INTEGRATING AI INTO SUPPLY CHAINS: DEVELOPING A FRAMEWORK ADDRESSING TECHNICAL AND SOCIAL DIMENSIONS

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ABSTRACT

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This study explores the integration of Artificial Intelligence (AI) into supply chains through the lens of a socio-technical systems (STS) approach. The study responds to a growing need to balance technological innovation with human and organizational factors in digital transformation processes. The purpose of the study is to develop a comprehensive socio-technical framework that supports organizations in integrating AI into supply chains in a balanced and sustainable manner. The research combines a systematic literature review with an expert survey conducted among ten professionals representing international and local companies. The survey collected qualitative and quantitative insights on technical and social success factors, challenges, and strategies for AI adoption.

The results reveal that successful AI integration depends on strong data foundations, effective system integration, leadership commitment, and an innovation-oriented culture. Social and human factors, including digital skills, communication, and cross-functional collaboration, emerged as equally critical for achieving long-term success. Among the main barriers identified were poor data quality, lack of digital competence, and resistance to change. Respondents emphasized that structured change management, employee engagement, and gradual scaling through pilot projects are the most effective strategies for overcoming these challenges.

The findings confirm that AI implementation in supply chains is not merely a technical project but a complex socio-technical transformation. The study proposes a practical profiling tool that allows organizations to assess their socio-technical maturity and identify areas for improvement across data infrastructure, culture, skills, and governance. This framework bridges a notable gap in the existing literature, offering both theoretical contribution and managerial guidance.

In conclusion, the research demonstrates that organizations achieving the most sustainable AI outcomes are those that align technological progress with social readiness. By integrating technical capabilities and human factors, companies can build supply chains that are not only intelligent but also adaptable, transparent, and resilient.

SYMBOLS AND ABBREVIATIONS

Abbreviations

AI	Artificial Intelligence
EDI	Electronic Data Interchange
ERP	Enterprise Resource Planning
IoT	Internet of Things
MES	Manufacturing Execution Systems
MLO	Machine Learning Operations
SCADA	Supervisory Control and Data Acquisition systems
SCM	Supply Chain Management
SLA	Service Level Agreement
STA	Socio-technical Approach
STB	Socio-technical Barrier
STS	Socio-technical Systems
STS-D	Socio-technical Systems Design
TMS	Transport Management Systems
WMS	Warehouse Management Systems

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1. Introduction

This section examines necessity and significance of the proposed study Integrating AI into Supply Chains: Developing a Framework Addressing Technical and Social Dimensions. First, the background is described to understand the context in which the work will be carried out: discovering evolution of supply chains in response to globalization, digitalization, and the demand for sustainability, highlighting how artificial intelligence has become a central tool for improving forecasting, logistics, and decision-making processes. However, the review of existing literature reveals a persistent gap: current research focuses on the technical aspects of AI implementation (such as algorithms, data quality, and automation) while underestimating social dimensions like employee adaptation, trust, and organizational culture. Moreover, socio-technical systems (STS) theory, though widely recognized in organizational design, has been insufficiently applied to the context of supply chain management and AI integration. This lack of comprehensive frameworks limits the ability of companies to balance technological innovation with human and organizational factors.

Consequently, this study aims to develop a socio-technical framework that integrates both technical and social dimensions of AI implementation in supply chains. The research seeks to identify the key factors influencing successful integration, to analyse the applicability of the socio-technical approach in supply chain contexts, and to design practical tools for profiling and planning socio-technical balance. The research questions therefore address (1) which technical and social factors determine successful AI adoption in supply chains, (2) how the STS approach can guide the design of AI implementation processes, and (3) what challenges and barriers typically emerge in this transformation.

1.1. Background

Over the decades supply chains have been through a major overhaul. Globalization, the rise of technology, and growing pressure to be sustainable, fast and flexible have all played a part in this change.

Today, supply chains account for nearly 90% of a company's environmental impact and up to 80% of total operating costs (McKinsey & Company, 2016). Despite massive investments in digitalization, inefficiencies appear: some studies estimate that global supply-chain disruptions can cost firms and large enterprises trillions of dollars annually (for example, GEP estimates US$2-4 trillion across major US/EU firms in 2020 (GEP, 2023). Multiple studies also indicate that forecasting and coordination errors commonly lead to excess inventory in the order of 15-20% of volume - for example, one study found 15 % of sales volume was subject to extreme undervaluing of demand forecasts (Forecasting and Inventory Benchmark Study, 2018; Inventory Statistics: Key Trends and Insights, 2024). Such inefficiencies not only undermine competitiveness but also contribute to waste, emissions, and resource overuse - issues that have become critical in the era of climate crisis and unstable global trade.

In this turbulent environment, organizations are under growing pressure to build supply chains that are not only faster and more cost-efficient but also adaptive, transparent, and sustainable. This challenge has accelerated the integration of artificial intelligence (AI) into supply chain management. AI-driven solutions (ranging from demand forecasting and route optimization to predictive maintenance and dynamic pricing) have already demonstrated significant benefits, with studies reporting up to 35% improvement in forecast accuracy, 28% reduction in inventory costs, and significant reduction in manual processing time (Sharma et al., 2022; Prakash et al., 2025). As a result, the global market for AI in supply chains is projected to exceed USD 51 billion by 2031 (AI in supply chain market size, share analysis, 2025).

However, while the technical promise of AI is clear, the path to effective implementation remains uncertain. Many companies report difficulties translating algorithmic potential into organizational value, largely because they underestimate the social and human dimensions of AI integration such as employee acceptance, trust, and the ethics of automated decision-

making. Without addressing these aspects, even the most advanced technologies risk failing to deliver lasting impact.

This study responds to that challenge by developing a comprehensive socio-technical framework that bridges the technical and social dimensions of AI adoption in supply chains, aiming to support organizations in building systems that are both technologically advanced and human-centered.

Many studies revie that artificial intelligence has started to make an impact in several business activities like predicting demand, managing inventory and figuring out the best routes for transportation. It has also promoted paperwork automation and transparency of the whole supply chain processes (Russell & Norvig, 2021). Researchers have found out that companies that consistently use AI in their day-to-day operations tend to save money, make reliable decisions and get insights faster. For example, Sharma et al. (2022) have discussed that this can be an advantage in the business world. Back in 2022 it became clear that AI could significantly enhance the way things work, making processes more flexible, easier to predict and more efficient. This created possibilities for predicting demand, managing inventory, streamlining logistics and becoming more sustainable (Sharma et al., 2022).

However, with technology advancing at a rapid pace, putting AI into practice in supply chain management does not always go smoothly. Many companies usually focus just on the technical aspects when bringing in the intelligence: setting up the right algorithms, establishing digital systems and getting the software up and running. This narrow approach tends to overlook some human factors, for instance, how employees will adjust to the new technology, how it will affect the company culture and the ethics of decision making, how it will get different teams to work together seamlessly - these elements are crucial in AI implementation project (Makarius et al., 2020).

