI optimizes transportation routes, warehouse operations, inventory management, and perishables monitoring, reducing emissions and improving responsiveness. Finally, in the return phase, AI-driven automation increases operational efficiency, reduces costs, and supports environmental sustainability through better resource utilization and network-wide optimization.

Although participants acknowledged the opportunities, they also highlighted key barriers to adopting AI applications**.** Technological challenges include high energy consumption, digital waste, lack of explainability, and poor data quality. Organizational barriers involve high implementation costs, outdated legacy systems, rigid structures, slow decision-making, and a shortage of skilled talent. Environmental obstacles stem from regulatory uncertainty and the complexity of global supply chains. Human-related barriers include fear of job loss, resistance to change, limited understanding of AI among both employees and leaders, and low trust in AI systems. Collectively, these challenges hinder the integration of AI into sustainable supply chain practices.

5.0 Discussion

Building on the previous findings, this part of the thesis discusses how the observed opportunities and barriers align with or diverge from established theories in SSCM and AI adoption. The discussion integrates insights from the SCOR model and TOEH framework to highlight both expected patterns and surprising deviations, contributing to a deeper understanding of AI's role in promoting sustainability across supply chain functions.

5.1 AI Adoption in SSCM: Practical Realities Versus Theoretical Optimism

Based on our research, it is evident that while the academic literature presents a sophisticated and technically advanced understanding of how AI supports SSCM, the actual adoption of AI in companies is far more uneven and pragmatic. The literature often describes AI as a mature and integral enabler across all key supply chain functions, ranging from demand forecasting and supplier selection to predictive maintenance, logistics optimization, and reverse logistics. In contrast, our interview findings paint a more nuanced picture in which companies are at varying stages of AI adoption, with many still exploring or piloting applications rather than fully integrating them into their supply chain strategies.

The literature strongly emphasizes AI's capacity to handle complex and ambiguous supply chain data, especially in planning, where it enables accurate demand forecasting and resource optimization (Sohrabpour et al., 2021; Kochakkashani et al., 2024). AI techniques such as artificial neural networks, data mining, and fuzzy models are widely highlighted as key tools in refining consumption patterns and managing inventory more efficiently (Harrir & Triqui, 2024; de Mattos et al., 2024). Interviewees echoed this potential but described implementation as being in early or experimental phases. For example, several participants noted their companies had only recently begun to explore AI for forecasting or logistics, primarily in reaction to market trends, rather than as part of a proactive digital strategy.

Moreover, while literature identifies AI as integral across a wide range of SSCM activities—including supplier selection (Qu & Kim, 2024), production (Govindan et al., 2022), and reverse logistics (Bhowmik et al., 2024)—interviews indicate that actual deployments are more narrowly focused, often driven by cost reduction and efficiency goals. AI-enabled tools for supplier evaluation, such as those combining genetic algorithms and Fuzzy-AHP to enhance sustainability decision-making (Bigaud et al., 2016; Sudarsanam et al., 2022), were not explicitly mentioned by interviewees. This absence may reflect both confidentiality concerns and a general lack of detailed technical understanding among supply chain professionals.

A key area where literature and practice do align is in the recognition of AI's role in improving economic sustainability. Numerous studies highlight how AI contributes to minimizing system costs, improving demand planning, and avoiding operational losses (Fu & Chien, 2019; Kochakkashani et al., 2024). Similarly, interview participants repeatedly emphasized AI's economic benefits. For instance, participants referred to AI tools helping with cost optimization, improved forecasting, and reduced inventory waste, mirroring outcomes reported in the literature. Yet, while studies like those by Danach et al. (2024) quantify economic gains (e.g., 25% reduction in downtimes via predictive analytics), such specific metrics were generally absent in practitioners' narratives.

When it comes to environmental sustainability, literature stresses AI's role in reducing waste, emissions, and energy usage through predictive maintenance, CO_2 optimization, and route planning (Akhshik et al., 2022; Hussain et al., 2025; Danach et al., 2024). Interviewees also highlighted these benefits, with route optimization and forecasting seen as tools that indirectly contribute to emissions reduction and energy efficiency. Participants noted that smarter resource management led to fewer inefficiencies and less waste, consistent with studies that link AI-driven logistics to sustainability outcomes (Qu & Kim, 2024; Daios et al., 2025).

However, the biggest divergence emerges around social sustainability. The literature identifies clear opportunities for AI to support CE practices and improve workplace safety and job quality through automation and reskilling (Wilson et al., 2022; Bhowmik et al., 2024). While some interviewees acknowledged AI's role in workplace safety, such as monitoring ergonomics or preventing accidents, and in facilitating employee development, most did not associate AI directly with social sustainability. In fact, many confused it with corporate social responsibility and considered it beyond their individual or departmental scope. This indicates a limited operational understanding of how AI might address broader social goals, in contrast to the integrated perspective presented in academic work.

Cost considerations presented another interesting point of comparison. Both the literature and interviews recognize the potential barrier of high implementation costs (Govindan et al., 2022; Daios et al., 2025). However, interview findings suggest a shifting perspective. Participants noted increasing access to affordable AI solutions, including ready-made enterprise tools and outsourced services. This is not heavily emphasized in the literature, which tends to focus more on AI's technical capabilities than its accessibility for implementation.

Overall, while the literature presents a comprehensive and optimistic picture of AI as a transformative force in SSCM—technically sophisticated and aligned with triple-bottom-line sustainability goals—our findings show that practice is often lagging, with companies primarily focused on economic returns and efficiency. Environmental benefits are typically secondary, and social impacts are underexplored. The challenge ahead lies not only in deploying more advanced AI technologies but also in fostering organizational capabilities and mindsets that embrace AI as a strategic enabler for all dimensions of sustainability.

5.2 Bridging Theory and Practice: AI's Role in SSCM Across SCOR Phases

5.2.1 Plan

The findings from this study largely align with the existing literature in recognizing the critical role of AI in the Plan phase of the SCOR model, particularly through its ability to enhance forecasting accuracy, inventory optimization, and operational efficiency (Sohrabpour et al., 2021; Harrir & Triqui, 2024; Jackson et al., 2024). Both empirical data and prior research support the notion that AI technologies, especially ML techniques like artificial neural networks, reinforcement learning, and anomaly detection, are instrumental in managing complex, nonlinear demand patterns and improving supply chain responsiveness. However, the interview findings provide additional depth by surfacing practical and contextual insights that extend beyond the scope of existing literature. For example, while scholars have explored AI's contribution to inventory and demand planning (de Mattos et al., 2024; Kochakkashani et al., 2024), participants in this study emphasized AI's day-to-day operational role, such as automating scheduling, reducing human errors in data analysis, and improving workload efficiency. These dimensions are less prominent in prior academic work, which tends to focus more on algorithmic outcomes than on human-AI collaboration or workplace efficiency gains.

5.2.2 Source

The interview findings reinforce the conclusions of existing literature by confirming that supplier selection is a central application area for AI in the sourcing phase of SSCM. Similar to what Qu and Kim (2024) and Brintrup et al. (2024) outline, the participants in this study emphasized AI's growing role in automating and improving supplier evaluations, especially around sustainability criteria. This is also consistent with earlier works such as Bigaud et al. (2016), who developed AI tools using genetic algorithms and neuro-fuzzy systems to assess suppliers from a TBL perspective, and Sudarsanam et al. (2022), who applied Fuzzy-AHP models to handle the uncertainty and complexity of supplier assessments.

However, this study provides several novel insights that expand upon the existing literature. First, the broadening of AI's role beyond supplier selection to include contract management, document digitization, and automation. While existing research focuses predominantly on upstream selection processes, participants described AI applications in contract compliance monitoring, automatic contract renewal, and paperless trade documentation—functions that are critical for improving both efficiency and environmental performance in sourcing. These applications underscore the role of AI in enabling digital sustainability, which is less emphasized in the current literature.

The emergence of AI-enabled centralized platforms is also a distinctive insight from the interviews. Participants described how AI helps create shared, real-time data environments across the sourcing network, which improves visibility, mitigates risks, and prevents waste through more synchronized sourcing activities. This system-wide perspective—where AI connects various points of the supply chain through a single data layer—has not been adequately explored in prior sourcing-focused literature, which tends to treat sourcing as a more isolated decision function.

5.2.3 Make

The findings from this study confirm that AI is increasingly being applied to improve both sustainability and operational efficiency within the Make phase of the supply chain. These insights align well with current literature, which highlights the importance of AI and ML in reducing emissions, minimizing waste, and optimizing resource usage during production processes (Govindan et al., 2022; Danach et al., 2024; Hussain et al., 2025). In particular, both the literature and interviews identify predictive maintenance as a key AI application in this stage. Echoing Daios et al. (2025) and Danach et al. (2024), participants discussed the use of AI to anticipate equipment failures and plan maintenance, reducing unplanned downtime and associated emissions. This overlap confirms predictive maintenance as one of the most mature and impactful AI interventions in sustainable manufacturing.

However, the interviews contribute additional practical insights that go beyond what the literature commonly emphasizes. While much of the academic focus remains on process optimization and emissions reduction through AI (Danach et al., 2024; Akhshik et al., 2022), participants in this study highlighted AI-driven packaging optimization and simulation in design and production processes as important applications. For instance, AI's role in simulating packaging layouts to reduce material use and improve truckload efficiency introduces a tangible way AI contributes to both sustainability and logistics efficiency.

Furthermore, participants provided examples of design and engineering simulation tools, where AI helps create digital models to visualize and test manufacturing scenarios before physical implementation. While the literature does note AI's role in lightweighting and emissions prediction (Akhshik et al., 2022), the use of AI for cross-departmental innovation, rapid design prototyping, and customer-centric manufacturing adaptation represents a broader and more integrated approach that may be underreported in academic discussions. These insights position AI as a catalyst for innovation and agility in production, not just optimization.

