Collaborative Supply Chain and Sales Networks for Improved Customer Satisfaction and Market Responsiveness with AI Integration

by

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DEDICATION

I dedicate this work to my family, whose encouragement and belief in me provided the strength to pursue this journey. Your unwavering support has been my foundation. I also extend my deepest gratitude to my academic advisors and professional mentors, who inspired me to think critically, challenge the status quo, and lead with purpose. This achievement is as much yours as it is mine.

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René Grywnow

DECLARATION OF ACADEMIC INTEGRITY

For this project work, the masculine form is used explicitly. The reason is to make the text easier to read and understand. All persons and designations refer equally to all genders. I would emphasize that I have used QuillBot to secure the linguistic quality of this document on a high level; QuillBot was only used for spelling and grammar checking. Additionally, I used the tool too to check for potential plagiarism on June 17th, 2025. The tool confirmed that the similarity score was <0,2%, indicating that the content is original.

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ABSTRACT

AI-SUPPORTED COLLABORATION BETWEEN SUPPLY CHAIN AND SALES FUNCTIONS IN EUROPEAN INDUSTRY

Background

In today's volatile and competitive global market, industrial companies in Europe are under pressure to increase agility, customer responsiveness, and operational resilience. Traditional silos between supply chain and sales functions often result in misalignment, inefficiencies, and missed opportunities. This study investigates how artificial intelligence (AI) can support and enhance cross-functional collaboration between these two departments to improve customer satisfaction and business performance.

Methods

The research adopts a mixed-methods design to ensure both depth and breadth of insight. Qualitative data were collected through 15 semi-structured interviews with supply chain and sales executives across various industrial sectors in Europe. A complementary quantitative survey, distributed to 187 professionals, provided additional validation and scalability. Data were analyzed through thematic coding, descriptive statistics, regression, and chi-square testing using the software Jamovi.

Results

The study reveals that AI-supported collaboration significantly enhances forecasting accuracy, planning integration, and customer responsiveness. Firms with shared KPIs, cross-functional teams, and AI tools embedded in decision-making processes reported higher customer satisfaction and internal alignment. However,

challenges persist: organizational silos, limited digital maturity, and resistance to change remain major barriers.

Discussion and Conclusion

The findings suggest that technological tools alone are insufficient without cultural readiness, strong leadership, and strategic alignment. A conceptual framework and practical roadmap are proposed to guide industrial firms in their AI-enabled transformation. The research contributes to both academic understanding and practical implementation by addressing a critical gap in cross-functional digital integration within industrial supply chains.

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AI – Artificial Intelligence

AIoT – Artificial Intelligence of Things

B2B – Business-to-Business

B2C– BUSINESS-TO-CUSTOMER

CEO– CHIEF EXECUTIVE OFFICER

C-LEVEL– CHIEF LEVEL

CRM – Customer Relationship Management

DBA – Doctor of Business Administration

DESMI– DE SMITH COMPANY

DNA – Deoxyribonucleic Acid

DSS – Decision Support System

EMEA – Europe, Middle East and Africa

E.G. – EXEMPLI GRATIA

ERP – Enterprise Resource Planning

ET AL– ET ALII

F – F-Test Statistic (used in ANOVA or regression to test overall model significance)

GDPR – General Data Protection Regulation

H– HYPOTHESES

IoT – Internet of Things

IT – Information Technology

KPI – Key Performance Indicator

M – Mean

MES – Manufacturing Execution System

ML – Machine Learning

MVP – Minimum Viable Product

N – Sample Size

NVivo – Qualitative Data Analysis Software

OEM– ORIGINAL EQUIPMENT MANUFACTURER

OIPT – Organizational Information Processing Theory

OKR – Objectives and Key Results

p –Page

pp –Pages

P– PROBABILITY VALUE

R– PEARSONS CORRELATIONS COEFFICIENT

R^2 – Coefficient of Determination (explained variance in regression)

RBV – Resource-Based View

ROI– RETURN ON INVESTMENT

RQ – Research Question

S&OP– SALES AND OPERATIONS PLANNING

SCM – Supply Chain Management

SCO– SUPPLY CHAIN ORCHESTRATION

SD – Standard Deviation

SPSS – Statistical Package for the Social Sciences

SSBM – Swiss School of Business and Management

STS – Socio-Technical Systems Theory

TAM – Technology Acceptance Model

U.S.– UNITED STATES

UTAUT – Unified Theory of Acceptance and Use of Technology

VRIN–VALUABLE RARE INIMITABLE NON-SUBSTITUTABLE

CHAPTER 1

INTRODUCTION

1.1 Background of the Study

In today's globalized economy, supply chain and sales network collaboration has become essential for improving operational efficiency and customer satisfaction (Christopher, 2016; Choi et al., 2018). Over the past decades, supply chains have transformed from simple, transaction-based models into complex, interconnected ecosystems where collaboration among partners plays a critical role in creating a competitive advantage (Ivanov and Dolgui, 2020; Christopher and Holweg, 2017). Sales networks, meanwhile, serve as crucial intermediaries, ensuring that supply chains remain responsive to shifting market demands and customer needs (Christopher, 2016).

The rapid advancement of Artificial Intelligence (AI) offers unprecedented opportunities for both supply chains and sales networks. AI tools, including machine learning and predictive analytics, enhance key operations such as demand forecasting, inventory management, and customer relationship management (Choi et al., 2018; Wamba-Taguimdje et al., 2020). These innovations allow businesses to react swiftly to market changes, thereby improving their customer-centric strategies (Wamba-Taguimdje et al., 2020).

Despite its potential, AI integration faces significant barriers. Organizations often struggle with fragmented data systems, poor cross-departmental collaboration, and resistance to technological change (Cannas et al., 2024; Christopher, 2016). Addressing these challenges is crucial to unlocking the full benefits of AI-driven collaboration between supply chains and sales networks.

This research aimed to explore these dynamics and to develop actionable strategies that leverage AI technologies to optimize supply chain and sales network collaboration for improved customer satisfaction and market responsiveness.

1.2 Problem Statement

Global manufacturing industries face ongoing challenges due to rapidly changing customer expectations, market volatility, and disruptions in supply chains (Ivanov and Dolgui, 2020). Although technological advancements, including Artificial Intelligence (AI), have demonstrated the potential to streamline operations and improve responsiveness, the integration between supply chain operations and sales networks often remains fragmented (Goh and Eldrige, 2015). This disconnect is particularly problematic in industries where aligning production capabilities with market demands is crucial for maintaining competitiveness (Christopher and Holweg, 2017; Christopher, 2016).

AI technologies, such as predictive analytics and automated decision-making systems, can significantly improve operational efficiency by enabling better demand forecasting and resource allocation (Wamba-Taguimdje et al., 2020). However, several critical barriers hinder successful integration, including:

1. **Data Fragmentation:** Siloed and incompatible data systems prevent seamless communication across functions, reducing the effectiveness of real-time decision-making (Wang et al., 2016; Tuomikangas and Kaipia, 2014).
2. **Organizational Silos:** A lack of collaboration between departments often leads to misaligned goals and diminished efficiency, even when AI technologies are implemented (Goh and Eldridge, 2015, Lambert and Enz, 2017).

3. **Resistance to Change:** Both structural and cultural resistance to adopting new technologies can impede successful integration (Christopher, 2016).

Current literature often isolates AI's role in either optimizing supply chains or improving sales strategies but rarely examines the collaborative impact of AI on both functions within manufacturing industries. This study addressed this research gap by proposing a comprehensive framework that uses AI to foster collaboration between supply chains and sales networks. The research aimed to identify solutions that enhanced customer satisfaction and market responsiveness, thereby enabling organizations to achieve a sustainable competitive advantage.

1.3 Research Objectives and Research Questions

1.3.1 Research Aim

The primary aim of this research was to develop a comprehensive framework that leverages Artificial Intelligence (AI) to enhance collaboration between supply chain processes and sales networks within the manufacturing industry. This study sought to explore how AI integration can improve customer satisfaction and market responsiveness.

1.3.2 Research Questions

To achieve the research aim, the following research questions were formulated:

1. How can AI technologies improve the collaboration and integration between supply chain operations and sales networks?
2. What organizational and technological barriers hinder the successful implementation of AI in collaborative frameworks?
3. What impact does AI-driven integration have on operational efficiency, customer satisfaction, and market responsiveness?

4. What strategic measures can organizations adopt to overcome barriers and ensure sustainable collaboration through AI?

1.3.3 Research Objectives

The specific objectives of this research were:

1. To analyze the role and potential of AI technologies in improving collaboration between supply chains and sales networks (Wamba-Taguimdje et al., 2020).
2. To identify organizational, technological, and cultural barriers to the successful adoption of AI in collaborative frameworks (Cannas et al., 2024; Davenport and Ronanki, 2018).
3. To evaluate the impact of AI-driven collaboration on operational efficiency, market adaptability, and customer satisfaction (Christopher and Holweg, 2017).
4. To develop a scalable and sustainable framework for AI-enabled collaboration in the manufacturing sector (Davenport and Ronanki, 2018).
5. To provide practical recommendations for companies seeking to optimize their supply chain and sales processes through AI（Davenport and Ronanki, 2018).

1.4 Scope and Delimitations

This study investigated how Artificial Intelligence (AI) could enhance collaboration between supply chain operations and sales networks within the European manufacturing industry. The research focused specifically on medium- and large-sized industrial firms operating in international markets, where integrated coordination between commercial and operational functions is essential for maintaining competitiveness and customer satisfaction.

The scope of the study was limited to organizational, strategic, and process-related aspects of AI-supported collaboration. Technical details regarding AI development, software architecture, or algorithm design are excluded. Instead, the research addresses how AI technologies—such as predictive analytics and real-time decision-support systems—can be leveraged to improve cross-functional alignment, customer responsiveness, and operational efficiency.

Delimitations also include the research design. A cross-sectional, mixed-methods approach is applied, combining qualitative interviews and quantitative surveys with senior professionals in supply chain and sales roles. The study did not include real-time system testing or longitudinal analysis. Consequently, while the findings provided relevant insights and practical implications, they are bounded by temporal and organizational constraints.

Establishing clear delimitations enhances transparency, strengthens methodological coherence, and allows for more focused interpretation of the results (Creswell and Plano Clark, 2018). The findings are intended to inform managerial decision-making and academic discourse related to AI-enabled collaboration in complex industrial environments.

1.5 Significance of the Study

This research addressed both academic and practical gaps by exploring the integrated application of AI technologies to foster collaboration between supply chain operations and sales networks within the manufacturing industry.

From an academic perspective, this study contributed to the existing body of knowledge in the following ways:

- It closed a gap in the literature by investigating AI's dual role in both supply chains and sales networks, which are typically studied in isolation (Wamba-Taguimdje et al., 2020).
- It developed a comprehensive framework for AI-enabled collaboration that considers the unique challenges and characteristics of manufacturing industries (Davenport and Ronanki, 2018; Zangiacomi et al., 2023).
- It contributed to theoretical discussions on cross-functional collaboration and the application of AI in operational and commercial processes (Tuomikangas and Kaipia, 2014; Culot, Podrecca and Nassimbeni, 2024).

On the practical side, the study offered manufacturing companies concrete strategies to:

- Improve alignment between supply chains and sales networks through AI-driven tools that enhance data transparency and predictive planning (Goh and Eldridge, 2015).
- Overcome organizational silos and fragmented data systems by introducing collaborative AI platforms (Davenport and Ronanki, 2018).
- Enhance customer satisfaction and responsiveness by enabling real-time adjustments to market and customer demands, driven by AI-supported forecasting and analytics (Christopher and Holweg, 2017).

The significance of this study lay in its ability to link theoretical models with actionable, real-world recommendations. By addressing the disconnect between supply chains and sales networks in manufacturing and leveraging AI to enhance this relationship, the research not only supports academic progress but also delivers practical value to companies aiming to remain competitive in an increasingly volatile and customer-driven market.

1.6 Structure of the study

This dissertation was structured into eight chapters, each building upon the previous to provide a comprehensive understanding of AI-supported collaboration between supply chain and sales functions in industrial organizations.

- Chapter 1: Introduction – Introduced the background, problem statement, objectives, research questions, scope, and significance of the study.
- Chapter 2: Industry Profile – Outlined the operational context of supply chain and sales collaboration in manufacturing, including digital transformation trends and integration challenges.
- Chapter 3: Literature Review – Reviewed prior research on cross-functional collaboration, AI in supply chains, customer responsiveness, and identified relevant research gaps.
- Chapter 4: Theoretical Framework – Presented the conceptual foundations of the study including Resource-Based View (RBV), Organizational Information Processing Theory (OIPT), and Socio-Technical Systems Theory (STS).
- Chapter 5: Research Methodology – Described the research design, data collection methods, and the mixed-methods approach combining qualitative interviews and quantitative survey data.
- Chapter 6: Data Analysis and Findings – Presented the results of the quantitative and qualitative data analyses, followed by a synthesis of both.
- Chapter 7: Discussion – Interpreted the findings in light of the theoretical framework and literature, and discussed implications for research and practice.