Besides, the way we look at organizations should be more balanced - not focusing exclusively on the tech or the people. Several scientists define a perspective that considers them as full-fledged systems where both social and technical aspects are intertwined (Makarius et al., 2020). In supply chain management this suggests looking beyond general efficiency of the algorithms. It is essential to consider how they affect the people who work with them, partners along the way, and the inner workflow of the organization. Social factors

play a crucial role in technology related implantation activities: training employees to use new technologies, organizational culture, change management, interaction between departments (Yu et al., 2022; Makarius et al., 2020). In this regard, the use of a socio-technical barrier (STB), which involves balancing between technology, innovation and human resources, organizational factors, is becoming increasingly relevant (Govers & Van Amelsvoort, 2023). This can help find a balance between bringing in technology and managing the social changes that come along with AI implementation project.

To sum up, the research on AI integration into supply chains must include both technical and social aspects as it is not only using automation tools in question, but a complex adaptive system where both technology and people work together to improve the way supply chains operate.

1.2. Research gap, objectives and questions

The integration of artificial intelligence into supply chain management opens up new opportunities to improve the efficiency, sustainability, and adaptability of logistics processes. However, successful implementation requires a comprehensive approach that considers not only technical parameters (data quality, algorithm scalability, cybersecurity, compatibility with existing IT systems), but also social aspects (impact on employment, staff training, user trust, and transparency of decisions). Developing frameworks that combine these dimensions will allow organizations to minimize risks, ensure the ethical use of AI, and increase competitiveness in the global market.

1.2.1. Research gap

Despite the vast number of publications on digitalization and AI implementation in supply chain management, several gaps remain in the existing literature. The most obvious one is the predominance of technical focus. A significant part of the existing research is devoted to

forecasting, optimization and automation algorithms. At the same time, aspects related to organizational culture, personnel training, role and skill changes remain insufficiently developed.

Secondly, limited use of sociotechnical approaches is defined. Although the STS concept is well known in the field of organizational design and change management, its application in the context of SCM and AI integration is fragmented. There are no system models that would describe the interaction of technical and social subsystems when implementing AI in supply chains.

Lack of tools for practical diagnostics and planning is also a significant research gap. Existing frameworks in the field of SCM are often focused on business processes or IT infrastructure. However, there are practically no tools in the scientific literature that allow organizations to profile their current state and the target TO-BE state in terms of socio-technical balance when implementing AI. In addition, most studies are case studies of individual companies or industries. There is a lack of comparative studies that would allow identifying universal patterns applicable to different sectors of the economy.

Finally, the issues of transparency of AI solutions, trust from employees and partners, possible displacement of jobs and the need for new forms of cooperation are only partially covered.

Thus, there is an obvious gap between the theoretical potential of the STS approach and its practical application in integrating AI into supply chain management. This gap creates opportunities for developing a new framework that would combine the technical and social dimensions of transformation.

1.2.2. Research objectives and questions

Based on the questions posed, the objectives of the study can be formulated as follows:

1. Theoretical objective - to develop a conceptual framework for integrating AI into supply chains based on a socio-technical approach that considers the mutual influence of technical and social factors.

2. Analytical objective - to identify and classify key challenges, opportunities, and strategies associated with integrating AI into SCM.

3. Practical objective - to develop a supply chain socio-technical profiling tool that will allow organizations to map the current and desired state of supply chains from the perspective of socio-technical balance.

4. Applied objective - to offer recommendations for companies and their partners on building processes for implementing and scaling AI in supply chains, considering technical and social dimensions.

This study therefore aims to bridge the existing gaps between a techno-centric approach to digitalization and a more comprehensive socio-technical view, thereby increasing the chances of successful and sustainable integration of AI into supply chain management.

Further, three research questions are proposed for the development of the study.

1. *What are the key technical and social factors that determine the success of AI integration in supply chains? What strategies can help balance technical and social dimensions in AI integration?*

2. *How can the socio-technical approach (STS) be applied to analyse and design AI implementation processes in SCM?*

3. *What are the most common challenges and barriers (both technical and social) in implementing AI in supply chain management?*

1.3. Methods summary

The study is structured into two main parts, including mainly qualitative research methods. The first part is a literature review that briefly examines the methodological approaches and results of several studies related to the selected topic, which allows us to outline the current state of the scientific field and use it as a basis for this work. The second part focuses on processing and structuring the studied data, which will ultimately help to answer the research

questions posed, identify significant patterns and make practical conclusions. The work is based on systems analysis, literature review, application of the maturity concept and framework construction. Finally, practical aspect of the research - a questionnaire is prepared and shared with experts in a few international companies based in Europe: it includes open-ended questions, allowing participants to express their thoughts and experiences in their own words regarding research topic. The data gathered was categorized and analysed to find helpful patterns to give answer to the proposed research questions. Unfortunately, survey sample is limited due to the restricted research work time frame but still provides insights on current trends of AI utilization in business.

2. Literature review

This chapter reviews current research on the integration of AI into supply chains, major areas of technology implementation, and the concept of socio-technical systems (STS). The literature review covers 30 sources, including both classical works and recent studies published in leading international journals.

A literature review is a systematic, critical analysis of existing published research on a topic. It aims to outline the field and key concepts; to highlight existing knowledge, gaps, and controversies; to substantiate the relevance and novelty of the research; to develop a conceptual/theoretical framework and formulate research questions/hypotheses; to select appropriate methods and data.

Before analysing the body of literature in the studied area, it is essential to outline the strategy used to identify and select relevant sources. There are generally two main approaches to conducting a literature review: systematic and non-systematic (narrative). A systematic review follows a predefined and replicable protocol for selecting and analysing studies, aiming for completeness and objectivity. In contrast, a non-systematic or narrative review allows greater flexibility and depth of interpretation, focusing on conceptual understanding and the synthesis of diverse perspectives.

Given the exploratory and practice-oriented nature of this research, as well as time limitations of a master's thesis, a non-systematic narrative review was selected. This approach enabled the integration of findings from multiple disciplines - artificial intelligence (AI), supply chain management (SCM), and socio-technical systems (STS) - to build a conceptual framework rather than perform statistical synthesis.

Academic sources were primarily collected from Scopus and Web of Science, which were chosen for their strict indexing standards, high-quality peer-reviewed content, and comprehensive coverage of management and technology research. Additionally, Google Scholar was used to complement the search, especially to identify recent publications and grey literature that may not yet be indexed in Scopus or Web of Science. However, due to the variable quality of materials available through Google Scholar, each identified source was critically assessed for publication credibility and citation impact.

The literature search was conducted between August and November 2025 using a combination of electronic databases and academic search engines. The search strategy was developed around three main thematic clusters reflecting the conceptual scope of this study:

1. Artificial intelligence (AI) - including terms such as *"machine learning," "automation," "predictive analytics."*
2. Supply chain management (SCM) - including *"logistics," "operations," "supply networks."*
3. Socio-technical systems (STS) - including *"organizational change," "human factors," "technology adoption," "socio-technical integration."*

To capture the intersection of these domains, Boolean search operators were used, for example: ("artificial intelligence" OR "machine learning") AND ("supply chain" OR "logistics") AND ("socio-technical" OR "human factors" OR "organizational change")

Searches were limited to publications in English, between 2015 and 2025, to ensure relevance to current technological and organizational contexts.