One key divergence between interviews and literature lies in the perceived limitations of AI in quality control. While many studies frame AI as a universal solution for monitoring and control (Govindan et al., 2022; Hussain et al., 2025), this research found a degree of skepticism and caution among practitioners, particularly in engineering roles. Participants stressed the importance of human oversight in quality assurance tasks due to their complexity, sensitivity, and regulatory requirements. This finding highlights a critical boundary where current AI capabilities are perceived to be insufficient or untrustworthy, suggesting that trust, safety, and accountability remain concerns in real-world implementations. This perspective is not widely discussed in the literature, which tends to emphasize AI's potential over its organizational and ethical limitations.

5.2.4 Deliver

The findings of this study reveal that AI plays a pivotal role in transforming the delivery phase of the supply chain by enhancing transportation route optimization, warehouse operations, inventory control, and delivery scheduling. These practical insights align strongly with existing literature, which positions AI as a key enabler of sustainable and efficient logistics operations (Daios et al., 2025; Danach et al., 2024; Qu & Kim, 2024). In particular, transportation route optimization emerged as the most widely cited and impactful application among participants. AI applications were reported to dynamically adjust routes by analyzing real-time conditions such as traffic or weather, reducing delivery times and carbon emissions. This aligns with studies using genetic algorithms, ant colony optimization, and reinforcement learning to achieve similar outcomes (Daios et al., 2025).

What the interviews contribute beyond the literature is a granular view of how AI systems are integrated into daily logistics operations. Practitioners provided rich examples of AI-assisted tools being used not just for route planning, but for end-to-end delivery optimization—from inventory positioning and demand forecasting to automated packaging decisions and customs clearance support. For instance, one participant noted that AI is used to determine safety stock levels based on market variability—a point not directly emphasized in most logistics-focused AI studies, which typically emphasize vehicle routing and scheduling algorithms (Qu & Kim, 2024).

Another notable area where this study extends the literature is in the application of AI in warehouse operations. While Danach et al. (2024) mention AI-driven order fulfillment as a general benefit, participants elaborated on specific functions such as demand prediction, expiry date tracking, and automated sorting systems that use ML to determine packaging configurations. These practical examples show how AI is not only improving operational speed and accuracy but also significantly reducing waste and overstocking, directly supporting sustainability objectives.

Moreover, the interview findings reinforce the literature's emphasis on AI’s resilience-enhancing capabilities. Participants discussed how AI tools prioritize orders and automate delivery scheduling in response to variability, echoing Daios et al.'s (2025) focus on generative AI for disruption management. This consistency between theory and practice suggests that AI is becoming central to adaptive and responsive delivery networks, capable of mitigating risks from congestion, delays, and supply shocks.

5.2.5 Return

The findings indicate that AI plays a growing yet underexplored role in optimizing the Return process within the SCOR model. Participants consistently emphasized AI's ability to improve operational efficiency, reduce labor intensity, and support cost-effective and sustainable reverse logistics practices. These insights align with emerging academic literature, which frames AI as a key enabler of CE principles such as reduction, reuse, and recycling in reverse logistics (Wilson et al., 2022; Cannas et al., 2024).

AI's strategic role in network-wide optimization was underlined by participants like P13 and P8, who described how AI helps identify inefficiencies and optimize return flows across the network. These accounts resonate with Bhowmik et al.'s (2024) recent work, which outlines how AI, particularly DL models, are increasingly used to analyze complex reverse logistics networks, identify bottlenecks, and support smarter decision-making. While academic literature emphasizes the computational sophistication of DL and ML for returns, the interview data shed light on practical, real-time applications of these technologies in corporate environments.

Importantly, the findings also reflect AI's role in aligning reverse logistics with CE strategies. Though not always explicitly framed in CE terminology by participants, practices such as reducing waste, optimizing return flows, and increasing asset utilization echo CE goals.

However, the findings also reveal a potential gap in the maturity and visibility of AI in return logistics. Unlike its widespread use in the delivery or make phases, few examples detail specific technologies or deployment at scale in the returns context. This reflects a broader trend in the literature where reverse logistics often remains a secondary focus in AI-driven SCM research (Bhowmik et al., 2024). As such, the Return phase appears to be a promising but underutilized domain for AI innovation, with significant room for expansion.

Drawing from the above discussion, we updated the opportunities of AI adoption in SCOR functions regarding SSCM as shown in table 5.1. New insights, or more detailed points, from interview findings are written in red.

Table 5.1: *Opportunities of AI adoption in SCOR functions regarding SSCM (Updated)*

SCOR functions	AI applications	Environmental opportunity	Social opportunity	Economic opportunity
Plan	ML	Reduced waste Monitor emissions	Employees' upskilling	Cost efficiency Inventory control Improve agility Resource allocation Reduced human errors Workload efficiency
Source	DL ML	Sustainable supplier selection Paperless contracts	Sustainable supplier selection Employees' upskilling	Sustainable supplier selection Contract automation
Make	ML Simulation tools based on DL	Lower material usage Energy efficiency Lower emissions	Employees' safety Employees' productivity	Cost efficiency through reduced unplanned downtime Product simulation

Deliver	ML DL GenAI	Lower emissions through operational optimization	Employees' safety Employees' upskilling	Improve operational speed Avoid overstocking More resilient operation
Return	ML DL	Minimizing waste through optimized reverse logistics Lower emissions	Employees' upskilling	Cost efficiency through CE activities

5.3 Bridging Theory and Practice: Barriers of AI adoption

5.3.1 Technological barriers

Despite the clear potential of AI to improve sustainability across supply chain functions, this study reveals that technological barriers present significant challenges to its effective integration.

A major concern raised by participants was the high energy consumption associated with AI systems. Participants like P6 and P15 emphasized that while AI may drive sustainability outcomes, its reliance on energy-intensive computing infrastructure paradoxically undermines these very goals. P12 referred to this as "intangible emissions," pointing to the hidden environmental cost of powering AI servers and data centers. This perspective is often underexplored in academic work but resonates with emerging discussions around green AI—an approach advocating for energy-efficient algorithm design and renewable-powered computing infrastructure. The literature acknowledges this in passing (e.g., Daios et al., 2025), but empirical insights from practice highlight a more urgent and grounded awareness of this contradiction.

In addition to energy concerns, the issue of digital waste was raised by several participants (e.g., P13, the AI expert), highlighting that unused or "dark" data continues to consume storage resources and energy. This concept remains largely absent in mainstream SSCM literature, representing a novel contribution from the interviews. While sustainability assessments often focus on physical waste, the hidden impacts of digital waste present a new and underrecognized sustainability dilemma in AI deployment—one that requires closer integration between environmental and information systems disciplines.

Another barrier relates to the opacity and interpretability of AI systems. As P7 and P2 pointed out, supply chain professionals are hesitant to trust AI outputs when the logic behind decisions is unclear, particularly in high-stakes decisions such as supplier selection. This reflects ongoing academic debates about the “black box” nature of AI (Renigier-Biłozor & Janowski, 2024). While research acknowledges that many AI models, especially DL systems, lack explainability, the interviews stress that lack of interpretability is not merely a technical issue—it is a barrier to trust, adoption, and responsible decision-making in practice. This confirms literature findings and also highlights a pressing need for explainable AI in supply chain contexts.

Data quality and availability were also identified as critical technological constraints. Participants such as P11 and P3 emphasized the need for clean, real-time, and ethically sourced data, echoing concerns raised by Bigaud et al. (2016) and Renigier-Biłozor & Janowski (2024) regarding the incomplete or inaccessible nature of historical data, especially for supplier performance. Inadequate data inputs limit the effectiveness of predictive analytics and compromise the reliability of AI-generated decisions. Moreover, data sensitivity and privacy issues further complicate AI training processes, particularly in sectors dealing with confidential contracts or intellectual property. These concerns reinforce the literature but also bring a stronger focus on data governance and ethical AI practices in SSCM contexts.

5.3.2 Organizational barriers

Findings from the interviews suggest that cost, structural rigidity, leadership inertia, and talent shortages are some of the most persistent roadblocks, closely echoing and in some areas extending the academic discourse.

Cost and financial feasibility emerged as a primary organizational concern. Several participants, including P13 and P6, emphasized that AI implementation is resource-intensive, requiring not only substantial capital investment but also time, infrastructure, and skilled personnel. P5 underlined the magnitude of investment by stating it could take “millions of dollars” to develop certain AI tools internally. These findings reinforce the academic literature, which highlights budgetary constraints and long-term ROI uncertainty as critical barriers to AI deployment in supply chains (Daios et al., 2025; Naheed et al., 2025). What the interviews add, however, is a practical skepticism about value realization—a recurring doubt about whether the high investment will translate into measurable benefits. This concern about value capture complicates the business case for AI in SSCM and may hinder momentum even in well-resourced organizations.

Another significant barrier is technical debt and outdated IT infrastructure, which limit digital readiness. Interviewees explained that many firms, even large players, rely on legacy systems that are incompatible with modern AI tools. Without integrated, interoperable systems, it becomes difficult to extract and structure the data needed to drive AI insights. This aligns closely with Naheed et al. (2025), who argue that digital immaturity is a bottleneck for AI transformation, especially in traditional industries like automotive manufacturing. The findings indicate that technological and organizational readiness are deeply intertwined—a lack of one hampers the other, creating a loop of inertia.

Several participants noted the slow decision-making processes and hierarchical structures in large organizations, which pose a major impediment to innovation. As P12 put it, “flexibility is not our strength.” The requirement to escalate decisions up multiple levels, as P9 highlighted, demonstrates a leadership model that is risk-averse and not adaptive to rapid technological changes. This is echoed in the literature by Shrivastav (2022) and Daios et al. (2025), who link rigid structures and poor change management to AI adoption failures. However, your interviews place a stronger emphasis on cultural inertia—a subtler but equally formidable challenge, especially in long-established firms.

Leadership plays a pivotal role in digital transformation, yet participants identified leadership hesitancy and lack of vision as significant barriers. Some highlighted that decisions around AI need to be decentralized to foster innovation, but current leadership structures are not equipped for this. This concern is corroborated by Shrivastav (2022), who argues that resistance to change and unclear strategic direction are key factors slowing AI uptake. In practice, it appears that many leaders still view AI as a technical tool rather than a strategic enabler, which leads to underinvestment, missed opportunities, and fragmented implementation.