- Chapter 8: Conclusions and Recommendations – Summarized key findings, provided strategic and managerial recommendations, reflected on limitations, and outlined directions for future research.
- The Appendices included the survey questionnaire, raw responses, interview guides, informed consent forms, and additional documentation related to ethical and methodological transparency.

This structure ensured a logical and systematic flow, enabling the study to build a clear narrative from the identification of the research problem to the formulation of actionable recommendations.

CHAPTER 2

INDUSTRY PROFILE

2.1 Collaboration for Business Performance and Efficiency between Sales and Supply Chain

2.1.1 Introduction

In the context of modern business practices, collaboration between sales and supply chain functions had become a crucial driver of organizational performance and efficiency. Particularly in an increasingly competitive and globalized environment, companies were required to streamline their internal processes to respond flexibly to changes in demand and market dynamics (Christopher, 2016).

This chapter explored the industry-specific context of supply chain and sales integration, with a focus on AI-supported collaboration. It highlighted current practices, challenges, and emerging technologies that shaped how companies aligned their operational and commercial functions. These insights provided the foundational basis for the empirical parts of this study. Both the qualitative interviews and the quantitative survey drew on the themes and gaps identified in this chapter to evaluate how AI could improve collaboration, customer satisfaction, and market responsiveness in manufacturing industries.

2.1.2 Supply Chain Collaboration

Supply chain collaboration refers to the joint efforts of multiple entities or departments along the supply chain to gain competitive advantages and maximize shared success (Cao and Zhang, 2011; Christopher, 2016). Successful collaboration involves optimizing information sharing, decision synchronization, and incentive alignment, enabling a holistic view of the supply chain and faster adjustments to external disruptions and demand fluctuations (Christopher and Holweg, 2017). Studies have shown that organizations that improved their supply chain strategies through collaboration strengthen their market position and optimized their resource utilization (Ivanov and Dolgui, 2020).

2.1.3 Sales and Supply Chain Integration

One of the primary components of successful collaboration is the integration of sales and supply chain functions. Research demonstrates that the synchronization of sales and supply chain operations leads to improved demand-supply management, which in turn enhances customer satisfaction and reduces operational costs (Ruzo-Sanmartín et al., 2023; Tuomikangas and Kaipia, 2014). By utilizing Sales and Operations Planning (S&OP), companies can improve their forecasting accuracy, optimize production schedules, and ensure product availability, ultimately boosting overall business performance (Christopher, 2016).

2.1.4 Business Performance through Collaboration

Collaboration between sales and supply chain functions significantly contributes to business performance. Close alignment between these areas enables companies to use resources more efficiently, improve process flows, and maximize value creation opportunities (Flynn, Huo and Zhao, 2010; Cao and Zhang, 2011). Research shows that process integration and information sharing between sales and supply chain functions form the foundation for sustainable improvements in operational efficiency (Flynn, Huo and Zhao, 2010; Tuomikangas and Kaipia, 2014). Companies that promote strong collaboration are not only more adaptable to market changes but also experience improved returns and competitiveness (Ivanov and Dolgui, 2020).

2.1.5 Operational Efficiency and Collaboration

The close collaboration between sales and supply chain functions leads to a notable improvement in operational efficiency. Through coordinated information exchange and process integration, companies can optimize their supply chain structures, reducing costs and improving productivity (Choi et al., 2018). Additionally, modern technologies such as artificial intelligence (AI) and blockchain further support this process by automating tasks and providing real-time data for more efficient decision-making (Wamba-Taguimdje et al., 2020). This enhances a company’s ability to respond flexibly to demand changes and ensures that companies remain competitive.

2.1.6 Collaboration Impact on Supply Chain Performance

Effective collaboration within the supply chain has significant impacts on overall supply chain performance. Companies that successfully integrate their sales and supply chain processes benefit from increased visibility, better planning, and enhanced flexibility (Christopher and Holweg, 2017). This leads to improved cost control, reduced inventory levels, and faster responses to customer requirements, ultimately improving efficiency and competitiveness (Ivanov and Dolgui, 2020). Research shows that companies with an integrated supply chain are better positioned to achieve long-term competitive advantages and sustain operational efficiency (Flynn, Huo and Zhao, 2010; Cao and Zhang, 2011).

2.2 Challenges and benefits of sales and supply chain integration

2.2.1 Benefits of integration

Improved responsiveness and business performance. The integration of sales and supply chain is considered in the literature to be a central factor in increasing business performance. Ralston, Blackhurst and Cantor (2015) argue that a strategic integration of these functions not only improves operational efficiency but also increases a company's ability to respond more quickly and flexibly to customer demands (Ralston, Blackhurst & Cantor, 2015). This capability is critical to maintaining a competitive edge, especially in global markets where customers expect a rapid and precise response to their needs. Integrating sales and supply chain processes enables companies to synchronize logistics processes, thus avoiding bottlenecks in the supply chain, which leads to improved financial performance.

2.2.2 Optimization through Sales and Operations Planning (S&OP)

Another concept frequently highlighted in the literature is the implementation of Sales and Operations Planning (S&OP). Tuomikangas and Kaipia (2014) show that S&OP improves alignment between sales and supply chain, resulting in a reduction in lead times and improved forecasting accuracy. By using joint planning processes, companies can use their resources more efficiently and optimize delivery times, which has a positive impact on both customer satisfaction and operating costs. In the literature, S&OP is seen as a key process that supports the integration of sales and supply chain departments, enabling companies to be more agile and responsive to market changes.

2.2.3 Improving sales efficiency in international markets

The integration of sales and supply chain plays a particularly crucial role in international markets in improving sales efficiency. Christopher and Holweg (2017) emphasize that the coordination of sales and logistics processes is particularly advantageous in global contexts with high logistical complexity. A well-integrated supply chain enables sales representatives to meet customer demands faster and more accurately, leading to improved competitive advantage. These studies illustrate that close collaboration between logistics and sales in international markets leads to greater customer satisfaction and increased sales performance, which also promotes long-term corporate growth.

2.2.4 Challenges of integration

Despite the clear benefits of aligning sales and supply chain functions, the implementation of fully integrated collaboration remains a considerable challenge in many organizations (Goh and Eldridge, 2015; Lambert and Enz, 2017). A key obstacle is the existence of functional silos, where departments pursue independent objectives, resulting in fragmented processes and limited communication. These structural divisions can hinder the synchronization of demand planning, production, and customer delivery, ultimately weakening the organization's ability to respond effectively to market changes (Chopra and Meindl, 2019).

Another critical barrier is the lack of a shared data infrastructure. In many firms, incompatible IT systems prevent real-time data sharing across departments, making it difficult to align forecasts, inventory planning, and customer communications. This issue is particularly relevant to the adoption of Artificial Intelligence (AI), which depends on high-quality, connected data to operate effectively (Wamba et al., 2017; Wang et al., 2016).

Furthermore, organizational culture and resistance to change often inhibit integration efforts. Employees and managers may be reluctant to adapt to new roles, workflows, or technologies—particularly when integration is perceived as a threat to autonomy or control. These socio-organizational aspects are frequently underestimated, yet they pose significant hurdles to the successful implementation of AI-supported collaboration (Clegg, 2000; Faraj, Pachidi and Sayegh, 2018).

These challenges are not only well documented in the academic literature, but were also highlighted by practitioners in the qualitative interviews conducted for this study. Several respondents described integration as a "strategic intent, but operationally fragmented," underscoring the gap between organizational vision and daily practice. The quantitative survey further supports this view, showing that although many firms invest in collaboration tools, fewer than half of the respondents report consistent alignment between sales and supply chain KPIs.

To address these issues, companies must not only invest in enabling technologies, but also build supportive organizational structures, foster a culture of collaboration, and develop cross-functional competencies. These aspects are further explored in the empirical chapters of this study (Barney and Hesterly, 2019; Cao and Zhang, 2011; Trist and Bamforth, 1951).

2.2.5 Sustainability requirements and operational efficiency

The increasing demand for sustainable business practices presents a strategic and operational challenge for many industrial firms. On the one hand, companies are under pressure to reduce their environmental impact through measures such as lower emissions, energy efficiency, and waste reduction. On the other hand, they must continue to meet high standards of operational performance and customer satisfaction. This dual objective creates a tension between sustainability and efficiency, which can only be resolved through integrated and collaborative approaches.

Sales and supply chain functions play a pivotal role in achieving both goals. While supply chain teams are often responsible for optimizing processes and reducing the environmental footprint, sales teams are in direct contact with customer expectations and market-specific sustainability demands. If these departments operate in silos, misalignments between commercial promises and operational capabilities can occur—leading to inefficiencies or reputational risks.

The literature suggests that companies with a strong culture of cross-functional collaboration are more likely to develop strategies that align economic and ecological objectives (Beamon, 1999). Moreover, digital technologies such as Artificial Intelligence (AI) and real-time analytics are increasingly used to support this alignment. These tools can improve transparency in emissions tracking, enable scenario planning, and support decision-making that balances cost, speed, and sustainability (Bag et al., 2021).

This study assumes that the degree of sustainability integration into cross-departmental collaboration will vary depending on organizational maturity, technological capabilities, and leadership priorities. The empirical investigation—based on qualitative interviews and quantitative surveys—will explore to what extent companies integrate sustainability goals into their collaborative planning and how this affects operational efficiency.

2.2.6 Technological challenges of smart supply chains and AIoT

The integration of advanced technologies—such as the Artificial Intelligence of Things (AIoT), smart sensors, and real-time analytics—has the potential to transform modern supply chains. These innovations promise substantial gains in efficiency, automation, and responsiveness. However, the path to realizing these benefits is fraught with technological, organizational, and strategic challenges.

From a supply chain perspective, smart technologies require high levels of data availability, system interoperability, and cybersecurity. Real-time connectivity and continuous data flow are essential for predictive decision-making, process automation, and performance optimization. Yet, many organizations struggle with fragmented IT infrastructures, outdated legacy systems, and inconsistent data governance, which hinder the full deployment of smart supply chain solutions (Müller, Kiel and Voigt, 2018; Vial, 2019).

Organizationally, the implementation of AIoT technologies often necessitates new workflows, employee skill sets, and governance models. Departments such as sales and supply chain must collaborate more closely to define data priorities, interpret automated insights, and respond to dynamic customer needs. If this alignment is not achieved, the risk of data misinterpretation, operational bottlenecks, or technology rejection increases.

Initial insights from practice and the reviewed literature (Douaioui et al., 2018; Nozari et al., 2022) suggest that integration challenges are particularly acute at the intersection between commercial and operational functions, where data needs and decision-making logics may differ significantly. Furthermore, there is a growing awareness that technological investment alone is insufficient—without parallel investments in training, change management, and interdepartmental alignment, smart supply chain initiatives often fall short of expectations.

This study will investigate, through interviews and surveys, how companies approach the integration of AIoT and smart supply chain technologies, and to what extent technological challenges affect cross-functional collaboration, particularly between sales and supply chain teams. These findings will contribute to a better understanding of the practical conditions for successful digital transformation in industrial supply networks.

2.2.7 Future perspectives

Alignment of supply chain and marketing strategies. The future of sales and supply chain integration requires an even closer alignment of supply chain and marketing strategies. Sutia (2022) argues that an integrated alignment of these two functions will enable companies not only to better manage fluctuations in demand but also to achieve their sustainability goals. This strategic alignment is crucial to meeting both customer expectations and global environmental sustainability requirements. The literature suggests that companies that align their marketing and supply chain strategies more closely can achieve greater flexibility and agility, leading to improved competitive performance and customer satisfaction (Tuomikangas and Kaipia, 2014; Gligor, Esmark and Holcomb, 2020; Sutia, 2022).

2.3 Artificial intelligence in the supply chain

The application of artificial intelligence (AI) in the supply chain is a growing area of research that aims to improve efficiency, decision-making, and sustainability (Bag, Pretorius and Gupta, 2021; Wamba et al., 2017). Various studies show that AI is increasingly being used in the supply chain in areas such as demand forecasting, inventory management, and logistics optimization (Choi et al., 2018; Wang et al., 2016). AI enables companies to use resources more efficiently through intelligent automation and predictive analytics, resulting in cost reduction and improved resource allocation (Davenport and Ronanki, 2018; Babiceanu and Seker, 2016).

2.3.1 Use of AI for forecasting and decision-making processes

The use of Artificial Intelligence (AI) in forecasting and decision-making is increasingly regarded as a transformative capability in modern supply chain management. AI systems can analyze vast datasets, identify hidden patterns, and generate more accurate forecasts than traditional statistical methods (Choi, Wallace and Wang, 2018; Wang et al., 2016). This is particularly valuable for demand planning and inventory optimization in industries exposed to high market volatility and dynamic customer expectations.

Studies suggest that machine learning algorithms and predictive analytics allow companies to anticipate demand shifts more precisely, reduce overstock and stockout risks, and enhance customer responsiveness (Choi et al., 2018; Wang et al., 2016). AI also enables scenario-based planning by simulating the impact of external factors—such as raw material shortages, transport delays, or changes in customer behavior—on supply chain performance. These data-driven insights can support faster and more informed decisions.