The results of literature review are presented and discussed further. Five main subthemes were chosen for the literature review structure. They support the research questions, ensure better understanding of the research area, provide strong background on AI integration into

SCM and socio-technical approach, identify research gap, and finally contribute substantially to the further research process. These subthemes are:

- Integrating AI into supply chains
- Socio-technical approach
- Technical aspects of AI implementation
- Social aspects of AI implementation
- Barriers and drivers of digital transformation

2.1. Integrating AI into supply chains

AI is used for demand forecasting, inventory optimization, logistics, and risk management. According to recent studies, the implementation of AI allows reducing costs by 15–30% and increasing forecast accuracy by up to 90% (McKinsey & Company, 2017).

Research evidence shows that AI implementation enhances supply chain management efficiency through better demand forecasting and inventory optimization and improved process visibility (Sharma et al., 2022). According to Yu et al. (2022) AI implementation needs evaluation of technical aspects as well as social factors which include employee preparedness and organizational cultural transformation.

2.2. Socio-technical approach

STA (Socio-technical approach) views an organization as a system where social and technical elements interact. Successful digital transformation requires balancing these elements. STA suggests that effectiveness depends not only on technology, but also on organizational culture, leadership and employee engagement. The socio-technical approach considers the interaction of technology and social factors as a single process (Govers & Van Amelsvoort, 2023). Makarius et al. (2020) note that AI integration is impossible without considering organizational structures, communication practices, and staff training.

Further, researchers Govers and van Amelsvoort also review how approaches to socio-technical systems design (STS-D) can be adapted to modern digital conditions, considering the transformation of technologies and their impact on organizational structures. The authors aim to combine traditional thinking within the framework of STS-D with "digital thinking" that considers the new features that digital technologies bring to organizational design. By digital technologies, the authors mean everything that is based on the use of microprocessors: algorithms, applications, artificial intelligence, the Internet of Things, big data, blockchain, virtual and augmented reality, etc. The focus is on the creation of sustainable, innovative and quality-oriented work environments (Govers & Van Amelsvoort, 2023).

Nature of work is changing as digitalization erases the boundaries between people and machines: tasks previously performed exclusively by humans or machines become flexible, roles and division of labour change. The researchers outline the main principles of STS-D and a fresh adaptation of the “design sequence” for the digital age: strategic thinking remains in the first position, but it is complemented by “absurd reverse thinking” - an unconventional technique that helps to avoid a conservative approach and stimulate innovation. Design should occur simultaneously with the identification of digital affordances (opportunities) and limitations. That is, when creating a working system and a regulatory system, it is necessary to consider the digital reality before moving on to automation. This approach provides a methodological basis for designing a future where technology and social aspects are harmoniously intertwined (Dolgui & Ivanov, 2021; Hofmann & Rüsch, 2017).

2.3. Technical aspects of AI implementation

What exactly is “technically important” in AI integration in SCM? Technical aspects include data quality, cybersecurity, infrastructure and system interoperability (Riahi et al., 2023). Issues with big data management and the need to integrate different IT systems are often key barriers.

Modern supply chains rely on a combination of digital systems that together form the foundation for data-driven decision making. Enterprise Resource Planning (ERP) systems connect different business areas such as procurement, finance and logistics, ensuring a

consistent flow of information across departments. At the production level, Manufacturing Execution Systems (MES) monitor and coordinate shop-floor operations in real time, while Warehouse Management Systems (WMS) handle the movement and storage of materials within distribution centres. Alongside these platforms, the Internet of Things (IoT) enables machines, vehicles and products to communicate through sensors and smart devices, providing continuous feedback from physical processes. (Ben-Daya et al., 2019) To make use of this growing stream of data, companies increasingly rely on Machine Learning Operations (MLOps), which automate and maintain the life cycle of predictive models. Together, these tools create the technological environment needed for the effective application of artificial intelligence in supply chain management. Particularly, many studies reveal the following factors must be reviewed when implementing AI into SCM: heterogeneity of sources and opacity of data provenance; the need for standardization of interfaces and metadata; increasing role of explainability and observability of models for decision making by planners. (Toorajipour et al., 2021)

2.3.1. Data and Integration in context of AI implementation

In modern supply chain management, data serves as the single, most reliable source of truth on which all decisions and predictive systems depend. The variety and scale of this data are extensive. It encompasses telemetry from production lines collected through Manufacturing Execution Systems (MES) and Supervisory Control and Data Acquisition systems (SCADA), operational information from warehouses and transport networks provided by Warehouse Management Systems (WMS) and Transport Management Systems (TMS), and transactional records stored in Enterprise Resource Planning (ERP) systems. In addition to internal data, companies must also incorporate external variables such as weather conditions, major events, or fluctuations in raw material prices. Communication with suppliers often takes place via Electronic Data Interchange (EDI) or its modern digital equivalents, while the growing use of digital twins provides a dynamic simulation of physical assets and processes. (Wieland & Durach, 2021)

From a technical perspective, maintaining the reliability and transparency of these diverse data flows is essential. This includes creating stable and observable data pipelines that are

supported by continuous quality tests and clear data “contracts” between those who generate data and those who use it. Equally important is the versioning of data and features within so-called feature stores, which ensures that predictive models can be reproduced and remain consistent between their training and deployment stages. Furthermore, establishing clear data lineage and maintaining a comprehensive catalogue of datasets make it possible to trace the origins of business metrics and to explain how particular model decisions were reached. (Rupprecht et al., 2023)

If these foundational elements are not in place, even the most accurate models will show a rapid decline in performance once applied to real operations. Recent reviews of artificial intelligence in supply chain management and studies on supply chain resilience highlight that the ultimate success of AI initiatives depends not merely on algorithms but on the quality of data governance and the degree of integration across systems. (Teixeira et al., 2025)

2.3.2. Machine Learning Operations (MLOps) in context of AI implementation within SCM

The integration of Artificial Intelligence (AI) into Supply Chain Management (SCM) is not a one-time event but a continuous cycle that encompasses several critical stages: data preparation, model training, validation (including alignment with business criteria), deployment to production, and ongoing monitoring with feedback loops. This iterative process ensures that AI models remain effective and aligned with the dynamic nature of supply chains. (Wamba et al., 2020)

Machine Learning Operations (MLOps) practices play an important role in maintaining the reliability and transparency of AI models within SCM. These practices include reproducibility, traceability, Continuous Integration and Continuous Deployment (CI/CD), and automated testing. It must be ensured that models can be consistently reproduced by managing artifacts and environments as code. In addition, establishing clear version bindings between data, code, and models to facilitate accountability and understanding of model decisions is essential. When it comes to Continuous Integration and Continuous Deployment

(CI/CD), the integration and deployment processes must be automated to streamline updates and reduce manual interventions. Finally, implementing various tests, including unit, data, contract, bias, and robustness tests, is needed to maintain model integrity. (Bhatt et al., 2025)