The lack of AI-capable personnel also emerged as a critical organizational barrier. P9 remarked that older companies often lack in-house expertise, which limits their ability to develop or even understand AI initiatives. This reflects broader concerns in the literature, where the AI skills gap is identified as a key obstacle (Topraklı, 2024; Shrivastav, 2022). Importantly, interviewees suggested that the challenge is not just technical—it is also about translating AI insights into business action, a skill that is rare and requires both domain knowledge and technical fluency. This suggests that AI adoption is not just about hiring data scientists; it requires cross-functional upskilling and organizational learning.

While mentioned more in literature than in interviews, data privacy and cybersecurity concerns remain a notable organizational issue (Daios et al., 2025). Although not prominently featured by participants, this likely reflects an underlying tension in SSCM, where the use of confidential supplier or customer data must be balanced against compliance and ethical concerns. Organizations may hesitate to fully adopt AI tools due to fears of data breaches, regulatory violations, or reputational damage, especially when operating in sensitive sectors like chemical or manufacturing industries.

5.3.3 Environmental barriers

In both literature and practice, environmental barriers emerge as subtle but powerful forces shaping the trajectory of AI adoption in SSCM. While technical and organizational hurdles may be more visible, the environmental context, ranging from regulatory landscapes to geopolitical tensions, creates a foundation of uncertainty that can paralyze progress.

The literature strongly emphasizes regulatory ambiguity as a critical impediment. Scholars such as Dogru and Keskin (2020) have highlighted that AI currently operates in a legal grey zone, where the rapid development of the technology has far outpaced regulatory frameworks. This mismatch leaves companies navigating without a map, unsure of the legal boundaries around data usage, privacy, and liability. Interestingly, this concern was mirrored closely in the interview findings. Several participants acknowledged that AI's pace of innovation has outstripped the ability of policy to keep up, generating hesitation and ethical concerns about unregulated deployment. Thus, there is a clear alignment between scholarly discourse and real-world experience: both suggest that regulatory inertia is not just a bureaucratic inconvenience—it is a core risk factor undermining responsible and scalable AI adoption.

Geopolitical instability also emerged as a shared concern. Shrivastav (2022) argues that political conflicts, trade barriers, and economic sanctions directly impact the effectiveness of AI models by disrupting the data flows on which they depend. Interview participants reinforced this idea by pointing to the fragility of global supply chains. In their view, AI tools—even when powerful—struggle to remain effective when foundational elements like supplier reliability and international regulations shift rapidly. This indicates a strong parallel between academic observations and practitioner insights, especially regarding data volatility and operational disruption stemming from global uncertainty.

Where the perspectives diverge slightly is in the treatment of supply chain complexity itself. The literature often frames complexity as a technical or organizational challenge, focusing on how AI models might struggle with the high variability and non-linearity of global networks (Dogru & Keskin, 2020; Shrivastav, 2022). However, in the interviews, supply chain complexity was described more as an *environmental condition*—a contextual reality of operating in an interconnected, globalized world. Participants seemed to suggest that AI, rather than simplifying the system, often adds a layer of opacity or abstraction, particularly when it fails to deliver actionable clarity in a dynamic ecosystem. This reframing of complexity as an external constraint—akin to regulation or geopolitics—adds a new dimension to how environmental barriers are understood in practice.

5.3.4 Human barriers

While much attention in AI adoption is placed on algorithms and infrastructure, the most complex barriers often lie not in machines, but in people. The human dimension of SSCM is marked by deeply rooted behaviours, cultural norms, and emotional responses, all of which shape how new technologies like AI are received, resisted, or reimagined.

One of the most profound human challenges observed in both literature and practice is the fear of displacement. Scholars like Hangl et al. (2023) highlight that in traditional supply chain environments, resistance to change is common, especially when technology is perceived as a threat to existing roles or career trajectories. This concern came through clearly in the interviews, where several participants described how AI was seen not just as a tool, but as a force that could undermine jobs, status, and hard-earned expertise. For some, this fear was tied to a loss of opportunity, particularly among lower-skilled workers, while for others, especially senior leaders, it reflected a potential erosion of professional authority built over decades. Thus, both the literature and interview findings converge on the idea that psychological insecurity is a major inhibitor of adoption, especially when AI is introduced without a clear social safety net or reskilling strategy.

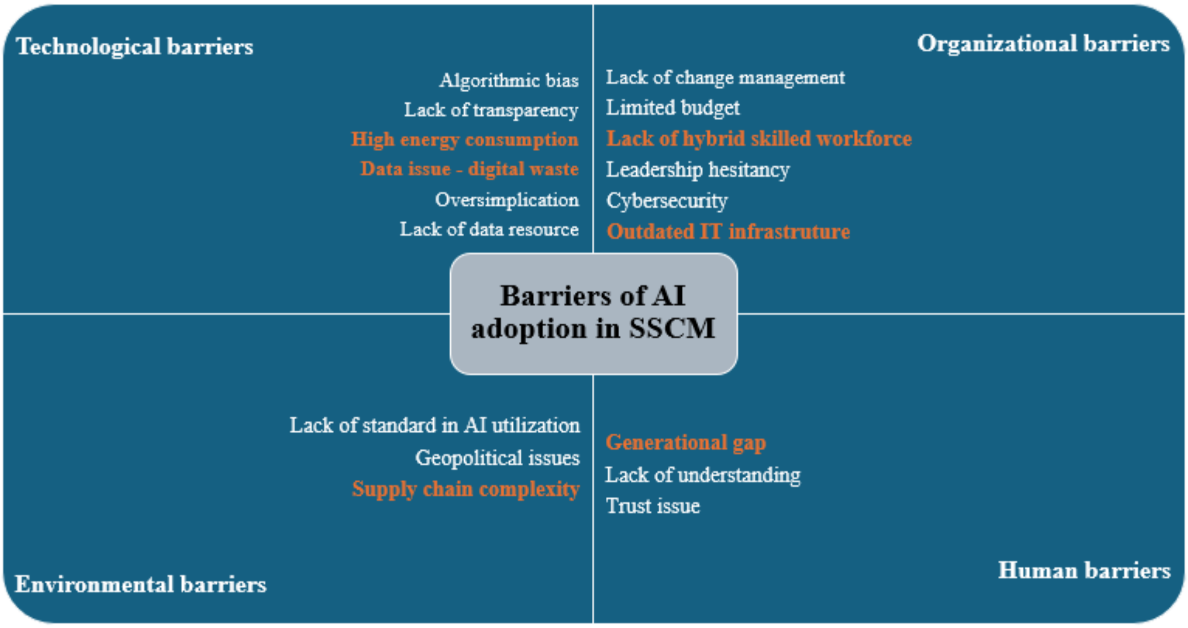
Beyond job security, another shared concern was the lack of understanding about AI's functions and potential. Literature has repeatedly noted that knowledge gaps among employees and managers create friction in implementation (Daios et al., 2025; Hangl et al., 2023). Interviewees proved this view, emphasizing that skepticism often stems not from opposition to innovation per se, but from limited exposure to AI's real-world applications. Managers, in particular, were seen as ill-prepared to make informed decisions about AI investments, leading to inertia or cautious half-measures. These insights reinforce the idea that education and capacity-building are not optional—they are essential prerequisites for AI integration to succeed.

A more subtle yet critical barrier that emerged in both the academic and empirical domains was the issue of trust. In theory, AI promises objective, data-driven decision-making. In practice, however, many supply chain professionals remain attached to legacy systems and workflows, whether spreadsheets, meetings, or manual checklists. As noted in Hangl et al. (2023), trust is a slow-moving variable in organizational culture. Interview participants underscored this dynamic, describing how teams were often hesitant to adopt AI-generated recommendations, especially when the rationale behind the algorithm's decisions remained opaque. This ties back to the wider challenge of *explainability*, but in human terms, it is about belief—whether people trust what they do not fully understand.

Interestingly, interviews also illuminated generational and cultural divides that are less prominent in the academic literature. Senior professionals were seen as more resistant, not only because of concerns over job loss but also due to entrenched mental models shaped by long-standing operational norms. Younger professionals or those with more exposure to digital tools appeared more open to experimentation. This suggests that barriers to AI adoption are not uniform across the workforce, but reflect broader organizational dynamics tied to hierarchy, history, and learning culture.

Based on the above discussion, we updated the barriers of AI adoption regarding the TOEH framework as shown in Figure 5.1. New insights, or more detailed points, from interview findings are written in red.

Figure 5.1: *Barriers of AI adoption in SSCM (TOEH framework - updated)*



6.0 Conclusion

This thesis has examined how AI can support SSCM, with a particular focus on the environmental, social, and economic dimensions of sustainability. Drawing on empirical insights from sixteen semi-structured interviews conducted with professionals across Swedish industries—including automotive, chemicals, electronics, logistics, and consumer goods—the study explored both the practical applications of AI and the challenges associated with its adoption. The analytical approach combined the SCOR model, which provides a functional structure of supply chain activities, with the TOEH framework, which captures the technological, organizational, environmental, and human barriers to implementation.

6.1 Answers to research questions

RQ1: What are the key opportunities that AI offers for SSCM?

This study reveals a range of key opportunities that AI offers for enhancing SSCM across all functions of the SCOR model. These opportunities reflect both the alignment with existing literature and the addition of valuable real-world insights provided by practitioners, highlighting AI's expanding role as a strategic enabler of sustainability, efficiency, and resilience in supply chains.

One of the most compelling opportunities lies in the Plan phase, where AI significantly enhances forecasting accuracy, inventory optimization, and overall planning agility. The ability of AI, particularly ML techniques, to process large volumes of historical and real-time data allows organizations to better predict demand fluctuations and respond more effectively to complex market dynamics. Beyond forecasting, AI supports day-to-day operations by automating scheduling, reducing human error, and improving workload distribution. These improvements not only increase planning precision but also contribute to reduced waste and resource efficiency, key pillars of sustainable supply chain practices.

In the Source phase, AI offers substantial value in improving supplier evaluation, especially in assessing sustainability-related criteria. Participants emphasized the ability of AI to automate and enhance supplier selection processes, ensuring alignment with environmental and social standards. Moreover, AI is increasingly being used for broader sourcing functions such as contract management, compliance monitoring, and document digitization. These capabilities streamline administrative processes, support regulatory alignment, and reduce paper-based transactions, further reinforcing digital sustainability. An emerging opportunity is the use of centralized AI-enabled platforms, which allow for shared, real-time data environments across sourcing networks. This connectivity enhances transparency, mitigates risk, and reduces duplication, ultimately supporting more synchronized and responsible sourcing.