Moreover, AI can facilitate semi- or fully automated decision-making processes. These capabilities are especially beneficial in complex supply networks, where the speed and quality of decisions are essential for maintaining efficiency and customer satisfaction (Davenport and Ronanki, 2018; Choi, Wallace and Wang, 2018). Nevertheless, the successful implementation of such systems depends not only on technical capabilities but also on data quality, system integration, and organizational readiness.

Despite its growing adoption, the literature identifies several research gaps. These include the long-term impact of AI-based forecasting on strategic decision-making, the integration of AI with existing enterprise systems, and the role of human oversight in AI-enabled decisions (Davenport and Ronanki, 2018; Vial, 2019; Dignum, 2019). Furthermore, there is limited empirical evidence on how manufacturing firms align AI-generated forecasts with sales strategies and operational execution.

To explore these aspects, this study will examine how decision-makers perceive the role and effectiveness of AI in forecasting and planning. Through qualitative interviews and quantitative surveys, the research seeks to understand:

- Which forecasting functions are currently AI-supported
- How AI forecasts are integrated into sales and supply chain decisions
- What organizational conditions support or hinder effective AI use

These insights are critical for developing a framework that supports data-driven collaboration between supply chain and sales functions—an essential objective outlined in Chapter 1.

2.3.2 Impact of AI on supply chain transparency and automation

Artificial Intelligence (AI) is increasingly regarded as a critical enabler of transparency and automation in supply chains. Literature emphasizes that real-time data analytics powered by AI can significantly enhance visibility across multiple supply chain tiers, including inventory levels, transport routes, and supplier performance (Choi, Wallace and Wang, 2018; Wang et al., 2016; Fosso Wamba et al., 2018). Enhanced transparency facilitates faster and more informed decision-making, which in turn strengthens the alignment between supply chain operations and sales forecasts.

In addition to improving visibility, AI supports the automation of various supply chain processes, such as warehousing, inventory replenishment, and logistics coordination. Through the integration of AI with Internet of Things (IoT) devices, organizations can automate repetitive tasks, reduce human error, and lower operational costs while improving process speed and consistency (Babiceanu and Seker, 2016; Bag, Pretorius and Gupta, 2021). For example, AI-powered systems can dynamically adjust replenishment parameters or optimize route planning without manual intervention, thereby improving both efficiency and service reliability.

However, while the theoretical advantages of AI in increasing transparency and automation are compelling, practical implementation is often hampered by barriers such as data quality issues, lack of system interoperability, and insufficient organizational readiness (Vial, 2019; Müller, Kiel and Voigt, 2018; Davenport and Ronanki, 2018). Furthermore, the successful deployment of AI requires not only technical infrastructure but also cross-functional collaboration between supply chain and sales departments. In this context, the upcoming mixed-methods investigation will explore how AI is currently used to support transparency and automation in manufacturing supply chains. By combining qualitative perspectives from supply chain and sales professionals with quantitative survey data, the study seeks to assess the actual maturity level of AI-supported automation and its role in enhancing cross-functional collaboration.

2.3.3 Future prospects and ethical implications

The integration of Artificial Intelligence (AI) in supply chains is expected to evolve rapidly in the coming years, driven by emerging technologies such as blockchain, quantum computing, and autonomous systems. These technologies promise to enhance the resilience, responsiveness, and sustainability of supply chains by enabling real-time data synchronization, decentralized decision-making, and advanced optimization algorithms (Ivanov and Dolgui, 2020; Choi, Wallace and Wang, 2018; Queiroz, Telles and Bonilla, 2022). AI will likely continue to play a pivotal role in bridging operational and commercial processes, particularly by aligning sales forecasts with dynamic supply capabilities.

However, as AI becomes more embedded in organizational decision-making, several ethical and regulatory considerations arise. The literature increasingly highlights concerns related to algorithmic bias, data privacy, and transparency in automated decision-making (Dignum, 2019; Dignum, 2018; Pandey, Kumar and Sharma, 2023). For instance, AI models trained on incomplete or biased datasets may inadvertently reinforce existing inequalities or lead to suboptimal resource allocations. Furthermore, the opacity of many AI systems ("black box" issue) can hinder trust and accountability, especially in high-stakes supply chain contexts.

From a socio-technical systems perspective, it is essential that AI implementations be accompanied by governance frameworks that ensure responsible usage. Ethical guidelines, regulatory compliance, and employee training must become integral parts of AI adoption strategies, particularly in multinational manufacturing environments. This includes clarifying data ownership, defining accountability structures, and fostering transparency in AI-supported decision chains.

In this study, future prospects and ethical considerations will be addressed through a dual lens. On the one hand, qualitative interviews will explore managers' perceptions of AI's potential and their concerns regarding its ethical use. On the other hand, the quantitative survey will assess the current state of AI governance and transparency mechanisms in the participating organizations. Together, these insights will help identify critical success factors for responsible AI integration and highlight areas where additional guidance or policy development may be needed.

2.4 Customer Satisfaction and Market Responsiveness

In global contexts, supply chain management (SCM) was especially important in assessing customer satisfaction and an organization's capacity to adapt to changing market conditions. Numerous studies highlighted how data-driven supply chains positively impacted both manufacturing capabilities and customer satisfaction by enhancing efficiency, accuracy, and flexibility (Chavez et al., 2017). As global competition intensified, companies had to rely on efficient SCM practices to meet customer expectations and remain competitive in dynamic markets (Christopher, 2016; Zhang et al., 2022).

2.4.1 Customer satisfaction and the performance of the supply chain.

Customer satisfaction had become a key metric for evaluating supply chain performance in manufacturing industries. In increasingly volatile and globalized markets, the ability to fulfill customer expectations regarding product availability, delivery reliability, and service quality was essential to sustain long-term relationships and competitive advantage. Studies have consistently showed that agile and data-driven supply chains significantly contributed to improved customer experiences, particularly by enabling accurate forecasting and faster response times (Chavez et al., 2017; Gligor et al., 2020).

Supply chain integration—characterized by synchronized planning, real-time data sharing, and cross-functional collaboration—was found to directly influence customer satisfaction outcomes. Integrated processes reduced delivery lead times, minimize stockouts, and increase transparency across the value chain (Flynn, Huo and Zhao, 2010; Puche et al., 2016; Wang et al., 2016). Furthermore, the adaptability of logistics providers and supply networks played a crucial role in ensuring service continuity, especially under disruptive conditions (Ivanov and Dolgui, 2020; Gligor, Esmark and Holcomb, 2020).

In this study, customer satisfaction was explored as a dependent variable influenced by the degree of collaboration between sales and supply chain units. The qualitative interviews will helped capture nuanced insights into how managers perceived the relationship between internal alignment and customer outcomes, while the quantitative survey will investigated measurable patterns across firms and industries.

2.4.1.1 Supply Chain Integration and Customer Satisfaction

Supply chain integration had been widely recognized as a critical enabler of customer satisfaction in both business-to-business (B2B) and business-to-consumer (B2C) contexts. Integrated supply chains enabled firms to streamline operations, align internal and external processes, and respond more effectively to customer needs. Studies suggested that when sales and supply chain functions shared data, goals, and decision-making processes, the result was improved product availability, shorter delivery lead times, and higher service reliability—all of which were essential for customer satisfaction (Cao and Zhang, 2011; Flynn, Huo and Zhao, 2010; Tuomikangas and Kaipia, 2014).

Moreover, supply chain integration supported proactive customer service through real-time tracking, flexible inventory allocation, and personalized delivery commitments. These capabilities contributed to stronger customer trust and loyalty by reducing uncertainty and improving communication transparency across the order lifecycle

(Chavez et al., 2017; Christopher, 2016). In particular, visibility across the supply chain enabled firms to anticipate potential disruptions and inform customers in advance, which was increasingly valued in volatile global markets.

This study explored how supply chain integration—particularly in the context of AI-enabled collaboration—contributed to perceived customer satisfaction within manufacturing industries. The qualitative interviews were used to capture managerial perspectives on how cross-functional integration affected service levels, while the quantitative survey examined correlations between integration indicators and customer satisfaction metrics. This dual approach allowed for a deeper understanding of the mechanisms through which supply chain and sales alignment impacted customer experience.

2.4.1.2 Challenges in Balancing Customization and Efficiency

One of the most persistent tensions in modern supply chain management was the need to balance operational efficiency with increasing demands for product and service customization. In manufacturing industries, particularly those operating globally, customers increasingly expected tailored solutions that met specific technical, regulatory, or regional requirements. At the same time, companies were under pressure to maintain cost efficiency, minimize lead times, and manage limited resources effectively (Christopher, 2016).

This trade-off presented a strategic challenge: customization often led to increased complexity in planning, production, and logistics, which strained the supply chain and reduced economies of scale. Conversely, overly standardized processes might fail to meet nuanced customer expectations, thereby negatively impacting customer satisfaction and loyalty. As a result, companies had to develop mechanisms to offer flexibility where it mattered most—while preserving standardization in back-end processes.

AI technologies and digital tools were increasingly explored as a means to resolve this tension. For instance, AI-driven configuration systems and advanced demand segmentation helped tailor offerings without disrupting the core operational model. However, successful implementation also required organizational alignment between sales and supply chain teams to agree on where flexibility was strategically valuable and where standardization should be maintained.

This study investigated how manufacturing firms approached the customization-efficiency trade-off, both from a strategic and operational perspective. Qualitative interviews explored how managers perceived this tension and managed priorities across departments, while the quantitative survey assessed how the degree of perceived customization correlated with customer satisfaction and cost-related performance indicators.

2.4.2 The Role of Market Responsiveness in Global Companies

In a volatile and highly competitive global business environment, market responsiveness emerged as a strategic imperative for manufacturing companies. Market responsiveness referred to an organization's ability to detect, interpret, and react quickly to external changes—such as shifting customer needs, emerging technologies, geopolitical risks, or supply chain disruptions. For firms operating in international markets, this capability was essential to remain competitive and relevant (Gligor et al., 2020; Zhang et al., 2022).

Responsiveness became especially important in industries where product life cycles were short and customer preferences evolved rapidly (Christopher, 2016). Companies that were able to reconfigure their supply chains, adjust production capacities, or launch modified offerings on short notice gained a decisive competitive advantage (Zhang et al., 2022; Teece, 2007). However, this adaptability depended not only on flexible production and logistics but also on real-time alignment between commercial functions—such as sales and marketing—and operational departments like supply chain management (Tuomikangas and Kaipia, 2014; Goh and Eldridge, 2015; Christopher, 2016).

Technology, and particularly Artificial Intelligence (AI), served as an enabler of market responsiveness by providing predictive insights and automating response mechanisms. AI-driven tools forecasted demand shifts, monitored supply risks, and optimized resource allocation dynamically (Choi, Wallace and Wang, 2018; Wamba et al., 2017). Still, technology alone was not sufficient. Organizational structures, decision-making processes, and cross-functional collaboration had to be designed to allow rapid communication and action across departments and geographies (Tushman and Nadler, 1978; Galbraith, 1973; Daft and Lengel, 1986).

This study investigated how market responsiveness was achieved in European manufacturing firms, especially in the context of AI-supported integration between sales and supply chain teams. The qualitative interviews explored how decision-makers defined responsiveness in their specific market contexts and what organizational enablers or barriers they encountered. The quantitative phase measured perceived responsiveness, responsiveness-related KPIs, and their correlation with customer satisfaction and operational performance.

2.4.2.1 Supply Chain Agility and Competitive Advantage

Supply chain agility referred to the ability of a supply chain to rapidly adjust its operations and configurations in response to internal and external changes. In global manufacturing contexts, agility was particularly vital for managing supply and demand variability, minimizing risks, and maintaining service levels across diverse markets (Gligor, Esmark and Holcomb, 2020; Ivanov and Dolgui, 2020; Zhang et al., 2022).

Agile supply chains were characterized by flexibility, speed, and the capability to make data-informed decisions in real time (Gligor, Esmark and Holcomb, 2020; Christopher, 2016).

Agility was not only an operational capability but also a strategic one. It enabled firms to capture emerging market opportunities and to mitigate disruptions such as raw material shortages, geopolitical instability, or shifting regulatory environments. From a strategic standpoint, agile supply chains were closely linked to a company's ability to generate and sustain competitive advantage (Gligor et al., 2020; Dubey et al., 2021).

This research considered agility a central construct in understanding market responsiveness. The study examined how AI-supported collaboration between sales and supply chain departments contributed to agility through real-time information sharing, predictive analytics, and proactive resource management (Tuomikangas and Kaipia, 2014; Choi, Wallace and Wang, 2018; Wang et al., 2016). The qualitative interview phase investigated how practitioners perceived agility and the role of cross-functional processes in supporting rapid response capabilities. In the quantitative phase, agility was assessed through indicators such as lead time flexibility, supply chain reconfiguration speed, and responsiveness to customer changes.

2.4.2.2 The Role of Logistics Adaptability in Customer Retention

Logistics adaptability referred to a company's ability to adjust its transportation, warehousing, and distribution processes in response to changing market demands or unexpected disruptions. In global and volatile markets, adaptable logistics systems were crucial to ensuring reliable delivery performance and service quality, two key factors in maintaining customer satisfaction and retention (Ivanov and Dolgui, 2020; Gligor, Esmark and Holcomb, 2020; Chavez et al., 2017).