Without the automation provided by MLOps, the risk of "manual interventions" increases, leading to potential issues such as "freezing" changes and producing non-reproducible results, which can undermine the effectiveness of AI models in SCM. (Bhatt et al., 2025)

The next factor to take into consideration while implementing AI in SCM is supply chain dynamics. Supply chains are inherently dynamic, influenced by factors such as seasonality, promotions, weather events, macroeconomic shocks, and supplier disruptions. To adapt to these fluctuations, AI models must be equipped to handle data drift (monitoring changes in data distributions over time), label drift (detecting shifts in the relationship between input data and target labels), and concept drift (identifying changes in the underlying processes generating the data). (Pasch, 2025)

Additionally, establishing Service Level Agreement (SLA)-oriented alerts is crucial to monitor metrics like latency, service errors, and "anomalous" decisions. Implementing scheduled and event-driven retraining cycles ensures that models remain current and effective in the face of evolving supply chain conditions. (Bhatt et al., 2025)

Empirical studies have demonstrated that combining observability with rapid response mechanisms, such as retraining and rollback capabilities, significantly enhances the availability, responsiveness, and recovery of supply chains. These practices contribute to a more resilient SCM system, capable of swiftly adapting to disruptions and maintaining operational continuity. (Pasch, 2025)

2.4. Social aspects of AI implementation

As discussed earlier, the implementation of AI in supply chain management has progressed past its technological origins. The success of implementation depends on social elements which include culture and leadership, together with employee cooperation with algorithms

and transparency, and trust between supply chain partners and participation, learning mechanisms and organizational structure and role alignment. Sociotechnical systems theory (STS) provides an effective framework to analyse AI adoption because it requires technical subsystems (data, models, IT architecture) to match social subsystems (people, processes, structure, norms, power, and motivations). (Baryannis et al., 2019) The combination of appropriate technology with proper social implementation leads to sustainable results according to this framework. The STS approach enables organizations to move their focus from delivery methods to employee interaction with technology thus revealing crucial barriers to change and effective change mechanisms (Yu et al., 2022; Makarius et al., 2020).

The successful implementation of Artificial Intelligence (AI) in supply chain management extends beyond technical considerations and relies heavily on social factors. Employee perceptions of AI, for instance, play a critical role in shaping the acceptance and effectiveness of new technologies. Resistance to change can arise when staff feel uncertain about the impact of AI on their roles, or when they lack the necessary skills to interact confidently with AI-driven systems (Yu et al., 2022). These human elements, if not addressed, can significantly impede the potential benefits of AI initiatives.

Moreover, effective collaboration within supply chains, particularly when sustainability objectives are involved, depends on more than just technological solutions. The study by Chen et al. (2017) highlights that trust, knowledge sharing, and alignment on shared goals are essential for coordinated action across organizations. The social dimension - including labour practices, workforce development at supplier sites, and broader human resource considerations - is frequently undervalued relative to economic and environmental goals. Neglecting these aspects can compromise the overall effectiveness of supply chain strategies, even when advanced AI tools are deployed.

To realize meaningful benefits from AI in inter-company processes such as demand and inventory planning, supplier selection, or sustainability monitoring, organizations must establish clear frameworks for collaboration and governance. Transparent rules regarding data access, well-defined agreements on how algorithms are applied, and mechanisms for distributed responsibility - often referred to as data stewardship between companies - are

critical. By attending to these social and organizational elements, firms can enhance trust, improve coordination, and ensure that AI supports not only operational efficiency but also the broader strategic objectives of the supply chain. (Chen et al., 2017; Yu et al., 2022)

To sum up, all review studied mention the lack of empirical evidence on: (a) the long-term effects of AI on labour practices and inter-firm trust; (b) cross-cultural differences in known "algorithmic" strategies; (c) international key performance indicators in the area of econometric assessments of results; (d) mechanisms for the participation of trade unions and manufacturer representatives in the design of AI in logistics/warehouses; (e) the impact of AI on the "social sustainability" of suppliers in the economy. These gaps are partly identified by Riahi et al. (2023) and reinforce STS's arguments for the need for joint calibration of social and technical subsystems. Chen et al. (2017) highlight the importance of supply chain collaboration to achieve sustainable digitalization effects.

2.5. Barriers and drivers of digital transformation

Digital transformation process is complex and multidimensional, and it has own barriers and drivers. General barriers include low data quality, resistance to change, high implementation costs, while potential drivers feature increased competition, availability of cloud technologies, and increasing customer demands. Studies suggest that some of the main barriers to adopting AI are resistance within organizations, limited financial investment, and inflexible IT systems (Seyedghorban et al., 2020). At the same time, important drivers include the need to stay competitive and the ability to make supply chains more resilient in times of crisis. (Queiroz et al., 2020)

S. Modgil with colleagues propose valuable examples on how artificial intelligence (AI) technologies contributed to supply chain resilience in the context of COVID-19 (Modgil et al., 2022). Z. Seyedghorban and fellow researchers have carried out qualitative content analysis of hundreds of articles with around twelve thousands of references to confirm the patterns. According to their studies, AI technologies enhance the flexibility and adaptability of supply chains, and key findings on digital transformation drivers are the follows:

Visibility: AI allows "control tower" systems to quickly monitor risks, deviations and weak links in the chains - which increases the ability to recognize threats.

Scenario analysis: AI can simulate "what-if" situations, forecast demand and conduct stress testing.

Process redesign: Automation, network reconfiguration, tracking, and physical security management are all enabled by AI.

Activation and governance: AI helps to generate rules, manage demand, and manage supply chain shock, maintaining resilient operations.

Procurement and delivery agility: AI enables personalized decisions, reduced disruption costs, and more flexible procurement strategies.

Integration and collaboration between participants to improve logistics efficiency and innovation.

Technological tools: Big Data, cloud computing, IoT, artificial intelligence - all this supports the creation of integrated self-managing systems.

On the contrary, according to the researchers' general approach, several significant barriers that slow down digital transformation are:

Limited expertise: Experts may have limited experience with only a few AI roles, which limits their understanding of the technology.

Infrastructure limitations: Challenges in integrating AI solutions with existing systems, especially in older or legacy IT infrastructures.

Resistance to change and employee skills: Insufficient employee skills and reluctance to adopt new digital working models.

Limited resources and management support: Lack of management support and limited budgets often slow down implementation.

Data sharing and transparency issues: The problem is especially acute between different organizations in the value chain - pairs are exacerbated by COVID-19, when access to data is extremely critical.

In addition, when it comes to technical aspects, several studies on patterns, barriers and enablers of AI adoption in supply chains identifies the following key barriers: poor quality and siloed data, integration gaps with legacy systems, lack of platform engineering and MLOps skills; enablers include platform approach (cloud/hybrid solutions), data standardization, DevOps/MLOps practices and collaboration between domain and data teams (Riahi et al., 2023).