Within the Make phase, AI provides powerful tools for optimizing production processes in ways that promote both sustainability and innovation. Predictive maintenance stands out as a mature application that reduces unplanned downtime and emissions by identifying issues before they escalate. Additionally, AI supports packaging optimization and simulation, helping to minimize material use and improve logistics efficiency. Participants also pointed to AI's growing role in design and engineering simulations, enabling faster prototyping, cross-departmental collaboration, and customer-centric customization. These capabilities not only reduce resource use but also foster innovation and adaptability. Importantly, the interviews introduced a nuanced view of AI's limitations in quality control, highlighting the need for human oversight in sensitive and complex tasks, underscoring the importance of balanced human-AI collaboration.

In the Deliver phase, AI contributes significantly to transportation efficiency, inventory control, and warehouse optimization. The ability to dynamically plan routes based on real-time conditions leads to reduced fuel consumption and emissions. Beyond routing, AI helps optimize the entire delivery process, including safety stock management, packaging decisions, and customs clearance—functions that contribute directly to logistics efficiency and environmental sustainability. Warehouse operations benefit from AI in areas such as expiry tracking, demand forecasting, and automated sorting, helping reduce waste and streamline operations. These applications collectively enhance the responsiveness and resilience of delivery networks, especially in the face of disruptions.

Lastly, in the Return phase, AI offers a growing yet underutilized opportunity for enabling CE practices. By optimizing return flows, identifying inefficiencies, and supporting reuse and recycling, AI can help organizations extend product life cycles and reduce environmental impact. While the maturity of AI in reverse logistics is not yet on par with other phases, the potential for innovation is clear. Participants discussed the role of AI in aligning reverse logistics with broader sustainability goals, although often implicitly, by improving efficiency, asset utilization, and waste reduction.

In summary, AI presents a spectrum of opportunities that go beyond technical optimization, offering tangible contributions to sustainability, efficiency, innovation, and risk mitigation across the entire supply chain. As organizations deepen their understanding and trust in AI technologies, these opportunities will likely expand further, positioning AI not just as a tool for automation, but as a key driver of sustainable transformation in SCM.

RQ2: What are the main barriers organizations face when adopting AI in SSCM?

Organizations face a complex and interconnected set of barriers when adopting AI in SSCM. These challenges span technological, organizational, environmental, and human dimensions, often reinforcing each other and creating a layered resistance to transformation.

Technologically, while AI holds the promise of driving sustainability, its implementation is hindered by concerns about energy consumption and digital waste. The high energy demand of AI systems and data centers poses a paradox, where tools meant to enhance sustainability inadvertently contribute to environmental strain. Moreover, digital waste—unused data that continues to consume energy—represents an emerging issue that has yet to be fully acknowledged in mainstream sustainability discussions. Another significant barrier is the opacity of AI systems; many supply chain professionals struggle to trust algorithmic decisions when they lack transparency, particularly in high-stakes contexts. Data quality further compounds these issues, with the success of AI heavily dependent on clean, real-time, and ethically sourced data resources that are often incomplete or inaccessible.

From an organizational perspective, the high cost of AI adoption and the uncertainty of ROI present formidable challenges. Many organizations operate with outdated infrastructure and legacy systems, making it difficult to integrate AI tools effectively. In large and traditional firms, rigid hierarchies and slow decision-making processes further impede innovation. Leadership hesitancy, especially when AI is not viewed as a strategic enabler, contributes to fragmented or stalled implementation efforts. A lack of skilled personnel, particularly those who can bridge the gap between technical capabilities and business needs, exacerbates these challenges, highlighting a critical need for cross-functional talent and continuous learning.

Environmental factors, while less visible, exert a powerful influence. Regulatory uncertainty creates hesitation, as the rapid pace of AI development far outstrips the evolution of legal and ethical frameworks. Geopolitical tensions and global instability add another layer of unpredictability, disrupting supply chains and affecting the reliability of AI-driven insights. Additionally, the sheer complexity of global supply networks can act as a barrier, especially when AI systems fail to simplify operations or produce actionable clarity in dynamic conditions.

Human factors are perhaps the most deeply rooted barriers. Fear of job displacement is pervasive, particularly among lower-skilled workers and senior professionals who see AI as a threat to their expertise and status. Beyond fear, there is a significant knowledge gap; many employees and leaders simply do not understand AI well enough to engage with it confidently. This contributes to skepticism and mistrust, especially when AI outputs are difficult to interpret. Organizational culture, shaped by long-standing practices and generational divides, plays a critical role in either resisting or enabling change.

Together, these barriers reveal that AI adoption in SSCM is not just a technical upgrade—it is a multifaceted transformation that requires thoughtful navigation of organizational structures, cultural norms, environmental realities, and human emotions. Addressing these barriers holistically is essential for unlocking the full potential of AI in driving sustainable and resilient supply chains.

6.2 Contributions, Limitations, and future research suggestions

The study contributes to academic literature by offering a process-level, empirical perspective on AI in SSCM. While existing research often emphasizes technical models or single-function applications, this thesis presents a holistic understanding of how AI is used across different supply chain stages and how various barriers interact to affect adoption outcomes. For practitioners, the findings provide practical insights into which functions benefit most from AI tools, what types of organizational adjustments may be needed, and how to align sustainability goals with digital transformation efforts.

Nonetheless, the study is subject to several limitations. It is based on a qualitative analysis of Swedish firms, which may limit the generalizability of results to other regions or industries. The focus on standalone AI tools also excludes broader digital technologies such as Robotic IoT, Blockchain, or Big Data Analytics. Furthermore, the study captures a snapshot of AI adoption at a particular point in time and does not track how implementation and outcomes evolve in the long term.

Future research could expand on these findings by conducting comparative studies across countries or sectors, investigating the long-term impact of AI on sustainability performance, and exploring the combined effect of AI with other digital technologies. There is also a need for more research on how AI can directly support social sustainability outcomes, such as fair labor practices, inclusion, and employee well-being, which are currently underrepresented in both practice and academic discourse.

In conclusion, while AI holds significant promise for enhancing supply chain sustainability, realizing this potential requires more than technological investment. It calls for a shift in organizational mindset, stronger digital capabilities, and a clearer strategic alignment between innovation and sustainability goals. By shedding light on the complex dynamics of AI adoption in SSCM, this thesis offers valuable guidance for both scholars and practitioners seeking to design more intelligent, responsible, and sustainable supply chains.

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Appendix

Appendix A: Semi-Structure Interview Guides

This appendix outlines the interview guide used to collect qualitative data through semi-structured interviews with professionals in the fields of supply chain management, sustainability, and artificial intelligence (AI). The purpose of these interviews was to explore the real-world opportunities and challenges associated with AI adoption in sustainable supply chain management (SSCM).

Interview Introduction

Hi, and thank you for agreeing to take part in this interview.

My name is —-, and this is —. We are Master's students in Innovation and Industrial Management at the University of Gothenburg in Sweden. This interview is part of our thesis project exploring the topic:

"The Key Opportunities and Barriers to AI Adoption in Sustainable Supply Chain Management"

While AI is increasingly applied to improve efficiency and reduce costs, its role in supporting sustainability goals—such as reducing emissions, optimizing resource use, and promoting ethical sourcing—has not been fully explored. This interview seeks to understand how organizations are navigating AI adoption in the context of sustainability.

The interview will last approximately 30–45 minutes. With your permission, I would like to record the conversation solely for transcription and analysis purposes. Your responses will remain confidential and anonymized in the final thesis report.

Do you have any questions before we begin?

Section 1: Background & Role

1. Could you please briefly introduce yourself?
2. What is your current role and main area of responsibility?
3. What does your typical workday involve?
4. Could you share your background or experience in any of the following areas?

- Sustainability
- Supply Chain Management
- Artificial Intelligence

5. How is your organization currently involved in sustainable supply chain management?
6. Are there any specific sustainability goals that your supply chain team is working toward?

Section 2: AI in SSCM – Adoption & Opportunities

1. Is AI currently being used in your supply chain operations? If yes, in which areas or processes?
2. Can you describe any specific AI applications you are using or exploring? (e.g., predictive demand modeling, carbon footprint tracking, inventory optimization, supplier risk analysis, etc.)
3. From the economic, environmental, and social perspectives, what benefits or opportunities has AI provided in your work?
4. Could you share an example or project where AI has helped your organization achieve measurable sustainability improvements?

Section 3: Barriers to AI Adoption

Now let's discuss some of the difficulties your organization may have faced—or might expect to face:

1. What are the main challenges or barriers your organization has faced—or anticipates—when adopting AI in SSCM?
2. Do compliance requirements, data privacy, or regulatory constraints create difficulties?
3. Have you encountered challenges related to data (e.g., availability, quality, integration, or security)?
4. From a cost perspective, how do you evaluate the investment in AI versus the expected or realized returns?
5. Have you faced resistance from employees or stakeholders during AI implementation? If yes, what were the concerns?
6. Do you believe that organizational structure, decision-making processes, or lack of relevant skills limit AI adoption?

Section 4: Reflections & Future Outlook

To wrap up, let's look to the future:

1. In your opinion, what factors will most influence the success or failure of AI adoption in SSCM in the near future?
2. What advice would you give to other companies considering the adoption of AI in their sustainable supply chains?
3. Is there anything else you'd like to add regarding your experiences with AI, SSCM, or both?

Conclusion

Thank you again for your time and insights—this has been incredibly helpful.

Would it be alright if I contacted you again in case I need to clarify or follow up on anything? Also, would you like me to share a summary of the final findings with you once the project is completed?

Thanks again!

Appendix B: Gioia Data Structure of This Study

This appendix presents the full data structure developed through the Gioia methodology. It shows how first-order concepts, derived from participants' own words, were grouped into second-order theoretical themes and synthesized into aggregate dimensions. This structure forms the foundation for the grounded model discussed in Chapter 4 and enhances the transparency and rigor of the thematic analysis.