Customer retention was not solely driven by product quality or price competitiveness; rather, it was increasingly influenced by the perceived reliability and flexibility of logistics services (Christopher, 2016; Świtała et al., 2018; Chavez et al., 2017). Companies with adaptable logistics structures were better equipped to absorb supply-side shocks, re-route shipments, or adjust inventory distribution in near real-time. This capability became especially critical in sectors where customers required fast turnaround, such as spare parts supply, customized production, or perishable goods logistics.

This study evaluated logistics adaptability as a bridging concept between operational resilience and customer loyalty. The qualitative interviews explored how decision-makers in sales and supply chain functions assessed the adaptability of their logistics systems in relation to customer expectations. In the quantitative phase, respondents evaluated adaptability using metrics such as lead time stability, alternative routing capabilities, and responsiveness to urgent customer requests. These findings supported the broader goal of identifying how collaborative, AI-enhanced planning contributed to long-term customer retention strategies.

2.4.2.3 The Impact of Predictive Analytics on Market Responsiveness

Predictive analytics became a central enabler of market responsiveness, allowing companies to anticipate demand fluctuations, supply chain disruptions, and shifts in customer preferences before they occurred. Especially in the manufacturing industry, where long lead times and complex networks were common, early insights led to significant competitive advantages. By leveraging large datasets and machine learning algorithms, predictive systems generated actionable forecasts that supported strategic and operational decision-making (Wang et al., 2021).

Market responsiveness referred to a company's capacity to quickly adapt to market changes and realign its operations accordingly. Predictive analytics supported this by enabling proactive, rather than reactive, adjustments in production planning, inventory allocation, and order fulfillment. For example, AI-driven tools could detect early signs of changes in customer behavior or market demand and suggested supply chain actions such as stock repositioning or supplier shifts.

In this study, predictive analytics was examined as a key capability for enhancing responsiveness within AI-supported collaboration frameworks between sales and supply chain. The qualitative interviews explored how decision-makers currently used predictive data in planning and decision-making. The quantitative survey assessed the perceived effectiveness of predictive tools, including their influence on reducing lead times, improving forecast accuracy, and supporting flexible customer responses.

By analyzing these aspects, the research aimed to uncover how the integration of predictive analytics into collaborative processes impacted not only operational agility but also customer satisfaction and business continuity in dynamic market environments.

2.4.2.4 Challenges of Implementing Market Responsiveness in Global Operations

Despite the strategic importance of market responsiveness, global organizations faced persistent challenges when attempting to align their operations with shifting market demands. These challenges stemmed from the complexity of coordinating across different regions, legal frameworks, infrastructure capabilities, and cultural expectations. For example, what may have been considered a flexible and rapid customer response in one region might have been subject to regulatory delays or logistical bottlenecks in another (Zhang et al., 2022; Christopher, 2016; Ivanov and Dolgui, 2020).

One of the key barriers was the tension between global standardization and local adaptation. While centralized processes could drive efficiencies and cost reductions, they might have limited the ability of local teams to respond autonomously and quickly to region-specific needs. Additionally, limited access to real-time data across regions could hinder informed decision-making and slow down critical supply chain adjustments.

From a sales and supply chain collaboration perspective, these issues were amplified when interdepartmental communication was fragmented or when performance metrics were not aligned across functions and geographies. Even with AI-based technologies in place, a lack of clear governance structures, shared data platforms, and empowerment of local teams could significantly limit the organization's responsiveness.

In this study, both the qualitative interviews and quantitative survey investigated these implementation barriers. Interviewees were asked to describe the degree of local flexibility in their organization's supply chain and sales processes, while survey questions explored how organizational structures and information flows supported or hindered market responsiveness across regions.

Understanding these implementation challenges was key to identifying actionable strategies for enabling more agile and customer-centric operations in global manufacturing environments.

2.4.3 Silo-Thinking as a Barrier to AI-Enabled Collaboration

One of the most persistent organizational barriers to effective collaboration between sales and supply chain departments was silo-thinking. This phenomenon referred to a structural and cultural tendency within organizations where functional departments operated independently, with minimal data sharing, communication, or strategic alignment across units (Tushman and Nadler, 1978; Daft and Lengel, 1986; Christopher, 2016). Silo structures often resulted from hierarchical segmentation, historical patterns of role specialization, and fragmented performance metrics—each reinforcing isolated decision-making and resource allocation.

In the context of AI-supported integration, silo-thinking significantly undermined the potential of digital technologies to create end-to-end transparency and cross-functional optimization. As current studies emphasized, AI tools could only unfold their full potential when data flowed freely across departmental boundaries, enabling real-time analytics, coordinated planning, and aligned responses to market signals (Tuomikangas and Kaipia, 2014; Choi, Wallace and Wang, 2018; Davenport and Ronanki, 2018).

Several characteristics of silo-driven behavior had been identified in the literature as detrimental to supply chain performance and sales responsiveness:

- Data fragmentation and reporting verticality: Departments focused on internal KPIs and reporting lines rather than shared business outcomes (Kinaxis, 2023).
- Misaligned objectives and incentives: Conflicting priorities between sales (growth, revenue) and supply chain (efficiency, cost) created goal dissonance (GEP, 2023).
- Technology disintegration: Planning and execution systems often lacked integration, preventing seamless data exchange and joint decision-making (Relex Solutions, 2024).
- Communication bottlenecks: Especially in globally distributed teams, coordination was weakened by time zones, culture gaps, and lack of shared platforms (Anark Corporation, 2022).

A recent survey found that 73% of organizations faced difficulties aligning on common priorities between supply chain and commercial functions, with many reporting duplicated efforts and poor information flow as a consequence (LEAFIO, 2023). These barriers not only reduced organizational agility but also negatively impacted customer experience, as planning errors, delays, and service inconsistency often resulted from disconnected internal workflows (Flynn, Huo and Zhao, 2010; Vial, 2019).

To address this challenge, scholars and practitioners proposed concepts such as Supply Chain Orchestration (SCO), which advocated for horizontal and vertical integration across planning, execution, and organizational systems (BVL, 2024). SCO frameworks called for shared governance, collaborative planning cycles, and synchronized performance metrics that aligned all departments on customer-centric goals.

In addition, balanced scorecard frameworks offered a strategic tool for aligning financial, operational, and customer-facing KPIs across business units (Kaplan and Norton, 1996). When supported by AI-enabled dashboards, these tools could transform siloed data into shared insights, facilitating transparency and accountability across departments.

Organizational culture and leadership also played a central role in breaking down silos. Creating a culture of trust, open information exchange, and cross-functional accountability was a prerequisite for successful AI integration (Edmondson, 1999; Kotter, 1996; Trkman, 2010). This included flattening hierarchies, promoting interdisciplinary teams, and investing in integrated platforms such as ERP, CRM, or collaborative AI systems that fostered joint planning and decision-making (Choi, Wallace and Wang, 2018).

In summary, silo-thinking posed a systemic risk to the realization of AI-driven collaboration. Overcoming this barrier required not only technological integration but also strategic alignment, cultural transformation, and leadership commitment. As this study demonstrated through empirical data, organizations that succeeded in dismantling silos were better positioned to achieve responsiveness, efficiency, and customer satisfaction through AI-enabled coordination between sales and supply chain.

2.5 AI-Supported Collaboration Between Supply Chain and Sales

In the context of increasingly complex manufacturing environments, the collaboration between supply chain and sales functions became critical for maintaining agility, customer satisfaction, and competitive positioning (Christopher, 2016; Tuomikangas and Kaipia, 2014; Goh and Eldridge, 2015). While traditional coordination between these departments had relied on manual processes, periodic meetings, and siloed data systems, technological advancements—especially in Artificial Intelligence (AI)—redefined how cross-functional integration could be achieved (Davenport & Ronanki, 2018). AI had the potential to act as a transformational enabler that bridged gaps between supply chain execution and commercial strategies by supporting real-time information exchange, proactive planning, and data-driven decision-making (Wamba-Taguimdje et al., 2020).

Recent developments in AI-driven systems offered opportunities to transition from reactive to predictive collaboration. These systems allowed for the seamless integration of internal and external data sources, real-time scenario modeling, and adaptive learning from transactional histories (Wang et al., 2021). Yet, despite growing interest in digitalization and automation, many manufacturing companies still struggled to achieve consistent and scalable collaboration between supply chain and sales departments. Challenges included fragmented system architectures, lack of organizational readiness, and unclear accountability structures across functions (Capgemini Research Institute, 2020; Vial, 2019).

This study explored how AI technologies could be used not only as tools for operational optimization, but also as catalysts for cultural and procedural integration. Specifically, the research examined how AI influenced coordination quality, operational alignment, and customer-centric responsiveness between supply chain and sales. These themes were empirically explored through a mixed-methods design that included qualitative interviews with industry professionals and a complementary quantitative survey. The intention was to evaluate both the perceived and measurable impacts of AI-supported collaboration in real-world manufacturing contexts.

Three central dimensions are used to frame this investigation:

1. Technological Capabilities (e.g., data analytics, automation, integration platforms),
2. Organizational Readiness (e.g., leadership support, digital maturity, employee skills), and
3. Collaboration Dynamics (e.g., information sharing, joint planning, trust) (Cao & Zhang, 2011; Vial, 2019).

These dimensions reflected the interplay between the technical and social prerequisites for successful AI-supported integration. They also corresponded to the theoretical underpinnings that were elaborated in Chapter III (Literature Review) and Chapter IV (Theoretical Framework), which introduced the Resource-Based View (RBV), Organizational Information Processing Theory (OIPT), and Socio-Technical Systems Theory (STS) as the foundation for understanding this interplay.

2.5.1 Improved Coordination Through AI-Supported Systems

One of the most immediate benefits of AI in collaborative environments was the enhancement of coordination between supply chain and sales functions. AI-powered systems allowed both departments to access and act upon shared data sets, such as sales forecasts, production schedules, inventory levels, and customer order patterns (Choi, Wallace and Wang, 2018; Wang et al., 2016; Davenport and Ronanki, 2018). The resulting real-time transparency significantly reduced the latency of decision-making, minimized the risk of information asymmetry, and fostered better alignment in customer commitments (Wang et al., 2021).

For instance, AI-enabled demand sensing tools analyzed external data (e.g., market trends, economic indicators) in combination with internal sales data to generate short-term forecasts that were more accurate and timely than traditional methods (Choi, Wallace and Wang, 2018; Waller and Fawcett, 2013). These forecasts then automatically triggered updates in procurement, production, and logistics planning. In turn, sales teams provided customers with more precise delivery information and adjusted their strategies based on anticipated constraints or opportunities (Deloitte, 2023).

This study assessed how companies implemented such technologies to support end-to-end visibility and synchronized planning. The qualitative interview component explored decision-makers' perceptions of how AI-supported coordination altered their processes, responsibilities, and internal communication practices. Moreover, interview data shed light on the organizational enablers—such as interdepartmental trust, leadership commitment, and digital infrastructure—that influenced successful implementation (Wamba-Taguimdje et al., 2020). The quantitative survey complemented this by measuring the correlation between perceived coordination effectiveness and AI deployment maturity across a broader sample of firms.

Key aspects to be examined included:

- The use of shared AI dashboards for planning meetings (Choi et al., 2018; Wang et al., 2016; Tuomikangas and Kaipia, 2014),
- The automation of cross-functional alerts (e.g., low stock affecting open sales offers),
- AI-based tools for joint S&OP decision-making (Tuomikangas and Kaipia, 2014; Ruzo-Sanmartín et al., 2023).

2.5.2 Process Optimization and Customer Service Improvement Through AI

Beyond coordination, AI also played a central role in the optimization of core business processes that directly impacted customer service and satisfaction. By automating repetitive, time-consuming tasks such as inventory management, order processing, or demand reforecasting, AI systems freed up resources that could be redirected toward value-adding activities (Davenport and Ronanki, 2018; Waller and Fawcett, 2013; Wang et al., 2016). This not only enhanced internal efficiency but also contributed to more responsive and customer-centric operations (Choi et al., 2018). AI-driven process optimization involved several mechanisms:

- Predictive analytics for anticipating shifts in customer demand (Wang et al., 2021),
- Machine learning algorithms for dynamically adjusting reorder points and safety stock levels (Ivanov and Dolgui, 2020),
- Cognitive automation for handling routine customer inquiries or exceptions in order processing (Davenport and Ronanki, 2018).

Such capabilities contributed to shorter lead times, more accurate delivery commitments, and greater personalization of service offerings, all of which were critical for building customer trust and loyalty in B2B manufacturing contexts (Wamba-Taguimdje et al., 2020).

The study explored how AI-supported optimization translated into improvements in key performance indicators (KPIs) related to customer satisfaction, such as:

- Order accuracy and fulfillment rates,
- Delivery reliability,
- Responsiveness to order changes or urgent customer needs.

These aspects were investigated through both qualitative (experiential insight) and quantitative (survey-based KPI mapping) methods. Moreover, the study explored barriers to process optimization through AI, including data quality issues, change resistance, lack of skilled personnel, and integration costs (Vial, 2019; Davenport and Ronanki, 2018; Pandey et al., 2023).