Taken together, findings from the above literature review show that the integration of AI into supply chain management is far from a simple, linear process. Rather, it represents a complex, multidimensional undertaking in which technical and social factors interact and influence one another in significant ways. On the technical side, organizations must address challenges related to data quality, system integration, model deployment, and the ongoing monitoring of AI systems. At the same time, social considerations - including employee perceptions, organizational culture, collaboration between departments, and trust among supply chain partners - play an equally critical role in determining whether AI initiatives succeed or fail.

Viewing AI adoption through a socio-technical lens allows organizations to understand the interdependence between these technical and social dimensions. By recognizing how human factors and technological components affect one another, managers can design implementation strategies that balance efficiency, adaptability, and workforce acceptance. This perspective not only helps in anticipating potential obstacles but also guides decision-making in areas such as training, communication, data governance, and process redesign. In doing so, organizations increase the likelihood of achieving a successful and sustainable digital transformation in their supply chains (Kache & Seuring, 2017).

3. Expert Survey: Integrating Artificial Intelligence into Supply Chains

The implementation of AI in supply chain management (SCM) presents both significant opportunities and challenges. While AI has the potential to improve forecasting accuracy, optimize inventory, and enhance logistics, its successful adoption depends on a combination of technical capabilities and social factors. Understanding these dynamics requires input from professionals who have hands-on experience in both supply chain operations and digital technology implementation. To this end, an expert survey was conducted to gather insights into the factors that influence AI integration, as well as potential strategies and tools for assessing organizational readiness.

The primary aim of this survey was to identify the key technical and social factors that shape the successful adoption of AI in SCM. Additionally, the study sought to uncover common barriers to implementation, effective strategies for overcoming these obstacles, and tools or frameworks that companies could use to assess their maturity level in managing AI-driven processes. By exploring these dimensions, the survey aimed to provide a practical foundation for organizations planning to integrate AI technologies into their supply chains.

The survey targeted professionals with direct experience in supply chain management, digital transformation initiatives, and IT or operations management. This group was selected to provide an informed perspective on the socio-technical aspects of AI adoption. Participation was voluntary and responses were collected anonymously to encourage honest and unbiased feedback. The survey employed a combination of quantitative and qualitative questions, allowing respondents to provide structured answers while also offering context or additional insights based on their experience.

A total of 10 experts participated in the survey. Number of participants was limited by the tight thesis conduction schedule. The respondents were selected to reflect a mix of organizational types and operational scopes. Eight participants represented international corporations with globally distributed operations, while two were drawn from local enterprises primarily operating in regional markets. This distribution enabled the study to

capture a broad range of perspectives, from companies with complex, multinational supply chains to smaller firms with more localized operations.

Respondents provided answers based on their professional experience in supply chain management and digital technology deployment. The survey results were categorized into quantitative findings and qualitative insights, allowing for a combined analysis that highlights patterns, trends, and individual perspectives. The collected data was then summarized in tables, presenting both statistical measures and narrative interpretation. This approach facilitated the identification of recurring themes related to technical implementation, social dynamics, organizational barriers, and strategies for successful AI integration.

The survey findings reveal a nuanced view of AI adoption in supply chains. Participants emphasized the interplay between technical infrastructure - such as data pipelines, AI models, and system integration - and social elements, including employee readiness, collaboration between departments, and trust among supply chain partners. Responses also highlighted common challenges and suggested best practices, providing valuable guidance for companies seeking to enhance their AI maturity and effectively manage socio-technical changes in SCM.

Below is a summary, showing quantitative findings, qualitative insights, and interpretation. As mentioned earlier, it relies on real data from 10 respondents representing companies of varying sizes and digital maturity levels. Of these, 8 respondents work in international corporations with globally distributed operations, while 2 respondents represent local enterprises operating primarily in regional markets. The survey itself can be found as Appendix 1 at the end of this thesis work.

1. Organizational Context and AI Maturity

- **Industry Distribution**: Most participants came from manufacturing (4), logistics (3), and energy and process industries (3).
- **Company Scale**:
    - 8 respondents indicated **international or multinational operations**.

- 2 respondents represented **local firms** focused on domestic markets.

- **AI Maturity Level** (on a 1-5 scale):
  - Average score: **3.6**
  - **International firms** averaged **3.9**, suggesting moderate progress toward structured AI integration.
  - **Local companies** scored **2.5**, reflecting early-stage experimentation.

The following statement from the above data can be made: most companies are moving beyond pilot stages toward structured integration, but smaller and local firms still face resource and capability constraints.

2. Key Technical and Social Success Factors

Respondents rated the importance of various factors for successful AI integration:

Factor	**Average Importance (1-5)**
Data quality and infrastructure	4.8
System compatibility and integration	4.4
Leadership support and strategic vision	4.6
Digital skills of employees	4.3
Innovation-oriented organizational culture	4.5
Ethical considerations and trust	3.9

Qualitative insights: Experts emphasized that “data is the foundation of everything” and that “without leadership commitment, even strong technology won’t scale.” Several respondents also mentioned cross-functional collaboration and agile project management as key enablers of success.

3. Application of the Socio-Technical Approach

- 90% of respondents agreed that balancing social and technical aspects is *“critical”* or *“very important.”*
- Most international companies reported structured changes in management practices and employee involvement in pilot projects.
- Local firms, by contrast, described ad hoc approaches and limited workforce engagement.

Commonly cited tools:

- Cross-functional workshops (6 mentions)
- Design thinking sessions (4 mentions)
- Continuous learning and upskilling programs (5 mentions)

4. Common Barriers and Challenges

Barrier	% of respondents mentioning
Poor data quality or limited access	80%
Lack of digital skills	70%
Resistance to change	60%
High implementation costs	50%
Legacy IT systems	40%
Ethical concerns / lack of trust	30%

Key differences based on the data above:

- Local companies emphasized budget constraints and limited technical expertise.
- International firms more often cited organizational silos and complex system integration as barriers.

A quote from one respondent summarized the challenge: “Technology is rarely the problem - people, processes, and legacy systems are.”

5. Strategies for Balancing Technical and Social Dimensions

Most respondents considered training, employee engagement, and incremental implementation (pilots) as effective strategies:

Strategy	Average Effectiveness (1-5)
Training and digital upskilling	4.7
Early employee involvement	4.5

Strategy	Average Effectiveness (1-5)
Pilot projects and gradual scaling	4.6
Cross-functional teams	4.3
Change management programs	4.4

Participants emphasized that “engagement must start early” and that “small wins build trust in AI.” One expert from a global manufacturing company noted that pilot projects combining technical testing with workforce feedback were essential to overcoming skepticism.

6. Diagnostic Tool and Maturity Profiling (RQ5)

- 100% of respondents found the idea of a diagnostic tool useful or very useful.
- **Key indicators suggested**:
    - Data and analytics infrastructure
    - Employee skills and readiness
    - Organizational culture
    - Strategic alignment
    - Governance and ethical standards

Respondents agreed that profiling helps visualize progress and prioritize actions. As one international respondent noted: “A structured model would help us go from trying out AI here and there to following a clear roadmap.”