Quotes	1st order concepts
" It can help optimize these processes and reduce waste. In waste reduction, predictive analytics play a key role, helping to minimize inefficiencies in your supply chain and improve overall performance.	AI enables waste reduction
"*AI used in predictive maintenance — helping schedule maintenance more efficiently, which reduces gas emissions and improves sustainability."*	Predict maintenance to avoid extra waste and emission
"*To change any physical adjustments in our production line, we first create simulation based on AI. It helps us avoid unnecessary rework, reduce material waste, and significantly cut emissions. Honestly, it's changed how we approach efficiency and sustainability*."	Manufacturing simulation to avoid extra emission
"*it's more like to help optimize the route, the route planning of the transportation in the logistics, which will save a lot of carbon emissions*."	Routing optimization for reducing emission
"*By using AI, we can monitor our energy consumption, it was different we've uncovered patterns we never noticed before—allowing us to adjust lighting, HVAC, and equipment usage more intelligently and sustainably*."	Track energy usage for indoor activities
"*AI really helps us figure out a product's carbon footprint by pulling data from different parts of the supply chain — like energy use in factories or transportation routes*."	Product carbon footprints calculation in supply chain
"*It (AI) makes choosing the right suppliers easier. Based on data like carbon emissions and ethical practices, not just price or speed, we can filter partners who actually match our values and help us stay on track with our sustainability goals*"	Suppliers' evaluation based on their sustainability performance
"*Many people from the IT sector are coming into into supply chain. many technical engineers, IT AI engineers. That coming into the supply chain. Why? Because, more technical engineers are necessary to maintain these autonomous driving tools. It's switching from one place and going to a different place*"	AI creates new roles and demands for tech-literate talent in supply chain
"*If the employee lifts up a little bit too heavy in the wrong way. If the camera detects that one is then it will update this, it will inform the system how he's doing, what mistakes. Doing everything. And it will*	Workplace real time monitor

notify the employee, the employee who is making mistakes will get special training instructions, and everything it will. In the case of social sustainability, it reduces accidents.”	
“it looks at workloads, deadlines, and even people's availability so we can plan more fairly and avoid burnout. It's like having a smart planner that keeps everyone on track without overloading anyone.”	Balanced work schedule
“AI is used to forecast demand more accurately to avoid overproduction,”	AI-enhanced forecasting to reduce overproduction
“*What AI really enables us to do is build smart logic — like microservices or optimization agents — that help us uncover insights or solutions we might not see otherwise. It's like having a tool that constantly looks for better ways to do things.”*	AI enables supply chain optimization via hidden inefficiency detection
“*We are using AI-based software for sorting, and machines would learn the items' size and weight, then make the decision of the package. It all shows on a screen.*”	AI-supported automation improves warehouse management
“AI Can be used in any department for engineering or customer team's or designers that can design based on their customer needs. It Provides personalized service for customers”	AI enables customer-centric services
“*AI helps us understand our customers better by noticing patterns in their behavior that we'd probably miss on our own. It then lets us group them more accurately and deliver what they really want.***”**	AI-supported customer behavior segmentation
“*We use a lot of process automation, I would say, and the AI, if I might say it's just the kind of logic. So instead of you doing all the manual work, we develop logic in micro services. So it will, it will make the decision based on a pre, pre-defined business logic that we control.*”	Process automation through predefined logic
“AI automates a bunch of different processes across the supply chain — from forecasting demand to managing inventory and even handling logistics. It keeps things running smoothly and frees up time for us to focus on bigger decisions.”	AI supports multi-process automation in supply chain operations
“*We use AI to review bugs and for automation. For example, in contract renewal, customer data is automatically populated, so we don't need to retype it — it's for efficiency.*”	AI in contract automation
“The AI demand forecasting and we we can calculate more precise in daily work. It will reduce a lot of waste.”	Improved forecasting and reduced waste
“I was able to know how many stock levels we had in the factory. I could also know how much that was being that was needed to import would help me forecast more on what would be needed within consecutive months of incoming inventory. I would also be able to track some of the inventory in the pipeline, which also I could I have access to the sales orders that were coming into the company. to help me plan, to make sure	Improved inventory forecasting

that we had enough stock, and to make sure that there was no global backlog in the supply chain."	
"Given a system that can predict the expiry date. And alert it to the various stakeholders in the company that they can give the products before expiring and give it to people in our discount rate that which can avoid wastages"	Reduces overstocking and waste through demand and expiry prediction
"In the end it saves money. The company can hire fewer people and use the remaining budget for other initiatives."	Constant cost reduction through optimization
"*we're able to plan ahead more accurately and fix problems before they get expensive. Whether it's predicting what customers will need or keeping machines running smoothly, it all adds up to real savings. Better optimization in production output will lead to more profit. So that means we can gain financial value*."	Financial gain as a result of better forecasting and predictive maintenance
"*Raw data is nothing unless professionals clean it make the structure. Unfortunately, such data is common in our system, consuming energy rather than making value. That's a big issue for companies to use AI. They need to clean their data first*"	Fragmented and unstructured data
"*A lot of people don't think about, which is the digital waste as well. But because it's it is kind of not visible to people. So they think it's free to refresh, it's free to use those automation, so that stuff, if you're not aware of it. It can create a lot of ways that are not the physical ways that you see*"	Dark data poses sustainability risks through digital waste
"*There is a lot of, like, confidential information and so on, so those things, how do you tackle that? Because they need better data, the results will be better. So, training data on confidential information could be challenging*."	Data confidentiality limits training data quality
	• Hallucinations and lack of model accuracy
"*Many supply chain professionals don't fully trust black-box AI. If the system says, 'Don't buy from supplier X next quarter,' you need to explain why. Explainability is a big issue.*"	Decision-making outputs lack transparency
"*AI is currently more suitable for large companies because implementation can be expensive. The return on investment isn't immediate, so it may be a financial constraint.*"	• High cost of cloud services and computing time
"*Many supply chain companies they are having very old systems, including [our company]. Having the data there, that's a technical thing. Being able to integrate it's also technical, but then being able to show the value of it*"	Integration of old system with new one

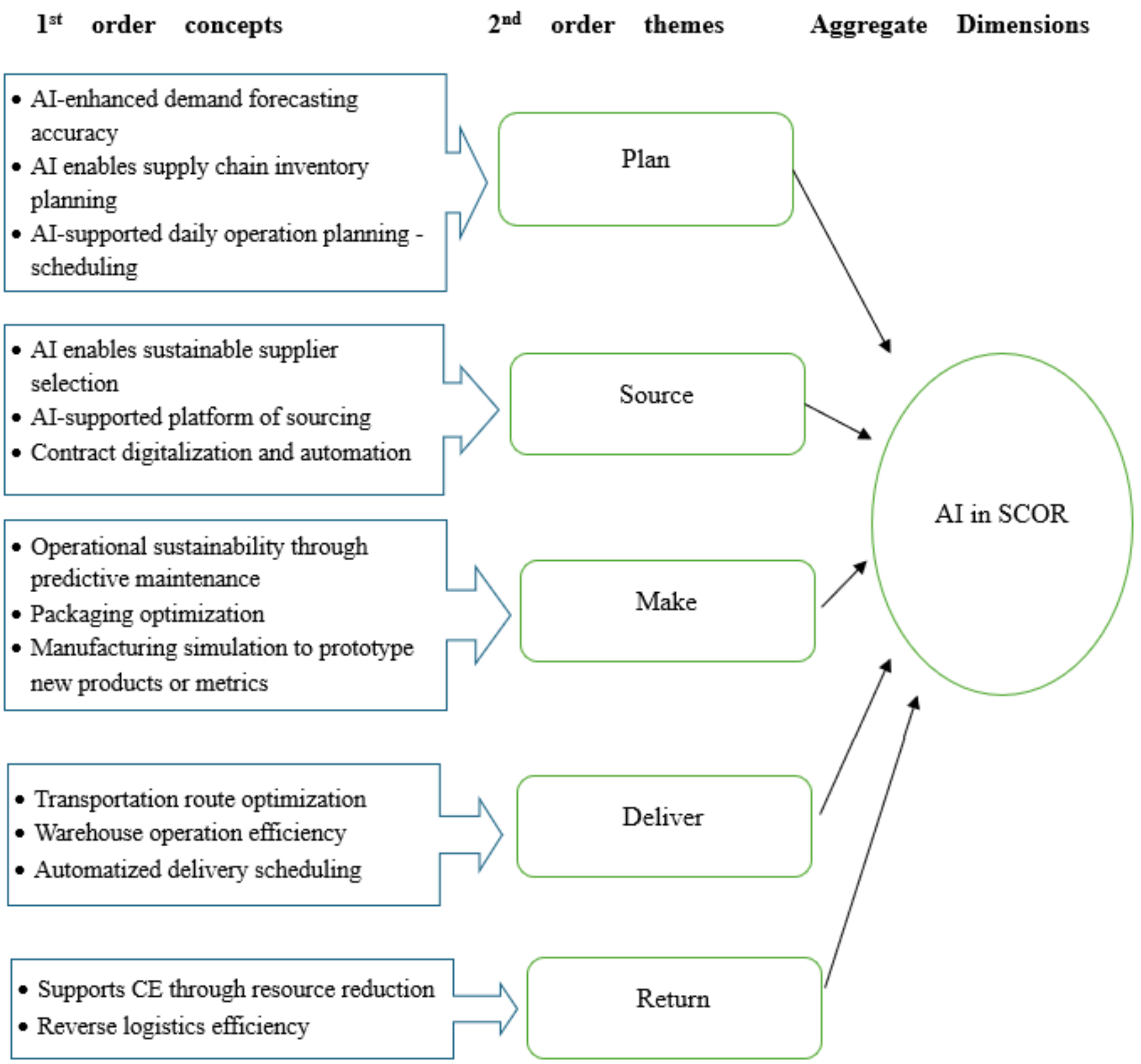
"*These computers and servers are producing a lot of energy and a lot of emissions at the same time. We call it intangible emission because you don't see it directly.*"	AI increases energy consumption
"Likewise, people also are no aware of indirect emissions from AI infrastructure. It is all about data storage and computation process. These take energy and other emissions to run properly"	Invisible emissions from AI infrastructure
"*I agree that AI develops fast and grows bigger. But the basic logic is still there. Automation. AI enables automation and prediction. But if we add more and more dimensions these AI systems will get easily confused and the result will not be good. On the other side, supply chain has complex structure. It is not impossible, but it is going to be very hard to simplify this huge structure*"	AI cannot simplify global supply chain structure
"*Probably IT complexity might be lot more issue compared to supply chain complexity. In fact, supply chain functions are connected through their IT functions. If we want fully automated SC system then we are going to have to deal with interconnection of various IT systems* "	IT complexity limits AI deployment
"*Every partner with different background has different rules about data sharing and transparency. Some may share, but in most cases important data is always missing. So without the proper input, the output would mislead.*"	Legacy systems in SCM companies hinder data availability
"*This fast pace of developing AI and the regulation is not going hand in hand. I think it's the development and implementation of AI is going very fast, and we are still struggling with putting regulations.*"	Regulation lags behind AI development
"*Another concern is information leakage. There's always a risk that sensitive company information could leak — especially if the data is handled by third-party systems. It's a powerful technology, but we have to be really cautious about where our data goes and how it's protected."*	Risk of information leakage
"*A lot of small firms just don't have the in-house expertise to work with AI, so they end up relying heavily on external consultants. It gets things moving, but it also means they're not building their own long-term capabilities*"	Lack of AI competence and consultant dependency in small and Medium-sized Enterprises.
"*For such an old company like us, we don't have that many people who know AI from the beginning, so we need to make an effort to get to know more.*"	Lack of AI knowledge among general workforces
"*AI sounds great, but the cost of setting everything is quite burden to companies and building the right systems is a big issue.*"	Cost of infrastructure and development is a concern
"It's hard to put a clear number on the return we'd get from AI usage. At one hand, it is promising efficiency, but on the other hand it costs a lot and not 100% of successful implementation So quantifying the financial return is important yet challenging."	Difficulty calculating financial value of AI