Additionally, ethical and strategic considerations were examined—such as the risk of over-automation leading to reduced human oversight, or the need for explainability in AI-driven decisions (Dignum, 2018). These themes, aligned with the Socio-Technical Systems Theory, underscored the importance of balancing technological innovation with responsible management and organizational adaptability.

2.6 Gaps in the Literature

Despite a growing body of literature exploring digital transformation, artificial intelligence (AI), and cross-functional collaboration, significant research gaps persisted regarding the specific interplay between AI capabilities and the integration of sales and supply chain functions in manufacturing firms.

2.6.1 Limited Empirical Evidence on AI-Enabled Collaboration

While various studies have acknowledged the potential of AI to enhance operational efficiency and decision-making in supply chains (Wamba-Taguimdje et al., 2020; Bag et al., 2021), there remained a lack of empirical research that investigated how AI concretely supported integration between sales and supply chain departments. Existing studies are often conceptual, focused on technology adoption in isolation, or limited to supply chain operations without considering the dynamics of cross-functional interaction.

2.6.2 Incomplete Understanding of Customer-Centric Outcomes

Current research had only partially explored the customer-related outcomes of integrated collaboration, particularly in B2B manufacturing settings. While customer satisfaction was widely acknowledged as a strategic objective (Homburg et al., 2005; Anderson, Fornell & Lehmann, 1994), few studies systematically examined how AI-enabled collaboration between sales and supply chain functions impacted delivery reliability, order responsiveness, or service personalization

2.6.3 Insufficient Insight into Organizational Enablers and Barriers

Another gap lay in the limited investigation of the organizational prerequisites and barriers that influenced the success of AI-supported collaboration. Although studies emphasized the relevance of leadership, culture, and change readiness (Westerman, Bonnet and McAfee, 2011; Kotter, 1996; Vial, 2019; Davenport and Ronanki, 2018), there was a lack of integrated frameworks that combined technical maturity with human and structural factors.

2.6.4 Lack of Mixed-Methods and Multilevel Research Designs

Finally, most previous research employed either quantitative or qualitative methods, but rarely both in a structured, sequential manner. There was also a lack of multilevel analyses that linked strategic, organizational, and operational perspectives. As suggested by Creswell & Plano Clark (2018), mixed-methods designs offered a more comprehensive view, but were underutilized in this context.

Summary of Identified Gaps

Research Gap	Description
1. Empirical Gap	Lack of evidence on how AI supports cross-functional collaboration in practice
2. Outcome Gap	Incomplete understanding of customer-centric benefits from integrated collaboration
3. Organizational Gap	Limited research on cultural, leadership, and structural enablers/barriers
4. Methodological Gap	Rare use of mixed-methods and multilevel designs for holistic understanding

Table 2.1: Summary of Identified Research Gaps

2.6.6 Managerial and Theoretical Implications of the Gaps

These research gaps were not merely academic but had important implications for practice. Many firms invested heavily in digital tools and AI platforms without aligning internal processes or addressing cultural barriers to collaboration. As a result, expected performance improvements often failed to materialize (Davenport & Ronanki, 2018). Understanding the interplay between technological capabilities and organizational readiness helped firms develop more realistic implementation strategies and enhanced return on investment.

Moreover, these gaps also signaled a need for theoretical refinement. While existing theories such as the Resource-Based View, OIPT, and Socio-Technical Systems Theory offered valuable perspectives, they needed to be operationalized in ways that reflected today's data-rich and fast-changing industrial environments (Barney, 1991; Tushman and Nadler, 1978; Trist and Bamforth, 1951; Vial, 2019; Dignum, 2018). This study contributed to this theoretical discourse by integrating findings into a conceptual model that linked AI capabilities, collaboration quality, and business outcomes—thus laying the foundation for Chapter 4.

CHAPTER 3

LITERATURE REVIEW

3.1 Collaboration for Business Performance and Efficiency between Sales and Supply Chain

3.1.1 Introduction

In the context of modern business practices, the collaboration between sales and supply chain functions has become a crucial driver of organizational performance and efficiency. Particularly in an increasingly competitive and globalized environment, companies must streamline their internal processes to respond flexibly to changes in demand and market dynamics (Puche et al., 2016). This literature review aims to analyze the key components and benefits of collaboration between sales and supply chain functions and assess how it impacts operational efficiency and business performance.

3.1.2 Supply Chain Collaboration

Supply chain collaboration refers to the joint efforts of multiple entities or departments along the supply chain to gain competitive advantages and maximize shared success (Puche et al., 2016). Successful collaboration involves optimizing information sharing, decision synchronization, and incentive alignment, enabling a holistic view of the supply chain and faster adjustments to external disruptions and demand fluctuations (Tuomikangas and Kaipia, 2014; Ralston, Blackhurst and Cantor, 2015). Studies have shown that organizations that improve their supply chain strategies through collaboration strengthen their market position and optimize their resource utilization (Puche et al., 2016).

3.1.3 Sales and Supply Chain Integration

One of the primary components of successful collaboration is the integration of sales and supply chain functions. Research demonstrates that the synchronization of sales and supply chain operations leads to improved demand-supply management, which in turn enhances customer satisfaction and reduces operational costs (Culot, Podrecca and Nassimbeni, 2024; Tuomikangas and Kaipia, 2014; Goh and Eldridge, 2015). By utilizing Sales and Operations Planning (S&OP), companies can improve their forecasting accuracy, optimize production schedules, and ensure product availability, ultimately boosting overall business performance (Ruzo-Sanmartín et al., 2023).

3.1.4 Business Performance through Collaboration

Collaboration between sales and supply chain functions significantly contributes to business performance. Close alignment between these areas enables companies to use resources more efficiently, improve process flows, and maximize value creation opportunities (Cao and Zhang, 2011; Flynn, Huo and Zhao, 2010). Research shows that process integration and information sharing between sales and supply chain functions form the foundation for sustainable improvements in operational efficiency (Nitsche et al., 2021). Companies that promote strong collaboration are not only more adaptable to market changes but also experience improved returns and competitiveness (Ruzo-Sanmartín et al., 2023).

3.1.5 Operational Efficiency and Collaboration

The close collaboration between sales and supply chain functions leads to a notable improvement in operational efficiency. Through coordinated information exchange and process integration, companies can optimize their supply chain structures, reducing costs and improving productivity (Culot, Podrecca and Nassimbeni, 2024). Additionally, modern technologies such as artificial intelligence (AI) and blockchain further support this process by automating tasks and providing real-time data for more efficient decision-making (Kashem et al., 2023). This enhances a company’s ability to respond flexibly to demand changes and ensures that companies remain competitive.

3.1.6 Collaboration Impact on Supply Chain Performance

Effective collaboration within the supply chain has significant impacts on overall supply chain performance. Companies that successfully integrate their sales and supply chain processes benefit from increased visibility, better planning, and enhanced flexibility (Flynn, Huo and Zhao, 2010). This leads to improved cost control, reduced inventory levels, and faster responses to customer requirements, ultimately improving efficiency and competitiveness (Culot, Podrecca and Nassimbeni, 2024). Research shows that companies with an integrated supply chain are better positioned to achieve long-term competitive advantages and sustain operational efficiency (Culot, Podrecca and Nassimbeni, 2024).

3.2 Challenges and benefits of sales and supply chain integration

3.2.1 Benefits of integration

Improved responsiveness and business performance. The integration of sales and supply chain is considered in the literature to be a central factor in increasing business performance. Ralston et al. (2014) argue that a strategic integration of these functions not only improves operational efficiency but also increases a company's ability to respond more quickly and flexibly to customer demands. This capability is critical to maintaining a competitive edge, especially in global markets where customers expect a rapid and precise response to their needs. Integrating sales and supply chain processes enables companies to synchronize logistics processes, thus avoiding bottlenecks in the supply chain, which leads to improved financial performance.

3.2.2 Optimization through Sales and Operations Planning (S&OP)

Another concept frequently highlighted in the literature is the implementation of Sales and Operations Planning (S&OP). Goh & Eldridge (2015) show that S&OP improves alignment between sales and supply chain, resulting in a reduction in lead times and improved forecasting accuracy. By using joint planning processes, companies can use their resources more efficiently and optimize delivery times, which has a positive impact on both customer satisfaction and operating costs. In the literature, S&OP is seen as a key process that supports the integration of sales and supply chain departments, enabling companies to be more agile and responsive to market changes.

3.2.3 Improving sales efficiency in international markets

The integration of sales and supply chain plays a particularly crucial role in international markets in improving sales efficiency. Coordination between sales and logistics yields stronger performance gains in countries with high logistics performance, as indicated by the World Bank’s Logistics Performance Index (World Bank, 2023; Gligor, Esmark and Holcomb, 2020). A well-integrated supply chain enables sales representatives to meet customer demands faster and more accurately, leading to improved competitive advantage. These studies illustrate that close collaboration between logistics and sales in international markets leads to greater customer satisfaction and increased sales performance, which also promotes long-term corporate growth.

3.2.4 Challenges of integration

Interdisciplinary collaboration and technological barriers. Despite the numerous advantages, there are significant challenges to implementing full integration between sales and supply chain. Lambert and Cooper (2000) point out that implementing integrated business processes requires close collaboration between different departments, which is often seen as a hurdle. This challenge is further exacerbated by the need for advanced technologies to enable seamless integration. Not only do companies need to invest in technological infrastructure, they also need to train employees to use the new systems effectively. Furthermore, there is a risk of internal silos developing if departments do not communicate sufficiently with each other, which makes integration more difficult and can lead to inefficient processes.

3.2.5 Sustainability requirements and operational efficiency

Another aspect discussed in the literature is sustainability in the supply chain. Walker et al. (2015) argues that by linking their supply chain processes with sustainability goals, companies can not only improve their operational efficiency but also fulfill their environmental obligations. However, integrating sustainability requirements presents an additional challenge because operational efficiency and environmental sustainability often conflict. Companies must therefore develop innovative approaches to achieve both their sustainability goals and efficient operational processes. The literature shows that close collaboration between sales and supply chain can also help promote more sustainable business practices, as both functions work towards optimized resource utilization and reduced environmental impacts.

3.2.6 Technological challenges of smart supply chains and AIoT

The integration of modern technologies such as Artificial Intelligence of Things (AIoT) also presents significant challenges. Nozari et al. (2022) emphasize that while the implementation of AIoT promises numerous efficiency gains, it also poses cybersecurity and infrastructure risks. Smart supply chains require high data availability and real-time communication to function effectively, which, however, places additional technical demands on infrastructure. Furthermore, Douaioui et al. (2022) point out that the complexity of smart supply chains often complicates coordination and decision-making within the supply chain, which presents additional hurdles for companies. These technological challenges make it clear that companies not only have to invest in new technologies, but also ensure that these technologies are seamlessly integrated into their existing processes.

3.2.7 Future perspectives

Alignment of supply chain and marketing strategies. The future of sales and supply chain integration requires an even closer alignment of supply chain and marketing strategies. Sutia (2022) argues that an integrated alignment of these two functions will enable companies not only to better manage fluctuations in demand but also to achieve their sustainability goals. This strategic alignment is crucial to meeting both customer expectations and global environmental sustainability requirements. The literature suggests that companies that align their marketing and supply chain strategies more closely can achieve greater flexibility and agility, leading to improved competitive performance and customer satisfaction.

3.3 Artificial intelligence in the supply chain

The application of artificial intelligence (AI) in the supply chain is a growing area of research that aims to improve efficiency, decision-making, and sustainability (Choi, Wallace and Wang, 2018; Wamba-Taguimdje et al., 2020; Bag, Pretorius and Gupta, 2021; Wang et al., 2016). Various studies show that AI is increasingly being used in the supply chain in areas such as demand forecasting, inventory management, and logistics optimization (Choi, Wallace and Wang, 2018; Wang et al., 2016). AI enables companies to use resources more efficiently through intelligent automation and predictive analytics, resulting in cost reduction and improved resource allocation (Davenport and Ronanki, 2018; Wang et al., 2016).

3.3.1 Use of AI for forecasting and decision-making processes

The use of AI for forecasting is a hotly debated topic in the current literature. Various studies underscore that AI is able to process historical data, market trends and real-time information to make more accurate predictions, particularly in the area of demand forecasting and inventory management (Choi, Wallace and Wang, 2018; Wang et al., 2016). This leads to optimization of inventory control by avoiding overstocking and minimizing shortages.

Furthermore, the literature emphasizes that AI-based systems can automate decision-making processes, particularly by applying machine learning algorithms based on data patterns. These automated decision-making processes enable faster responsiveness to market fluctuations and reduce the risk of wrong decisions (Wamba-Taguimdje et al., 2020). The efficiency of decision-making is significantly increased by AI, especially in dynamic and volatile markets (Culot, Podrecca and Nassimbeni, 2024).

Research gaps: Despite the numerous advantages of AI in the area of forecasting, there are still research gaps in the literature, especially with regard to the long-term implementation and sustainability of such systems. Future studies should focus on the ethical implications and transparency of decision algorithms (Cannas et al., 2024).