7. Summary of Key Findings

Dimension	Key Insight
Technical	Strong data foundation and integration capabilities are essential for scaling AI.
Social	Leadership, digital culture, and employee engagement determine adoption success.
Integration	Balanced socio-technical design supports sustainable transformation.
Barriers	Data quality, resistance to change, and skill gaps remain the most persistent.
Strategies	Training, communication, and phased implementation are most effective.
Tools	A maturity profiling system is widely seen as valuable for diagnosis and planning.

Interpretation of the survey results

The findings of this expert survey present a comprehensive and balanced view of how organizations are currently approaching the integration of Artificial Intelligence (AI) into supply chain management (SCM). While the level of digital maturity and available resources clearly varies across companies, the results consistently underscore that successful AI adoption depends as much on social and organizational factors as it does on technical infrastructure.

The survey indicates that most participating organizations are progressing beyond experimental or pilot phases toward structured AI integration. With an average maturity level of 3.6 on a 5-point scale, international corporations generally demonstrate stronger advancement (3.9) compared to local enterprises (2.5). This difference highlights a maturity gap shaped primarily by resource availability, technical capabilities, and organizational readiness. Larger, globally operating companies appear better positioned to develop scalable AI strategies, whereas smaller and local firms remain at early exploratory stages due to financial constraints and limited technical expertise.

The responses strongly emphasize that AI adoption is not purely a technological endeavor. Factors such as data quality (4.8), leadership support (4.6), and an innovation-oriented

culture (4.5) emerged as top success drivers. Experts repeatedly pointed out that “data is the foundation of everything,” but without leadership commitment and a shared strategic vision, even advanced technology fails to scale effectively.

Equally important is the human dimension - digital skills, collaboration across functions, and trust among stakeholders were repeatedly mentioned as prerequisites for sustainable implementation. Many respondents viewed AI projects as organizational change initiatives rather than isolated IT efforts, reinforcing the importance of communication, engagement, and cross-departmental alignment.

A striking 90% of respondents agreed that balancing social and technical dimensions is critical for AI success. International firms were more likely to employ structured change management frameworks and employee participation mechanisms, such as workshops and upskilling programs, while local firms tended to rely on ad hoc, less formalized approaches. This suggests that the socio-technical balance is not yet equally embedded across all organizational contexts, and its formalization may serve as a differentiator in achieving maturity.

When it comes to barriers and challenges, the most prominent barriers are poor data quality (80%), lack of digital skills (70%), and resistance to change. Interestingly, the type of challenges differed between company groups: local firms predominantly struggled with budget limitations and skill shortages, while international organizations faced systemic issues such as siloed structures and legacy IT integration. One respondent aptly summarized the sentiment: “Technology is rarely the problem - people, processes, and legacy systems are.” This highlights that technical readiness alone cannot drive transformation without addressing cultural and process-based obstacles.

The results show strong consensus on effective strategies for managing AI implementation. Training and digital upskilling (4.7), pilot projects (4.6), and early employee involvement (4.5) were seen as the most impactful measures. The pattern suggests that organizations value gradual, inclusive, and feedback-driven approaches over top-down or large-scale transformations. Respondents emphasized that early wins and employee engagement help build trust and acceptance, which in turn accelerates broader adoption. This aligns closely

with principles of agile transformation and change management, reinforcing the idea that AI integration is a process of continuous learning rather than a one-time deployment.

An interesting outcome of the survey is the unanimous (100%) agreement on the usefulness of diagnostic and maturity assessment tools. Respondents highlighted the importance of tracking progress across dimensions such as data infrastructure, workforce readiness, organizational culture, and governance. Such profiling not only helps to visualize where the company stands but also guides decision-making and prioritization. As one participant noted, "A structured model would help us go from trying out AI here and there to following a clear roadmap." This finding underlines a growing need for systematic frameworks that link technical performance with organizational capabilities.

Overall, the survey reveals that AI adoption in supply chains is advancing, but its success depends on how well organizations balance technology with people and processes. While larger international companies are taking a more structured approach, smaller firms face resource-related hurdles that limit their progress. Nonetheless, across all respondents, there is a shared recognition that sustainable AI integration requires investment in both data and human capital.

The results collectively point toward a socio-technical maturity model as a valuable approach - one that allows organizations to assess, plan, and evolve their AI initiatives in a balanced and coordinated manner. Building a strong data foundation, fostering a supportive culture, and ensuring ongoing employee engagement emerge as central pillars of success.

In essence, the survey demonstrates that AI transformation is not purely about technology - it is about organizational learning, leadership, and adaptability. Companies that align their technical capabilities with social readiness are the ones most likely to translate AI potential into real and lasting performance improvements in their supply chains.

4. Proposed framework

Based on the findings from literature review and the expert survey discussed ealier, this section presents a practical framework for integrating Artificial Intelligence (AI) into supply chain management (SCM).

The survey highlighted that organizations often face challenges in connecting their technological advancements with human readiness, cultural alignment, and strategic direction. To address these challenges, the proposed AI integration framework in SCM consists of three levels: technical, social and integration. It includes the stages of diagnostics, defining the target state, developing a roadmap, implementation and scaling. A practical tool is the maturity profiling system, which allows companies to assess the current state and build a development strategy.

Together, these tools provide a roadmap that helps organizations evaluate their current state, define clear objectives, and build the necessary balance between technology and people to achieve sustainable digital transformation in their supply chains.

4.1. AI Integration Framework for SCM

The proposed framework for integrating artificial intelligence (AI) into supply chain management (SCM) is based on three interconnected levels: technical, social, and integration. The technical level covers aspects of digital infrastructure, system compatibility, and AI technology selection. The social level encompasses human factors, organizational culture, digital competencies, and readiness for change. Finally, the integration level ensures

alignment between technological solutions and the company's social and organizational capabilities.

The framework is implemented through five sequential stages:

Diagnostics - analysing the current state of AI implementation and the level of technological and organizational maturity;

Target State Definition - defining the desired level of AI integration into the supply chain;

Roadmap Development - developing a strategy and action plan to achieve the target state;

Implementation - implementing planned initiatives at the technical and social levels;

Scaling - distribution and promotion of successful practices across the entire organization.

Proposed AI integration framework for SCM is presented in the figure below for better visibility.

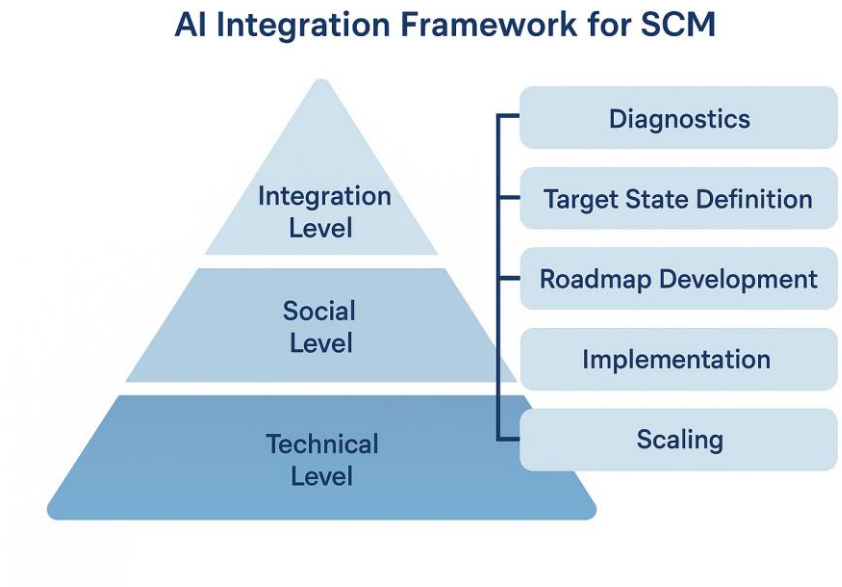

Figure 1. AI Integration Framework for SCM

To proceed with the implementation of this framework within an organization, a practical tool - maturity profiling system - is suggested. This would allow companies to assess the current state of AI integration; identify key gaps, barriers, and development opportunities; form a strategy and action plan to improve the effectiveness of AI implementation. The next chapter of this research contains a detailed description of the proposed profiling system.