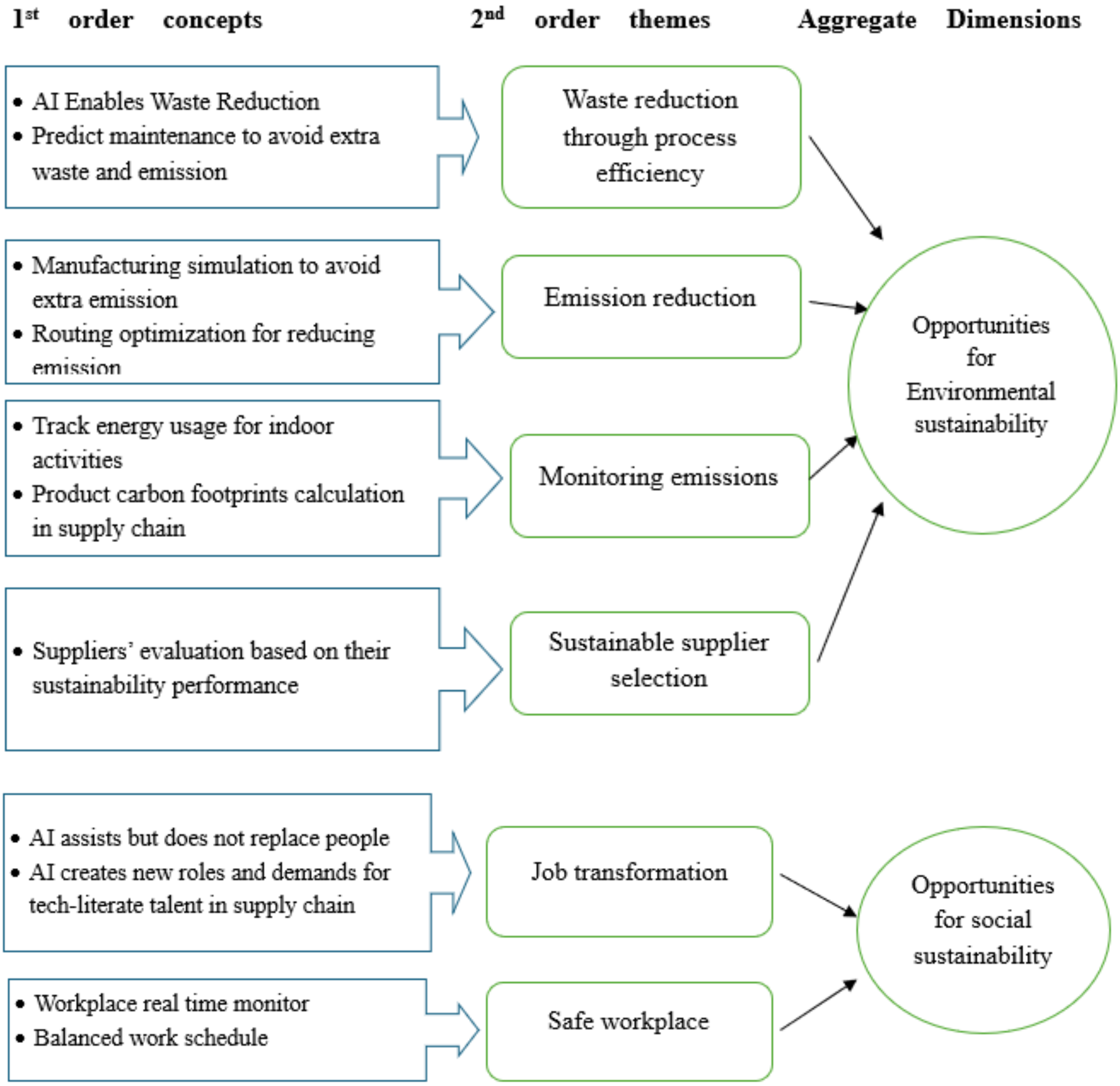
"*The upfront cost is huge, and the return doesn't come quickly. That makes it tough to justify AI investments, especially in the short term*."	High cost and slow ROI challenge AI implementation
"*Many people, mostly senior professionals in my company don't want to use AI, because they don't trust it. Or maybe they don't want to learn new skills. After all they have put so much effort to gain these skills, now they have to learn another new one. Maybe It must be hard for them*."	Employee resistance to change
"*More importantly, the mindset in supply chain teams was still quite traditional. In many organizations, especially in manufacturing, the focus was on cost reduction, delivery precision, and compliance. AI isn't seen as necessary or even trustworthy. You could say people were comfortable doing things the way they had always done—Excel, emails, meetings*"	Reliance on old know how
"*It is the leaders that are scared of this change because they have accumulated all this knowledge and the status and the whatnot during their twenty-year career, and they have reached this point*."	Leadership fear of losing status impedes change
"People are worried that once AI comes in, their roles might become useless. There's a real fear of job loss on the ground."	AI displaces traditional roles, triggering job loss concerns
"*It is true that factories and warehouses are transforming into automated facilities mainly driven by those intelligent systems and AI is contributing more. Jobs at such places are under threat of diminishing in near future*."	Job losses due to automation
"*I have encountered many managers, saying that 'Oh, we need AI'. It might sound fancy or trendy to use AI. But most of the task can still be done by our own ability with cheaper labor, with efficiency as well. In my opinion, firms need to articulate their strategic purpose first and then analyze how AI can align with it. Otherwise, it is just becoming another bubble.* "	Following the trend without strategic purpose
"*Don't apply it everywhere. It is not a magical tool as many people suggest. So, in a lot of places, it doesn't bring the value that you think it is. So managers get easily disappointed once they don't see the desired result and immediately stop. However, AI is a journey, it is not short term investment. Rather, it evolves. So does the company."*	Misconceptions about AI capability
"*There's a like a lot of stuff that they don't need AI. And I see people using AI just because it's fancy, or because it's it's AI*."	AI is not for every problem
"Start with a clear business problem, not a technology. Ask: What's the issue we want to solve? Is it late delivery? High returns? Supplier delays? Once you know that, you can explore whether AI can help."	AI adoption should be based on real business needs, not trends
"I would say start small. Pick very carefully sustainability metrics that AI may help and measure the benefits and costs, and risks."	Clarify Sustainability Metrics AI Should Target
"*At the beginning, just small project is enough to understand these tools. Like you know, demand prediction, customer classification etcetera.*	Adopt AI Gradually