3.3.2 Impact of AI on supply chain transparency and automation

AI has the potential to significantly improve transparency in the supply chain, which is seen as a crucial advantage in the literature. Studies show that AI systems can provide real-time data to enable monitoring of inventories, deliveries, and transport routes, resulting in increased responsiveness to disruptions and market fluctuations (Chaudhari, 2021; Douaioui et al., 2022). AI-based technologies enable companies to achieve better visibility into their global supply chains, which is a competitive advantage, especially in complex and multi-level supply chains (Nsisong & Eyo-Udo, 2024).

Automation in the supply chain is also considered an important area where AI plays a transformative role. By integrating AI with IoT technologies, processes such as warehousing, inventory management, and logistics can be fully automated (Qu et al., 2024). This results in cost savings and productivity increases (Culot, Podrecca and Nassimbeni, 2024). The automation of processes through AI is described in the literature as a means of optimizing resource utilization and reducing human error (Choi et al., 2018)

Challenges and research gaps: Despite the advantages of AI in the supply chain, there are significant challenges to implementation, particularly with regard to data quality, cybersecurity, and privacy (Pandey et al., 2023). The literature points out that companies need to implement comprehensive security measures to ensure the integrity of data. Furthermore, there is a shortage of skilled professionals needed to operate and maintain AI-powered systems (Cannas et al., 2024).

3.3.3 Future prospects and ethical implications

One area that is gaining increasing attention in the literature is the ethical implications of using AI in supply chain. Studies emphasize the importance of developing ethical guidelines for the use of AI, particularly regarding algorithmic transparency and privacy (Pandey et al., 2023). Future research should pay more attention to the ethical dimension of AI implementations to ensure that AI systems are used responsibly and fairly (Brintrup et al., 2023).

Furthermore, AI combined with emerging technologies such as blockchain and quantum computing is expected to have a significant impact on the resilience and sustainability of supply chains in the coming years. Future studies should focus on the long-term effects of these technologies and their interactions with AI (Brintrup et al., 2023).

3.4 Customer Satisfaction and Market Responsiveness

In global contexts, supply chain management (SCM) is especially important in assessing customer satisfaction and an organization's capacity to adapt to changing market conditions. Numerous studies highlight how data-driven supply chains positively impact both manufacturing capabilities and customer satisfaction by enhancing efficiency, accuracy, and flexibility (Chavez et al., 2017). As global competition intensifies, companies must rely on efficient SCM practices to meet customer expectations and remain competitive in dynamic markets (Gligor et al., 2020).

3.4.1 Customer satisfaction and the performance of the supply chain.

The performance of the supply chain directly influences customer satisfaction by ensuring timely delivery, product availability, and responsive service. According to Chavez et al. (2017), companies that implement data-driven supply chains can improve both manufacturing performance and customer satisfaction by enabling more accurate forecasting and reducing inventory shortages. The literature consistently shows that supply chain agility is a key factor in enhancing customer value for both B2B and B2C customers (Gligor et al., 2020). Improved customer satisfaction and loyalty can be attained by businesses through supply chain agility, which enables them to react faster to external changes and client needs.

3.4.1.1 Supply Chain Integration and Customer Satisfaction

Moreover, Świtała et al. (2018) found that the adaptability of logistics providers significantly impacts the performance of logistics outsourcing, which in turn affects customer retention. Effective SCM practices enable companies to provide high-quality services, ensuring that customers receive their products on time and in good condition, which is essential for building and maintaining customer loyalty (Ghoumrassi & Țigu, 2018).

The integration of the supply chain also plays a significant role in improving customer satisfaction. Studies suggest that supply chain integration—where all parties within the supply chain work together closely—leads to greater efficiency and ultimately better customer experiences (Flynn, Huo and Zhao, 2010). Additionally, supply chain visibility and real-time tracking systems are vital in creating transparency and trust between companies and their customers, further enhancing satisfaction (Wang et al., 2021).

3.4.1.2 Challenges in Balancing Customization and Efficiency

However, challenges remain, particularly when companies face high levels of customization or demand variability. These factors can strain the supply chain, making it difficult to maintain high service levels without incurring additional costs (Christopher, 2016). Therefore, firms must carefully balance the need for efficiency with the demand for customization to meet customer expectations effectively.

3.4.2 The Role of Market Responsiveness in Global Companies

In the context of global business, market responsiveness is defined as the ability of a company to quickly adapt to shifts in customer preferences, market trends, and external disruptions. Gligor et al. (2020) highlight that agility in the supply chain is essential for meeting these challenges, as it allows companies to quickly reconfigure their operations to respond to changes in customer demand. For global companies, being responsive to regional market differences while maintaining global efficiency is crucial for sustaining a competitive advantage (Gunasekaran et al., 2018).

3.4.2.1 Supply Chain Agility and Competitive Advantage

Studies show that supply chain agility, combined with lean and agile strategies, enhances business performance by enabling companies to balance cost control with customer responsiveness (Gligor et al., 2020). In particular, agile supply chains enable companies to respond quickly to market fluctuations, thereby improving customer satisfaction. Agile approaches also contribute to business continuity, as they allow firms to adapt their supply chains to unforeseen events such as natural disasters or geopolitical disruptions (Gligor et al., 2020).

3.4.2.2 The Role of Logistics Adaptability in Customer Retention

Świtała et al. (2018) emphasize the role of logistics adaptability in maintaining logistics outsourcing performance. Companies that work with adaptable logistics providers are better equipped to handle changes in market demand or supply chain disruptions, ultimately enhancing customer satisfaction and retention.

3.4.2.3 The Impact of Predictive Analytics on Market Responsiveness

The integration of advanced technologies such as AI and predictive analytics is increasingly helping companies improve their market responsiveness (Wang et al., 2021). These technologies allow companies to anticipate market shifts, adjust inventory levels, and reduce lead times, thereby increasing both supply chain efficiency and customer satisfaction.

Despite the clear benefits of market responsiveness, global companies face challenges in balancing cost efficiency with the need for flexibility. Companies operating across multiple regions must navigate logistical constraints and regulatory barriers, which can impede their ability to quickly respond to local market demands (Zhang et al., 2022). Future research should explore how digital transformation can further enhance market responsiveness, particularly in overcoming these operational barriers.

3.5 AI-Supported Collaboration Between Supply Chain and Sales

The integration of artificial intelligence (AI) in supply chain management (SCM) has been a game changer in recent years, significantly influencing collaboration between sales and supply chain teams. AI-driven systems enhance communication and coordination, enabling real-time information exchange, which is critical for maintaining supply chain resilience (Riad et al., 2024). AI optimizes various SCM processes, including demand forecasting, inventory management, and logistics, resulting in better alignment between sales forecasts and supply chain capacities (Nsisong Louis & Eyo-Udo, 2024; Richey et al., 2023).

3.5.1 Improved Coordination Through AI-Supported Systems

One of the key benefits of integrating AI into SCM is the improvement in coordination between sales and supply chain functions. AI enables predictive analytics that help both departments anticipate changes in customer demand, facilitating faster and more accurate decision-making (Choi et al., 2018). This predictive capability allows companies to optimize their resource allocation and manage their supply chains more effectively. Additionally, AI-driven technologies create real-time transparency across the supply chain, allowing sales teams to provide customers with up-to-date information on product availability and delivery times (Helo & Hao, 2022). By reducing the uncertainties associated with demand fluctuations, AI enhances the ability of sales and supply chain teams to work together seamlessly.

Despite these benefits, some challenges remain, including issues related to data quality, the need for skilled professionals, and the high investment costs required to implement AI technologies effectively (Cannas et al., 2024; Shrivastav, 2021). These barriers can slow down the adoption of AI in some industries, but the long-term benefits of AI-driven coordination in SCM are undeniable.

3.5.2 Process Optimization and Customer Service Improvement Through AI

AI also plays a critical role in process optimization within supply chain operations, leading to enhanced customer service. By integrating AI algorithms into SCM, companies can automate repetitive tasks such as order processing, inventory updates, and logistics scheduling, reducing the time and effort required to manage these processes manually (Alomar, 2022). This automation not only cuts operational costs but also improves the overall efficiency of the supply chain, enabling faster responses to customer inquiries and orders.

Furthermore, AI-powered predictive analytics enable companies to proactively manage their inventory levels and demand forecasts, reducing the likelihood of stockouts or overstocking, both of which can negatively impact customer satisfaction (Brintrup et al., 2023). The ability to predict market trends and customer demand allows businesses to offer more personalized and responsive services, ultimately enhancing customer loyalty.

While AI holds significant potential for process optimization and customer service enhancement, companies must also be prepared to address the challenges that accompany AI adoption, such as ethical considerations, data governance, and the need for continuous investments in AI technologies (Cannas et al., 2024). Nonetheless, the potential for AI to revolutionize supply chain operations and improve competitiveness and resilience is considerable, positioning companies that embrace these technologies at a distinct advantage in the evolving business landscape.

3.6 Gaps in the Literature

While much research has been conducted on both sales and supply chain management (SCM) as individual functions, there is a notable gap in studies that thoroughly investigate their integration and the impact of this integration on operational performance, customer satisfaction, and market responsiveness. These gaps leave several critical questions unanswered and highlight areas where further research is needed.

3.6.1 Lack of an Integrated Approach for Sales and Supply Chain

The literature indicates that many organizations continue to manage sales and supply chain as distinct silos, leading to a range of inefficiencies and misaligned strategies. Although research recognizes the importance of aligning sales forecasts with supply chain capabilities, there is a distinct lack of empirical studies that explore the mechanisms for achieving this integration effectively (Wang et al., 2021). The literature often focuses on theoretical frameworks for collaboration but falls short when addressing practical solutions and implementation strategies.

3.6.1.1 Coordination Between Sales and SCM

One key gap is the limited understanding of how to achieve effective coordination between sales forecasting and SCM. Most studies discuss the importance of aligning these two functions but do not provide comprehensive insights into the tools, technologies, or organizational structures that can support such integration (Christopher, 2016; Gligor et al., 2020). Furthermore, research often overlooks the role of cross-functional teams and real-time data-sharing platforms, which are critical to ensuring the successful integration of sales and SCM processes (Wang et al., 2021).

3.6.1.2 Impact on Customer Satisfaction

Another underexplored area is the direct impact of sales and supply chain integration on customer satisfaction. While it is generally accepted that seamless coordination can improve product availability and on-time delivery, few studies have empirically tested how supply chain agility and sales responsiveness directly affect customer loyalty and retention in various industries (Flynn, Huo and Zhao, 2010). Most existing research remains conceptual, with little focus on real-world outcomes (Ghoumrassi & Țigu, 2018).

3.6.1.3 Technological Integration

The role of technology, particularly artificial intelligence (AI) and automation, in bridging the gap between sales and SCM is still underexplored. Although there are many discussions on the benefits of AI for demand forecasting and inventory management, very few studies explore how these technologies can align sales strategies with supply chain capabilities in real time (Richey et al., 2023). Additionally, the challenges of integrating AI systems across sales and SCM departments, such as data silos, cybersecurity risks, and ethical concerns, are rarely addressed in the literature (Shrivastav, 2021).

3.6.1.4 Strategic Alignment and Operational Efficiency

Most of the existing literature does not adequately address the strategic alignment between sales and SCM, particularly in the context of global operations. Gligor et al. (2020) and Flynn, Huo and Zhao (2010) touch on the benefits of aligning these functions for improving operational efficiency, but they do not delve into the specific organizational changes or management practices required to achieve this. This gap highlights the need for further research into how companies can foster a culture of collaboration between sales and SCM and what metrics can be used to measure the success of such integration efforts.

3.6.1.5 Global Supply Chains and Market Responsiveness

Finally, there is a notable gap in research on the impact of sales and SCM integration on market responsiveness, particularly in global supply chains. While market responsiveness is crucial for maintaining a competitive edge in global markets, few studies focus on how companies can simultaneously optimize their global supply chain operations and local sales strategies (Gligor et al., 2020). Understanding this balance between global efficiency and local flexibility remains an open question in the literature (Zhang et al., 2022).

3.6.2 Need for research on the integration of sales and supply chain: technological approaches and strategy

In summary, the literature reveals several key gaps in understanding how to effectively integrate sales and supply chain management to improve operational efficiency, customer satisfaction, and market responsiveness. Further research is needed to explore technological solutions, cross-functional collaboration, and strategic alignment to address these challenges and optimize performance in an increasingly complex global environment.

3.6.3 Lack of an Integrated Approach for Sales and Supply Chain

In reviewing the literature, a significant gap exists in the understanding and application of an integrated approach between sales and supply chain management (SCM). While both functions are widely recognized as critical to operational success, research examining how these two domains can be effectively integrated to improve operational efficiency, customer satisfaction, and market responsiveness remains limited.

3.6.3.1 Coordination Challenges

The literature identifies coordination as one of the main challenges in aligning sales with supply chain operations. Many studies highlight the importance of synchronizing sales forecasts with supply chain capabilities, but there is little empirical evidence or case studies that provide practical frameworks for achieving this integration (Christopher, 2016; Gligor et al., 2020). Most research focuses on the benefits of integration without exploring operational models or decision-making tools that can facilitate real-time collaboration between these departments (Wang et al., 2021).