4.2. Profiling System (Diagnostic Tool) for "AI integration framework for SCM" implementation

The maturity profiling system is a practical diagnostic tool designed to assess the level of integration of artificial intelligence technologies into supply chain management. Its primary goal is to help organizations determine their current digital maturity stage, identify gaps and barriers, and determine the steps needed to achieve a balanced sociotechnical integration target.

The diagnostic tool is based on the principles of maturity assessment and strategic alignment. It can provide the following support to the companies:

- Assessing the current state of AI implementation across technical and social dimensions;
- Profiling the organization's maturity using a set of criteria (e.g., data quality, digital competencies, management support, innovation culture);
- Identifying gaps and success factors impacting integration effectiveness;
- Determining a target state aligned with strategic priorities and the principles of sociotechnical balance;
- Developing a roadmap and track progress through regular reassessment and scaling of successful practices.

The schematic view of the maturity profiling system is presented as Figure below:

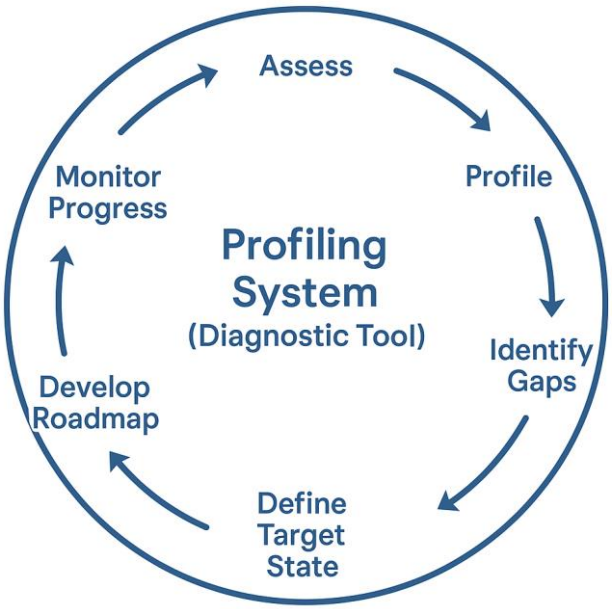

Figure 2. Profiling System (Diagnostic Tool)

Thus, the profiling system provides a comprehensive and evidence-based approach to assessing organizational maturity, facilitates informed decision-making, and strengthens alignment between technologies, people, and processes. In practice, the tool can be implemented as a self-assessment matrix, questionnaire, or dashboard combining quantitative metrics and qualitative assessments from key stakeholders.

4.3. Application Scenarios and Practical Recommendations for Companies

The proposed AI integration framework and maturity profiling system are designed to be practical tools that organizations can adapt to their own context. Because both have a modular structure and are flexible by design, they can be adjusted to fit a company's specific level of digital maturity, strategic priorities, and supply chain complexity.

Below are several examples of how these tools can be applied in real-world settings.

1. Strategic Planning and Digital Transformation

When a company is just beginning its digital transformation journey, it often faces a simple but crucial question: where are we now, and where do we want to be?

In this stage, the framework helps to evaluate the current level of readiness for AI adoption, connect technological initiatives with broader business objectives, and outline a clear vision for the future.

The profiling system adds structure to this process - it turns assumptions into measurable insights and helps build a realistic, data-informed roadmap for building AI into supply chain processes.

2. Competency Assessment and Gap Analysis

Successful AI integration depends on understanding both technical and human capabilities. The tool helps identify the areas where the organization may struggle with, for example, data quality issues, skills shortages, or limited openness to change.

Once these gaps are visible, leadership can focus attention and resources on what truly matters. This makes improvement efforts more strategic and achievable.

3. Change Management and Organizational Alignment

Introducing AI is not only a technical shift - it's a cultural one. The framework's socio-technical foundation helps organizations manage this transition more smoothly. It encourages a balance between technological adoption and employee engagement, ensuring that people feel part of the process, not left behind by it.

This approach is especially useful in companies where new technologies often meet skepticism or resistance, offering a structured yet empathetic way to build trust and readiness for change.

4. Performance Monitoring and Continuous Improvement

Change does not happen all at once - it is an ongoing process. Regular check-ins using the profiling system allow companies to track progress, reflect on what is working, and make course corrections when needed.

This cycle of assessment and adjustment supports a learning mindset, helping teams stay responsive to new challenges and opportunities as both markets and technologies evolve.

5. Cross-Industry Comparison and Knowledge Sharing

Because the profiling system follows a consistent structure, it can also be used for benchmarking - comparing maturity levels with peers, industry leaders, or other business units.

This kind of comparison not only highlights areas for growth but also encourages knowledge exchange, allowing organizations to learn from one another and spread effective practices across global supply networks.

Taken together, the framework and diagnostic tool can be applied on both a strategic level - to guide long-term planning and capability development - and an operational level, where they help teams make informed decisions day to day.

Ultimately, their purpose is simple: to help organizations move forward confidently, balancing technological progress with human understanding, and turning AI integration into a sustainable part of how the supply chain operates.

For better visibility and analysis, Table 1 is created to summarize and structure all the findings and highlights discussed earlier.