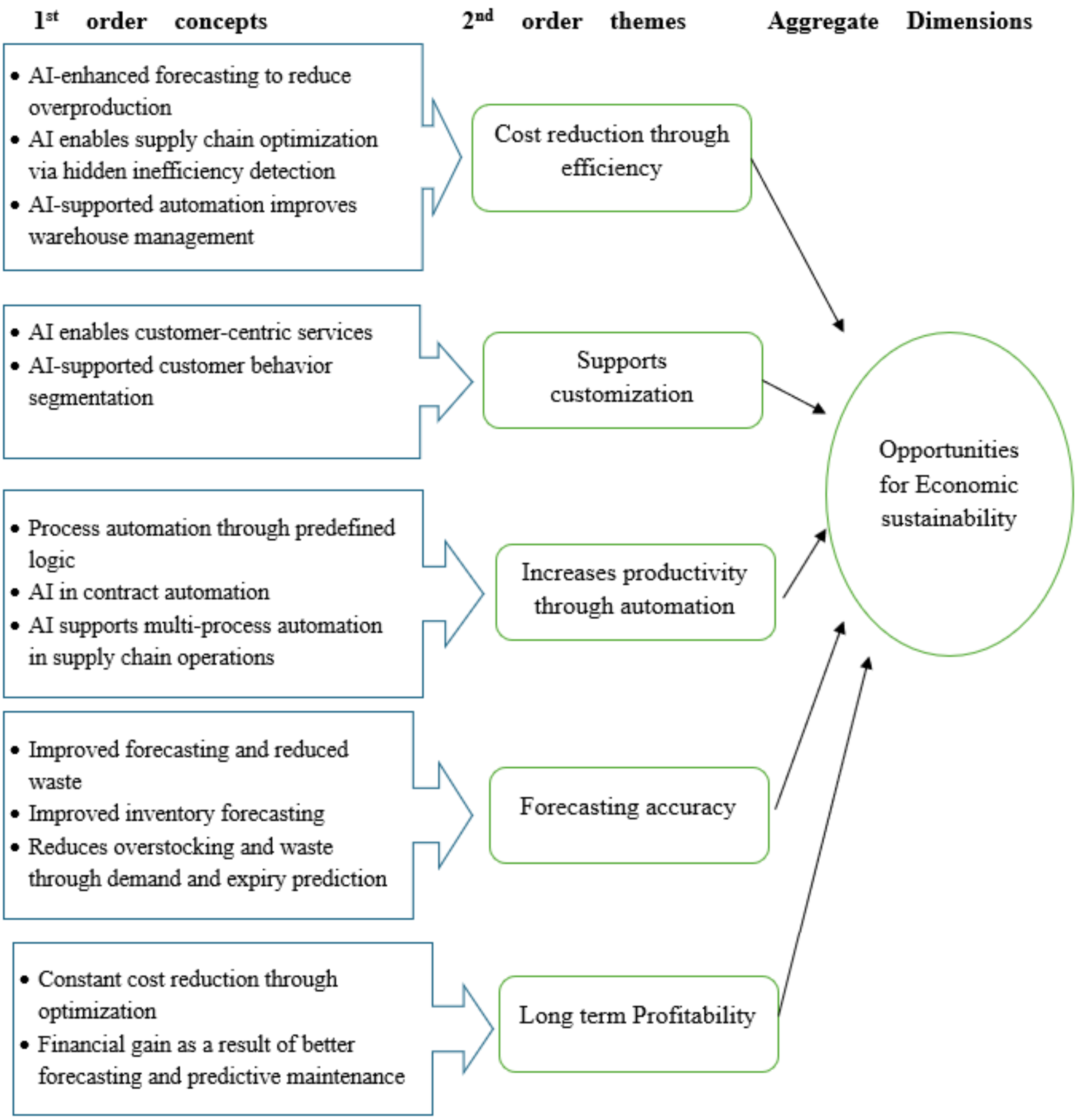
Once you understand how it works, then you can shift to more advanced models. ”	
“*Generally, AI is innovation. So, any new idea and innovation usually takes places under change management. I am sure other interviewees must have mentioned it. To adopt AI effectively, first we need to embrace with change management.”*	Adoption requires proper change management and training
“*Upskill your team, hire hybrid talent, and create internal ambassadors for AI. Change is not just about tech—it's about people*.”	Hire and grow hybrid supply chain - AI - sustainability talents
“When you see your competitors growing in this direction and the whole world going in this direction, it's not normal to be. playing, playing out of the group, you have to be in this area or you're gonna be out of the market.”	AI adoption motivated by competitor pressure
“Any company, if they don't do it. They will lose the competition in the long run. The big change, the big opportunity to adopt AI, is to keep the competition. And keep the advantages and the competitiveness of the company in the long run. being competitive.”	Competitive advantage through AI adoption
“Be strategic. AI is new tool and it is becoming more bubbly nowadays. So, there is common misunderstanding of these tools' capabilities. Managers need to be strategic and put the goals accordingly. Why do you want to use AI, for productivity or for sustainability? From there, you can see the lead”	Strategic purposes, like increasing productivity
“*We don't like to extensively use AI yet because we are still adapting to the AI chat bot has just now been released in our company. So we don't really use it that effectively yet. It's more like asking your questions. Use the way like chat GPT, copilot, but otherwise, not really part of the day to day function*.”	Being in early stage of AI adoption
“AI is not yet a core component of the sustainability roadmap, but it has the potential to support it, for example, improving forecasting accuracy for materials used to build cars, logistics, and reducing inefficiencies in energy use or emissions tracking. It's not fully incorporated yet.”	Conflicted but leaning toward AI adoption
“*We've started implementing AI in our supply chain—not because it's trendy or fancy, but because it could improve how we manage resources, forecast demand, and help us make better decisions, you know data driven decisions regarding sustainability*.”	Increased role of AI in SSCM
“I think AI and human jobs will work together. People are still needed to steer and manage AI. It won't replace jobs but will assist employees to be more creative or productive, therefore it shifts the focus.”	AI assists but does not replace people
“SAP has made things cheaper for companies, for example, they offer AI-enabled planning tools that are ready to go, and for many companies, that's a faster and more affordable path.”	New opportunities of SAP to cut cost for database

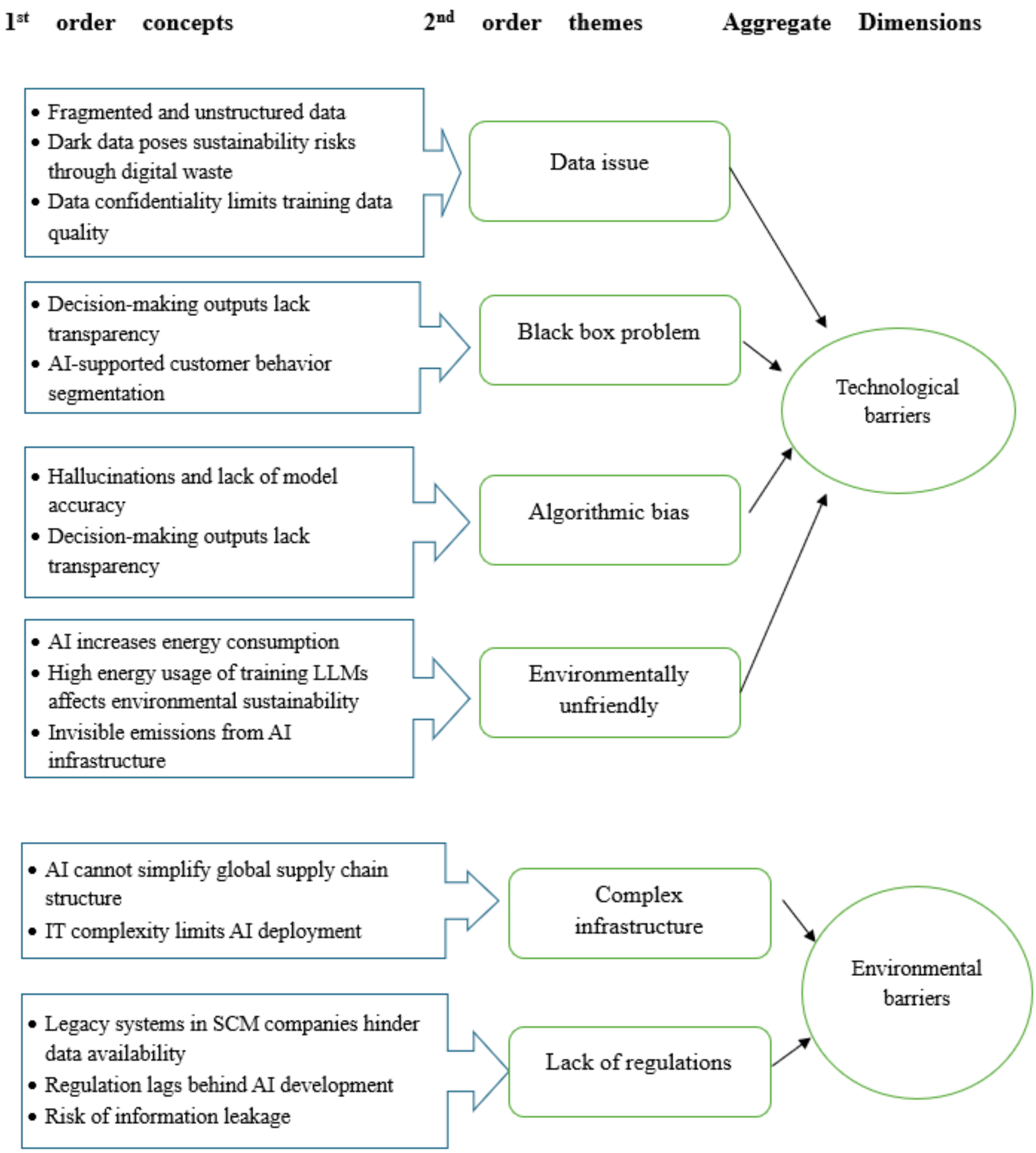
"*We don't need to build everything from scratch anymore. With ready-to-use IT platforms and tools, developing AI solutions has become faster, more cost-effective, and accessible—even for teams without deep AI expertise.*"	IT products to simplify development of AI solutions