3.6.3.2 Impact on Customer Satisfaction

Although customer satisfaction is often linked to supply chain performance, the specific effects of integrating sales and SCM on customer outcomes are underexplored in the literature. While it is accepted that supply chain agility improves delivery times and service levels, few studies investigate how this impacts long-term customer loyalty or customer retention in various sectors (Flynn, Huo and Zhao, 2010). Additionally, most of the research remains conceptual, with little empirical validation of the claims regarding the customer benefits of integrated sales and SCM strategies (Ghoumrassi & Tigu, 2018).

3.6.3.3 Technological Integration

Another critical gap concerns the role of technology—specifically, artificial intelligence (AI) and automation—in integrating sales with SCM. Although many studies discuss the potential of AI to enhance supply chain operations, few explore how AI-driven insights can be leveraged to align sales strategies with supply chain capabilities (Pandey et al., 2023). The literature lacks discussions on the technical barriers and organizational changes required to implement real-time AI tools that support cross-functional collaboration between sales teams and supply chain managers.

3.6.3.4 Strategic Alignment

The importance of aligning sales and SCM objectives is another area where gaps in the literature persist. While strategic alignment is often discussed in theoretical terms, there is limited practical guidance on how organizations can structure collaborative processes or design performance metrics that reflect the success of this integration (Goli, 2022). Studies often overlook the management practices necessary for fostering a collaborative culture between these two functions, especially in global organizations with complex supply chains (Gligor et al., 2020).

3.6.3.5 Global Supply Chains and Responsiveness

Finally, research on market responsiveness in global contexts is still insufficient. Global supply chains face unique challenges in aligning local market needs with global operations. There is a significant gap in how firms can balance global efficiency with local adaptability while integrating sales and SCM processes (Zhang et al., 2022). Although market responsiveness is recognized as essential for competitiveness, few studies provide models or frameworks for how sales teams and supply chains can work together to achieve this balance effectively.

3.6.3.6 Need for research into the practical integration of sales and supply chain: technological solutions and strategic approaches

In summary, while the literature provides theoretical discussions on the importance of integrating sales and SCM, there are clear gaps in understanding how this can be achieved in practice. Future research should focus on developing technological solutions, cross-functional collaboration models, and strategic alignment practices that can help organizations optimize operational performance, enhance customer satisfaction, and improve market responsiveness in a rapidly evolving global marketplace.

CHAPTER 4

THEORETICAL FRAMEWORK

4.1 Introduction

This chapter outlines the theoretical foundation of the study, which investigates AI-supported collaboration between supply chain and sales functions in manufacturing firms. Theoretical grounding is essential in empirical research to frame the study's conceptual underpinnings, interpret findings, and guide the choice of research methodology. In line with the research problem and objectives, three interrelated theories are adopted: the Resource-Based View (RBV), the Organizational Information Processing Theory (OIPT), and the Socio-Technical Systems Theory (STS). Together, these theories provide a multi-level perspective to understand how technological capabilities, information flows, and organizational structures interact to enable effective AI-supported collaboration between supply chain and sales teams.

4.2 Resource-Based View (RBV)

The Resource-Based View (RBV), developed by Barney (1991), asserts that firms achieve sustainable competitive advantage by acquiring and deploying valuable, rare, inimitable, and non-substitutable (VRIN) resources. In the context of this study, RBV explains how the strategic use of AI technologies—such as predictive analytics, real-time dashboards, and decision automation—can serve as critical organizational resources that enhance the firm's responsiveness and customer satisfaction (Wernerfelt, 1984; Barney & Hesterly, 2019).

When AI capabilities are integrated into both supply chain and sales functions, they generate cross-functional value by improving information accuracy, enabling better forecasting, and facilitating synchronized decision-making (Chavez et al., 2017). However, the mere possession of AI tools is not sufficient to generate competitive advantage. According to RBV, it is the firm's ability to combine these technologies with organizational capabilities—such as skilled personnel, learning routines, and aligned strategies—that determines their strategic impact (Wamba et al., 2017).

Furthermore, in manufacturing contexts characterized by high demand variability and complex customer requirements, AI can help firms better allocate resources, optimize planning, and respond quickly to market shifts. These AI-enabled routines can become "firm-specific" and difficult for competitors to imitate, especially when embedded into organizational culture and business processes (Teece, Pisano & Shuen, 1997). Thus, RBV underscores the need to view AI not merely as a tool, but as a core resource that supports collaborative advantage between supply chain and sales units.

4.3 Organizational Information Processing Theory (OIPT)

The Organizational Information Processing Theory (OIPT), introduced by Galbraith (1973) and later expanded by Tushman & Nadler (1978), focuses on the capacity of organizations to process information in order to reduce uncertainty and enhance decision quality. OIPT posits that when task uncertainty increases—due to environmental complexity, time pressure, or interdependent workflows—organizations must increase their information processing capability through structural or technological means.

This theory is particularly relevant in the context of AI-enabled collaboration. Modern manufacturing organizations operate in volatile environments, where supply chain disruptions, changing customer expectations, and global competition demand rapid responses and accurate decisions. The integration of sales and supply chain functions—each with different information needs and decision logics—exacerbates the need for timely, high-quality information exchange.

AI technologies fulfill this need by improving data accessibility, automating forecasting, and enabling real-time insights. For example, machine learning algorithms can provide sales teams with demand signals based on customer behavior, while supply chain planners can access sales forecasts and inventory levels through shared dashboards. These capabilities enhance the “information richness” required for cross-functional coordination, as suggested by OIPT (Daft & Lengel, 1986).

In this research, OIPT helps conceptualize AI as an enabler of information processing across organizational boundaries. It also underscores the importance of shared systems and communication structures that support joint decision-making between supply chain and sales managers.

4.4 Socio-Technical Systems Theory (STS)

The Socio-Technical Systems Theory (STS), first proposed by Trist and Bamforth (1951), highlights the interdependence between technical systems (e.g., technologies, tools, workflows) and social systems (e.g., people, culture, structures) within organizations. STS argues that technological implementations are most successful when accompanied by corresponding social and organizational changes (Pasmore, 1985; Clegg, 2000).

In this study, STS is crucial for understanding the implementation of AI tools in collaborative contexts. While AI provides significant technical benefits—such as automation, prediction, and optimization—its effectiveness depends on human factors such as acceptance, communication, training, and trust. For example, the success of AI-supported platforms for joint planning depends not only on technical reliability but also on the willingness of employees to share data, adjust workflows, and engage in joint problem-solving.

Furthermore, resistance to change, departmental silos, or lack of leadership support may act as "socio-organizational" barriers that inhibit collaboration, even when powerful technologies are available (Bostrom & Heinen, 1977). STS thus complements the technical focus of OIPT and RBV by introducing human-centric dimensions into the analysis of AI-supported collaboration.

In the context of this research, STS helps explain why some AI implementations succeed in fostering collaboration, while others fail due to cultural misalignment, inadequate training, or insufficient stakeholder involvement. It also justifies the study's inclusion of both qualitative and quantitative data on organizational enablers such as trust, leadership, and interdepartmental communication.

4.5 Conceptual Framework

Based on the three theories described above, the following conceptual framework guides the empirical investigation of this study. It posits that AI capabilities influence collaboration quality between sales and supply chain functions, and that this relationship is moderated by organizational enablers such as leadership support, data governance, and cross-functional trust. Improved collaboration is expected to lead to enhanced operational efficiency, customer satisfaction, and market responsiveness.

Key Constructs:

- AI Capabilities: predictive analytics, real-time data visualization, automation of planning and communication.
- Organizational Enablers: leadership involvement, change readiness, trust, data quality, and digital infrastructure.
- Collaboration Quality: frequency and richness of communication, joint planning activities, goal alignment, and feedback mechanisms.

- Outcomes: improved delivery performance, planning accuracy, customer service levels, and responsiveness to market changes.

The framework is designed to be tested through both qualitative interviews (to capture perceptions and lived experiences) and quantitative surveys (to measure relationships between constructs). This dual approach aligns with the mixed-methods strategy and ensures that insights are grounded in both theory and practice.

4.6 Hypotheses

Based on the research questions and the conceptual framework developed in this study, the following hypotheses were formulated to empirically examine the effects of AI-driven collaboration between Sales and Supply Chain functions in manufacturing industries:

- H1: AI-enabled collaboration between Sales and Supply Chain functions positively influences customer satisfaction in manufacturing organizations.
- H2: AI-enabled collaboration between Sales and Supply Chain functions positively influences market responsiveness.
- H3: The level of organizational collaboration moderates the relationship between AI usage and operational efficiency.
- H4: Data fragmentation and organizational silos negatively affect the effectiveness of AI-enabled collaboration.
- H5: Higher AI maturity levels within the organization are positively associated with overall business performance, as perceived by Sales and Supply Chain managers.

These hypotheses served as the foundation for the quantitative survey, which examined relationships between AI maturity, collaboration levels, organizational barriers, and performance outcomes. The results are analyzed in Chapter 6 and discussed in light of the theoretical framework in Chapter 7.

4.7 Summary

This chapter has established a robust theoretical foundation for analyzing AI-supported collaboration between supply chain and sales functions. By integrating RBV, OIPT, and STS, the framework captures the strategic, informational, and socio-organizational dimensions of the phenomenon under study. RBV explains the role of AI as a strategic resource; OIPT highlights its function as an information-processing enabler; and STS provides a lens for examining human and cultural factors.

These theories collectively inform the research design and instrument development, guiding both the qualitative and quantitative strands of the mixed-methods approach. The proposed conceptual framework not only offers a structured lens for empirical investigation but also lays the groundwork for generating actionable managerial insights on how to enhance collaboration in AI-augmented organizational settings.

CHAPTER 5

RESEARCH METHOLOGY

5.1 Introduction

This chapter outlines the research methodology adopted for investigating how artificial intelligence (AI) supports collaboration between supply chain and sales functions in manufacturing firms. The chapter details the overall research strategy, the rationale for adopting a mixed-methods approach, and the procedures for data collection, analysis, and validation.

The study is designed to explore both the organizational realities and perceived impacts of AI-driven collaboration by integrating qualitative and quantitative data sources. This triangulated approach is intended to ensure a deeper understanding of the complex dynamics between sales and supply chain integration, organizational enablers, and performance outcomes. As Creswell and Plano Clark (2018) argue, mixed-methods research enables researchers to capitalize on the strengths of both qualitative and quantitative traditions, offering a more complete and nuanced picture of social phenomena.

The qualitative strand of the study consists of semi-structured interviews with decision-makers from sales and supply chain management roles. These interviews aim to explore how AI tools are implemented, what organizational enablers and barriers exist, and how collaboration manifests in daily operations. The quantitative component, in contrast, is based on a structured survey designed to measure constructs such as AI capability, collaboration quality, and customer satisfaction using established scales and metrics.

The central research question—*"How does AI-supported integration between sales and supply chain functions influence collaboration quality, operational* *performance, and customer satisfaction?"*—is investigated using both exploratory and confirmatory data collection methods. The qualitative data will help develop themes and contextual understanding, while the quantitative data will validate these findings and test hypothesized relationships.

A pragmatic research philosophy underpins this approach, recognizing that complex business problems benefit from methodological pluralism. Pragmatism accepts that different types of data offer different but complementary insights and supports the combination of inductive and deductive reasoning (Tashakkori & Teddlie, 2010). This philosophical stance is especially relevant in management research, where practical applicability and real-world relevance are key objectives.

The remainder of this chapter is structured as follows: Section 5.2 outlines the philosophical foundation and research approach. Section 5.3 explains the design and rationale for using a mixed-methods strategy. Section 5.4 describes the data collection processes, including participant recruitment and instrument development. Section 5.5 details the data analysis techniques for both qualitative and quantitative data. Section 5.6 addresses ethical considerations, and Section 5.7 summarizes the methodological framework of the study.

5.2 Research Philosophy and Approach

The selection of a research philosophy provides the foundational worldview that guides methodological choices and influences how knowledge is constructed, interpreted, and validated (Saunders et al., 2019). For this study, a pragmatic philosophy was adopted due to its emphasis on practical solutions to complex organizational problems and its compatibility with mixed-methods designs (Morgan, 2007).

5.2.1 Pragmatism as Philosophical Foundation

Pragmatism asserts that the value of research lies in its ability to address real-world problems and improve practice. It recognizes that no single system of philosophy or reality is sufficient to address the intricacies of organizational behavior, especially in environments shaped by technological transformation, such as AI integration in manufacturing (Creswell & Plano Clark, 2018). Rather than adhering strictly to positivism (focused on observable facts) or interpretivism (centered on social constructs), pragmatism embraces both objective and subjective realities. This dual orientation makes it especially suitable for investigating how AI tools influence cross-functional collaboration, which involves both quantifiable metrics and socially embedded dynamics.

In this study, pragmatism supports the integration of deductive reasoning (used in the quantitative survey) and inductive reasoning (used in qualitative interviews). This allows the researcher to explore perceptions and practices around AI-supported collaboration and then test key relationships empirically across a broader sample.

5.2.2 Research Paradigm and Epistemological Position

From an epistemological standpoint, the pragmatic approach rejects the notion of absolute truth and instead values pluralism and contextual relevance (Biesta, 2010). Knowledge is viewed as situated and actionable, which aligns with the study's focus on generating managerial implications for AI-supported integration of sales and supply chain functions. The epistemological stance acknowledges that different stakeholders (e.g., sales managers, supply chain planners, IT leaders) may have different but equally valid perspectives on collaboration effectiveness and AI value creation.