Table 1. Application Scenarios for the AI Integration Framework and Profiling System

№	Scenario	Objective	Level of Application	Main Outcomes	Key Users / Stakeholders
1	Strategic Planning and Digital Transformation	To assess current readiness, align AI initiatives with strategic goals, and define the target state	Strategic	Clear vision of target maturity, roadmap for AI integration	Top management, strategy and innovation teams
2	Capability Assessment and Gap Analysis	To identify technical and social capability gaps and prioritize improvement areas	Operational / Strategic	Comprehensive view of strengths and weaknesses; prioritization of actions	SCM leaders, IT managers, HR, data teams
3	Change Management and Organizational Alignment	To balance technological change with human engagement, communication, and cultural readiness	Organizational / Operational	Reduced resistance, improved engagement and adoption of AI tools	HR, managers, department heads

4	Performance Monitoring and Continuous Improvement	To track progress over time and evaluate effectiveness of implemented initiatives	Operational / Tactical	Measurable progress, iterative learning, agile adaptation	Project managers, transformation offices
5	Cross-Industry Benchmarking and Knowledge Sharing	To compare AI maturity across industries and share best practices	Strategic / Comparative	Benchmarking data, enhanced collaboration and learning	Executives, consortiums, industry associations

Practical Recommendations for Companies

Applied objective of the study is to provide recommendations for businesses on building processes for implementing and scaling AI in supply chains, considering technical and social dimensions. To sum up, in order to o successfully integrate AI into supply chains, companies are advised to:

1. Invest in data management.

2. Develop employee competencies.

3. Build a culture of trust in AI.

4. Pilot projects before scaling.

5. Balance social and technical aspects.

6. Provide leadership and strategic management.

7. Integrate sustainability goals.

8. Create partnerships to accelerate implementation.

5. Results and Conclusion

The study was set out to explore how artificial intelligence (AI) can be effectively integrated into supply chains through a socio-technical lens, recognizing that technology and people jointly shape organizational transformation. The findings from the literature review, combined with the insights from the expert survey, help to understand both the enablers and obstacles of this process. Together, they demonstrate that successful AI integration depends on balancing technical foundations with an organizational culture that supports learning, collaboration, and trust.

The findings strongly confirm the theoretical premise outlined at the beginning of this thesis: that AI implementation in SCM cannot be understood purely as a technological challenge. The experts emphasized that technical systems and human factors are deeply collaborated. The high agreement (90%) from the survey on the need to balance technical and social dimensions supports the applicability of the STS framework to modern supply chains. The results thus validate the theoretical rationale for a socio-technical approach and form a basis for developing an integrated conceptual model.

One of the most important findings from the research is the universal acknowledgment of the need for a diagnostic tool to assess AI readiness: such a tool would help organizations visualize their progress and define action priorities. The proposed profiling framework directly answers this practical objective. This tool not only bridges the research gap identified in the literature (the absence of models linking technical and social maturity) but also provides a foundation for future organizational learning and strategic planning.

Despite the significance of this study and its contribution to understanding the integration of artificial intelligence into supply chains, it is important to acknowledge that this research has several limitations. Methodologically, the work relies heavily on a literature review, i.e., it utilizes secondary sources. This approach helps cover a wide range of studies, but makes the results dependent on the quality, relevance, and comprehensiveness of existing published data. In addition, it is important to conduct empirical validation of the proposed framework

based on specific cases and surveys of industry representatives. It would also be useful to test the model in different geographic and industry contexts to make it more generic. Finally, further research could include the development of methods for measuring the social aspects of AI integration and conducting long-term studies that will help track the dynamics of digital transformation over time.

In conclusion, the research contributes both theoretically and practically to the field of supply chain management. Theoretically, it extends socio-technical thinking to AI-enabled supply chains. Analytically, it identifies the intertwined drivers and barriers of AI adoption. Practically, it proposes a profiling tool that supports balanced development. And at the applied level, it offers actionable recommendations for companies and their partners to implement AI in a way that is both technologically powerful and socially responsible.

The key message of this study is clear: AI integration succeeds when data, technology, and human systems evolve together.

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Appendix 1: Expert Survey “Integrating Artificial Intelligence into Supply Chains”

Study Objective:

The purpose of this survey is to identify key technical and social factors influencing the successful implementation of artificial intelligence (AI) technologies in supply chain management, as well as to identify barriers, strategies, and potential tools for assessing an organization's maturity level in this process.

Instructions:

Please answer the following questions based on your professional experience in supply chain management and digital technology implementation. This is an exploratory survey; all responses will be aggregated.

I. General information (context)

1. Please indicate your job title and area of responsibility (e.g., Digital Transformation Manager, Supply Chain Manager, Data Analytics Expert, etc.):

2. What industry does your company operate in?

☐ Manufacturing

☐ Logistics and Transportation

☐ Energy

☐ Food Industry

☐ Pulp and Paper industry

☐ High Technology/Electronics

☐ Other (specify): _____

3. What is the scale of your company's operations?

☐ International (Multinational)

☐ Regional

☐ National

4. What level of maturity would you assess for your company's AI implementation in the supply chain? (rate on a scale from 1 to 5, where 1 is the initial level, 5 is a high level of integration)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

II. Technical and social factors of success

5. Please rate the importance of the following factors for successful AI integration in the supply chain (on a scale of 1 = not important to 5 = extremely important):

Factor	**1**	**2**	**3**	**4**	**5**
Data and infrastructure quality	☐	☐	☐	☐	☐
Compatibility of AI with current IT systems	☐	☐	☐	☐	☐

Management support and strategic vision	☐	☐	☐	☐	☐
Digital competence of employees	☐	☐	☐	☐	☐
Organizational culture open to innovation	☐	☐	☐	☐	☐
Ethical and trust aspects of using AI	☐	☐	☐	☐	☐

6. What social and organizational factors do you believe have the greatest impact on the success of AI implementation in SCM?

_ Open answer _

III. Application of the sociotechnical approach

7. How important do you think it is to consider the balance between technical and social aspects when implementing AI in supply chains?

☐ Not important at all

☐ Rather unimportant

☐ I find it difficult to answer

☐ Rather important

☐ Extremely important

8. What tools or methods (e.g., design thinking, staff training) have you used or found effective for integrating AI, considering sociotechnical factors?

Open answer

IV. Challenges and barriers of AI implementation

9. Please indicate which of the following barriers you have observed in the process of implementing AI in SCM:

☐ of quality data

☐ IT infrastructure limitations

☐ Lack of strategic vision

☐ Resistance to change among employees

☐ Lack of AI competences

☐ High implementation costs

☐ Ethical risks and mistrust of AI

☐ Other (specify): _____

10. Which barrier do you consider the most critical? Why?

Open answer

V. Strategies for balancing technical and social aspects

11. What strategies or management approaches do you consider most effective for ensuring a balance between technological solutions and the human factor?

_ Open answer _

12. Rate the effectiveness of the following strategies (1 - low, 5 - high):

Strategy	**1**	**2**	**3**	**4**	**5**
Employee training and digital skills development	☐	☐	☐	☐	☐
Involving employees in the early stages of implementation	☐	☐	☐	☐	☐
Gradual implementation (pilots)	☐	☐	☐	☐	☐
Formation of cross-functional teams	☐	☐	☐	☐	☐

Corporate change management programs	☐	☐	☐	☐	☐

VI. Maturity diagnostics and profiling

13. What criteria or indicators do you think should be used to assess an organization's maturity in the context of AI integration in SCM?

_ Open answer _

14. How useful do you think it would be to develop a diagnostic tool (profiling system) to assess the current and target state of an organization?

☐ Useless

☐ Rather not useful

☐ I find it difficult to answer

☐ Rather useful

☐ Very useful

15. What elements do you believe should be included in such a profiling system? (e.g., assessing infrastructure, competencies, organizational culture, trust levels, strategic readiness, etc.)

_ Open answer _

Thank you for your participation! Your answers will help us develop more precise and practical recommendations for integrating AI into supply chain management, considering socio-technical factors.