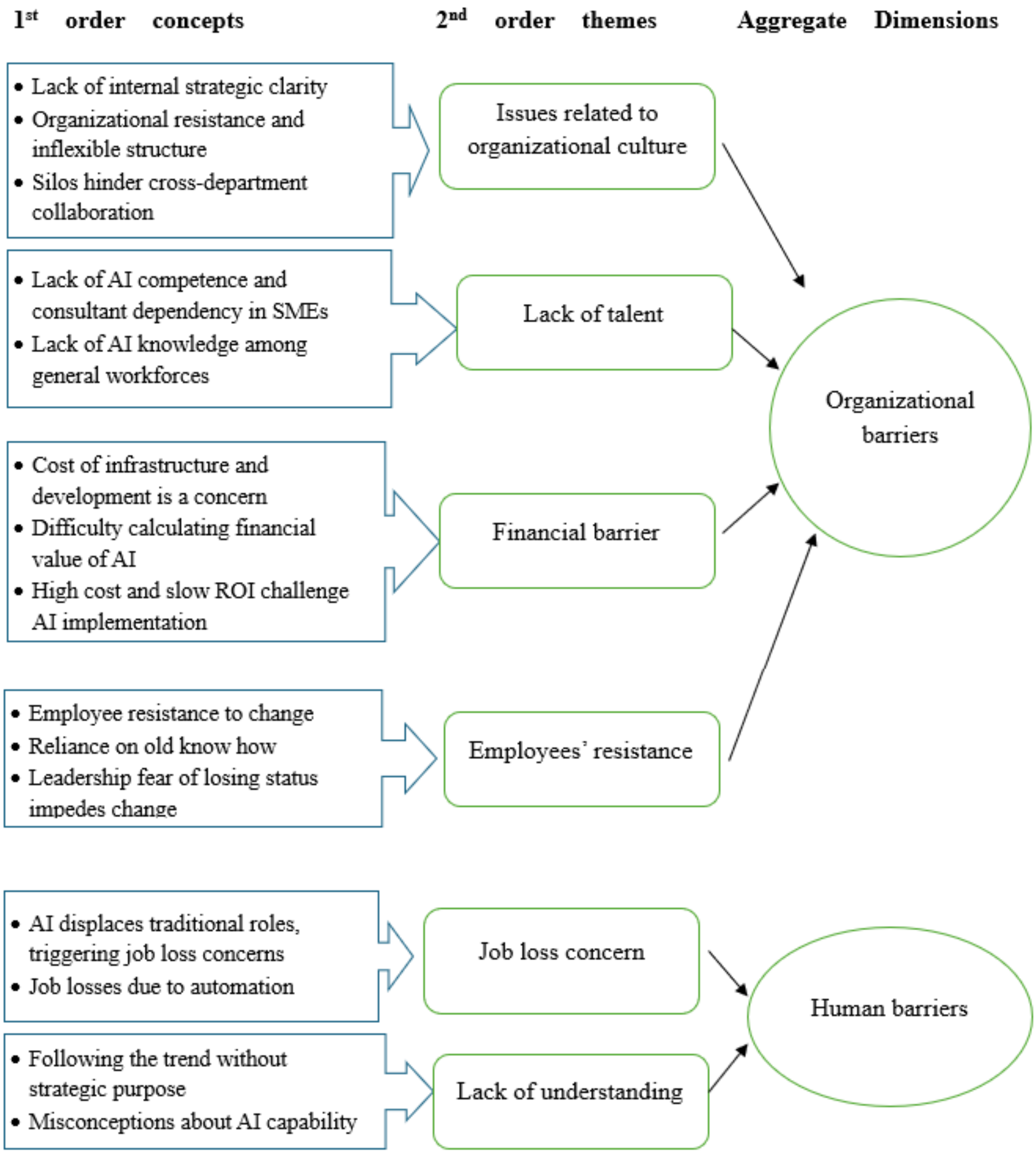
Note: Figures in this appendix present the Gioia data structure derived from the thematic analysis. Each figure includes three vertical columns: 1st-order concepts, 2nd-order themes, and aggregate dimensions. Some figures additionally provide a visual summary or model at the bottom to further illustrate the analytical logic or conceptual connections emerging from the data.



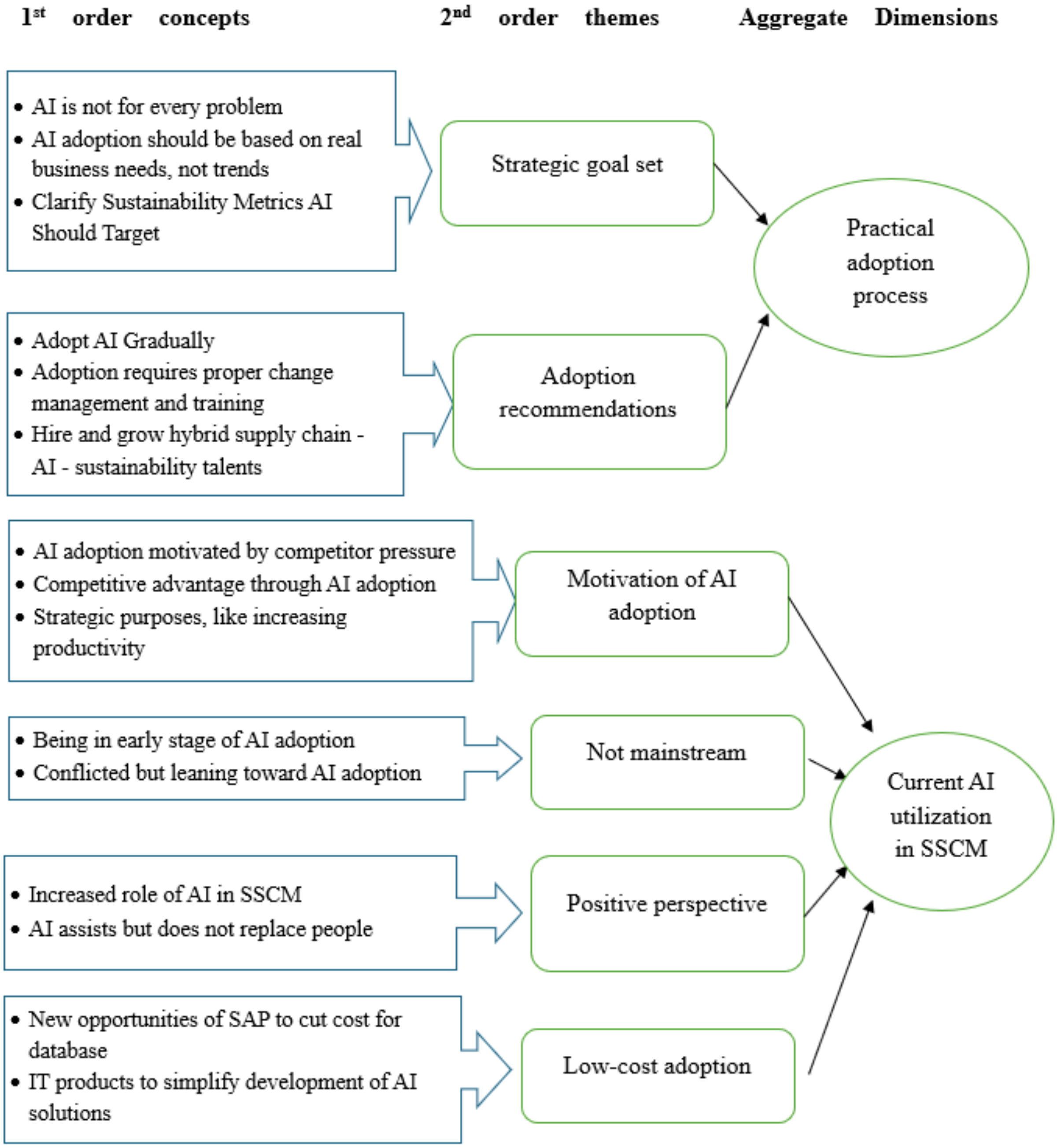

1st order concepts
2nd order themes
Aggregate Dimensions
• AI Enables Waste Reduction
• Predict maintenance to avoid extra waste and emission
Waste reduction through process efficiency
• Manufacturing simulation to avoid extra emission
• Routing optimization for reducing emission
Emission reduction
• Track energy usage for indoor activities
• Product carbon footprints calculation in supply chain
Monitoring emissions
• Suppliers' evaluation based on their sustainability performance
Sustainable supplier selection
Opportunities for Environmental sustainability
• AI assists but does not replace people
• AI creates new roles and demands for tech-literate talent in supply chain
Job transformation
• Workplace real time monitor
• Balanced work schedule
Safe workplace
Opportunities for social sustainability


1st order concepts
2nd order themes
Aggregate Dimensions
• AI-enhanced forecasting to reduce overproduction
• AI enables supply chain optimization via hidden inefficiency detection
• AI-supported automation improves warehouse management
Cost reduction through efficiency
• AI enables customer-centric services
• AI-supported customer behavior segmentation
Supports customization
• Process automation through predefined logic
• AI in contract automation
• AI supports multi-process automation in supply chain operations
Increases productivity through automation
• Improved forecasting and reduced waste
• Improved inventory forecasting
• Reduces overstocking and waste through demand and expiry prediction
Forecasting accuracy
• Constant cost reduction through optimization
• Financial gain as a result of better forecasting and predictive maintenance
Long term Profitability
Opportunities for Economic sustainability


1st order concepts
2nd order themes
Aggregate Dimensions
• Fragmented and unstructured data
• Dark data poses sustainability risks through digital waste
• Data confidentiality limits training data quality
Data issue
• Decision-making outputs lack transparency
• AI-supported customer behavior segmentation
Black box problem
• Hallucinations and lack of model accuracy
• Decision-making outputs lack transparency
Algorithmic bias
• AI increases energy consumption
• High energy usage of training LLMs affects environmental sustainability
• Invisible emissions from AI infrastructure
Environmentally unfriendly
Technological barriers
• AI cannot simplify global supply chain structure
• IT complexity limits AI deployment
Complex infrastructure
• Legacy systems in SCM companies hinder data availability
• Regulation lags behind AI development
• Risk of information leakage
Lack of regulations
Environmental barriers



1st order concepts
2nd order themes
Aggregate Dimensions
• Lack of internal strategic clarity
• Organizational resistance and inflexible structure
• Silos hinder cross-department collaboration
Issues related to organizational culture
• Lack of AI competence and consultant dependency in SMEs
• Lack of AI knowledge among general workforces
Lack of talent
• Cost of infrastructure and development is a concern
• Difficulty calculating financial value of AI
• High cost and slow ROI challenge AI implementation
Financial barrier
• Employee resistance to change
• Reliance on old know how
• Leadership fear of losing status impedes change
Employees' resistance
Organizational barriers
• AI displaces traditional roles, triggering job loss concerns
• Job losses due to automation
Job loss concern
• Following the trend without strategic purpose
• Misconceptions about AI capability
Lack of understanding
Human barriers



1st order concepts
2nd order themes
Aggregate Dimensions
AI is not for every problem
AI adoption should be based on real business needs, not trends
Clarify Sustainability Metrics AI Should Target
Strategic goal set
Practical adoption process
Adopt AI Gradually
Adoption requires proper change management and training
Hire and grow hybrid supply chain - AI - sustainability talents
Adoption recommendations
AI adoption motivated by competitor pressure
Competitive advantage through AI adoption
Strategic purposes, like increasing productivity
Motivation of AI adoption
Being in early stage of AI adoption
Conflicted but leaning toward AI adoption
Not mainstream
Current AI utilization in SSCM
Increased role of AI in SSCM
AI assists but does not replace people
Positive perspective
New opportunities of SAP to cut cost for database
IT products to simplify development of AI solutions
Low-cost adoption