This pluralistic orientation justifies the use of interviews to explore stakeholder-specific views and a survey to measure patterns and generalizable relationships. In doing so, the study reflects methodological complementarity, where different methods are used to explore different facets of a complex phenomenon (Tashakkori & Teddlie, 2010).

5.2.3 Ontological Assumptions

The ontological position of this research is relativist, as it assumes that reality is socially constructed and shaped by the perceptions, interactions, and experiences of organizational actors. AI-supported collaboration is not merely a technical process; it is also a socio-organizational one that varies between firms depending on leadership, trust, data quality, and company culture. The qualitative portion of this research is designed to capture these nuances and reflect how individuals make sense of AI systems in their specific work contexts.

Simultaneously, the study recognizes the existence of measurable patterns—such as collaboration frequency, perceived efficiency, and satisfaction levels—which justifies a positivist orientation within the quantitative strand. This dual ontological position is a hallmark of pragmatic research and allows for a rich and multidimensional understanding of the phenomenon under investigation (Saunders et al., 2019).

5.2.4 Research Approach: Mixed Deductive and Inductive Logic

The research adopts a hybrid logic of inquiry that combines both deductive and inductive reasoning. Deductive reasoning is employed to test hypotheses derived from the literature and conceptual framework (e.g., the impact of AI capabilities on collaboration quality), while inductive reasoning is used to derive new insights and themes from the interview data.

This iterative interplay between theory and data enhances the study’s rigor and relevance. As recommended by Bryman (2016), combining inductive and deductive strategies enables researchers to both validate existing theories and generate new conceptualizations that are grounded in practice.

5.3 Research Context

This section outlines the context in which the empirical data was collected, offering essential background on the industry environment, organizational characteristics, and regional dynamics influencing AI-supported collaboration between sales and supply chain. The chosen context significantly shapes the interpretation of findings and the relevance of managerial implications.

5.3.1 Industrial Context

The research focuses on the manufacturing sector, with a specific emphasis on companies involved in complex production, logistics, and sales processes across Europe, Middle East and Africa (EMEA) and North America. These firms typically operate within highly competitive markets characterized by global supply chains, customized customer requirements, and increasing demands for operational efficiency and responsiveness.

Due to the complex interplay between production planning, inventory control, order fulfillment, and sales forecasting, the manufacturing industry represents a highly suitable environment for studying AI-supported collaboration. In this context, organizations are under continuous pressure to synchronize planning and customer-facing activities in real time—making them ideal candidates for evaluating how AI technologies facilitate cross-functional integration.

5.3.2 Organizational Characteristics

The participating organizations vary in size, ranging from medium-sized enterprises to large multinational corporations. Most operate in B2B environments, supplying products such as pumps, valves, industrial systems, or mechanical components. These offerings often require tailored configurations, long lead times, and strict quality requirements, further emphasizing the need for seamless coordination between supply chain and sales functions.

Common characteristics among the firms include the presence of decentralized teams, multi-site production units, and regionally distributed sales forces. These structural features create inherent coordination challenges that demand robust communication frameworks and data-driven integration. As such, they provide an ideal testing ground for understanding the potential of AI to bridge organizational silos.

In addition to core manufacturing industries, the sample also includes firms from highly regulated sectors such as the pharmaceutical industry. These organizations face particularly stringent coordination requirements due to compliance obligations, batch traceability, and supply continuity. This underscores the importance of robust cross-functional collaboration and provides valuable insight into AI-supported integration under complex regulatory conditions.

5.3.3 Digital Maturity and AI Readiness

The participating organizations demonstrate varying degrees of digital maturity. Some are in the early stages of digitization, focusing on foundational technologies such as ERP or CRM systems. Others are further advanced, having already adopted AI-powered forecasting tools, machine learning algorithms for inventory optimization, or chatbots for customer communication.

This heterogeneity in digital readiness enables the study to capture a wide spectrum of organizational experiences, from aspirational to mature AI implementations. It also facilitates the examination of contextual enablers and inhibitors, including leadership support, data quality, and interdepartmental trust, which are critical for successful technology adoption and collaboration.

5.3.4 Relevance of AI-Supported Integration

The integration of AI in supply chain and sales activities is increasingly viewed as a strategic differentiator in the manufacturing sector. Real-time data analytics, predictive maintenance, dynamic pricing, and automated decision-making are no longer viewed as optional tools but as essential components of a competitive operating model.

By focusing on AI-supported integration, the study investigates not only technical deployments but also the broader organizational, behavioral, and cultural shifts required to translate technology into value. The qualitative interviews and quantitative survey questions are therefore designed to examine how AI tools impact communication, forecasting accuracy, customer satisfaction, and market responsiveness.

5.3.5 Geographic Scope and Cultural Considerations

To better understand the scope and composition of the quantitative dataset, this section provides a descriptive overview of the survey sample. A total of 187 participants completed the structured questionnaire, which forms the quantitative foundation of this mixed-methods study. While the detailed survey design, constructs, and measurement instruments are outlined in Section 5.4, the following subsections highlight the geographic, organizational, and sectoral characteristics of the sample. These attributes are crucial for interpreting the representativeness and generalizability of the findings.

The participant base covers five major global regions—Europe, North America, South America, Asia, and Africa—with the highest response rates recorded in Germany (30.77%), Denmark (11.24%), and the United States (11.24%). While the outreach was global, the final sample was predominantly composed of participants from the EMEA and Americas region. However, all participating firms operate production sites in Europe, ensuring contextual alignment with the study's regional focus. This global spread aligns with the study’s objective of generating insights that are both culturally diverse and globally relevant, especially in relation to AI-supported collaboration practices across different organizational systems.

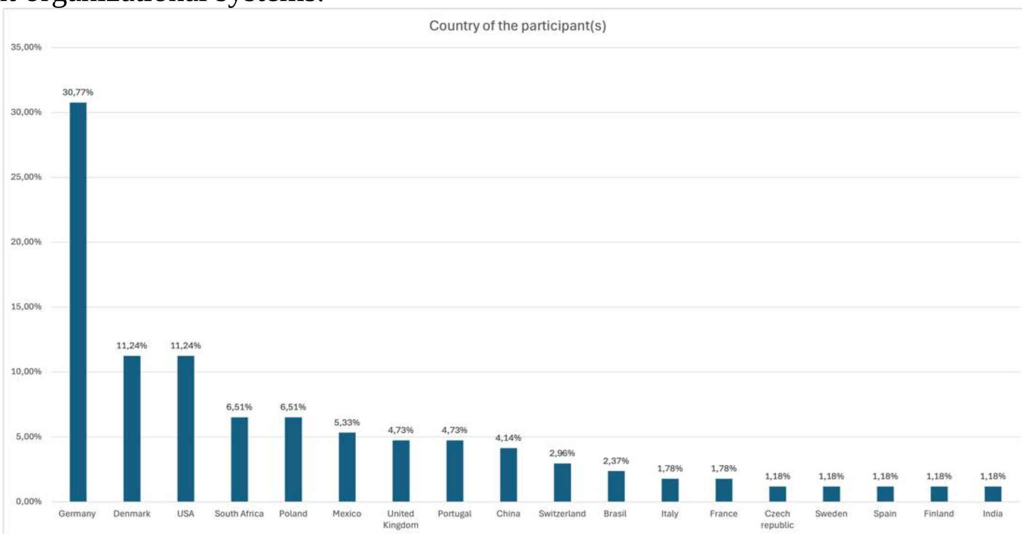

Figure 5.1. Geographic distribution of survey participants

The survey population reflects a range of industrialized economies with differing levels of digital maturity, regulatory frameworks, and AI adoption readiness. European countries such as Germany, Denmark, and Poland are known for their structured industrial processes, high compliance with GDPR data regulations, and growing focus on sustainability. In contrast, the U.S. and several emerging markets demonstrate greater organizational agility, faster AI experimentation, and a more decentralized decision-making culture. These contrasts enrich the analysis by offering comparative insights into how geography and culture shape AI implementation in supply chain and sales functions.

Participants were recruited through a targeted campaign on LinkedIn, explicitly aimed at professionals from Supply Chain Management, Sales, Information Technology (IT), and General Management roles. This strategy ensured a high level of functional relevance, as respondents were directly engaged in, or responsible for, AI-enabled cross-functional collaboration. This purposeful sampling approach strengthens the study's ecological validity by capturing real-world experiences and perspectives from business practice.

In terms of hierarchical position, 28.88% of respondents identified as Senior Management, while 23.53% belonged to Middle Management. Other respondents included team leaders, C-level executives, and domain specialists. These management-level responses provide rich insight into the strategic and operational dimensions of AI-supported collaboration, particularly regarding decision-making, cross-functional alignment, and technology implementation.

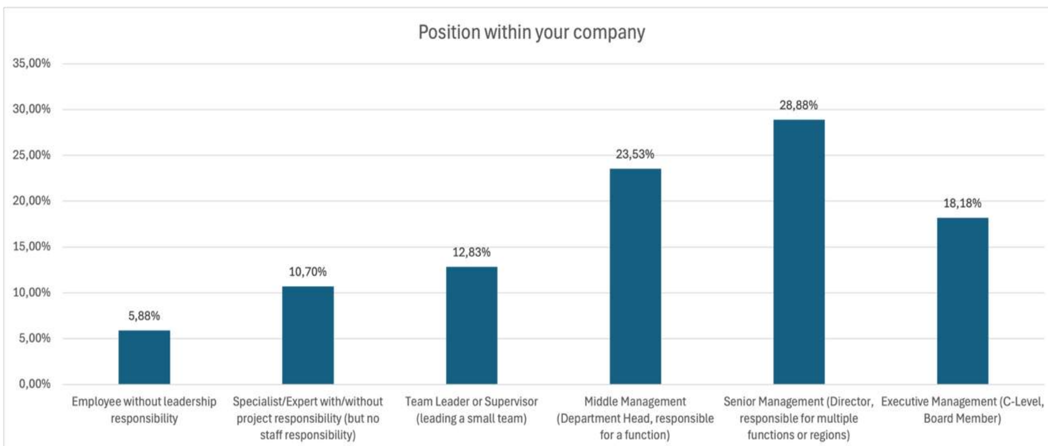

Figure 5.2. Position of participants within their organizations

The industry affiliation of participants was also diverse. The manufacturing sector accounted for the largest share (34.22%), followed by technology and IT (15.51%) and machinery and plant engineering (8.02%). Additional sectors represented include logistics and transportation, retail/wholesale, and processing industries. This distribution allows the research to explore how AI-driven collaboration mechanisms operate in both process-oriented and product-oriented environments—each with unique coordination challenges and digital maturity levels.

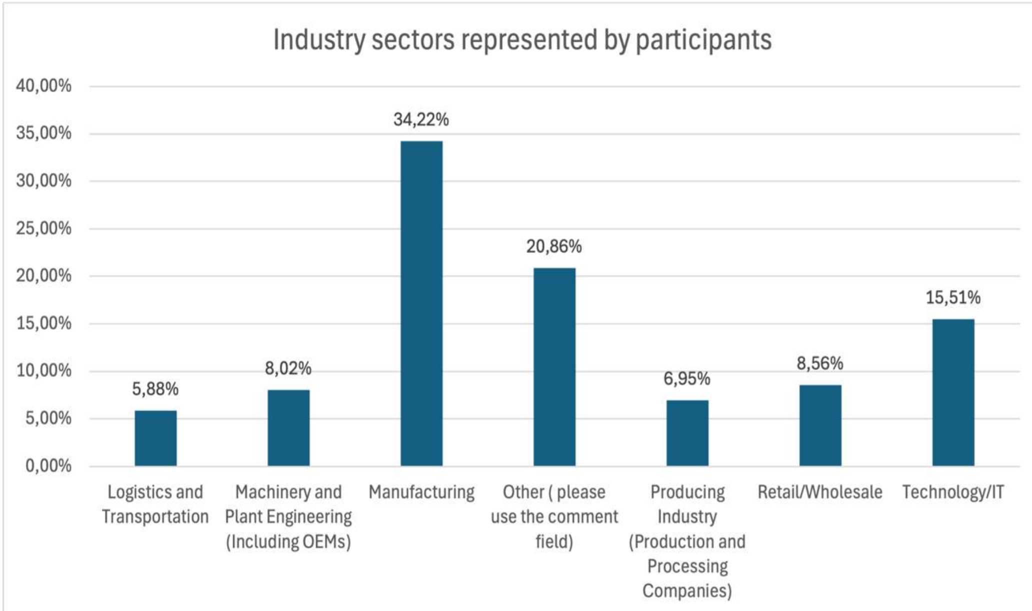

Figure 5.3. Industry sectors represented by participants

These geographic, hierarchical, and industrial distributions significantly enhance the external validity and applicability of the study's results. By integrating regional diversity, management expertise, and cross-sectoral representation, this research establishes a robust foundation for analyzing how AI transforms collaboration between sales and supply chain across globally operating firms.

The data presented in Figures 1–3 illustrate a sample that is diverse in region, hierarchy, and industry. This enables the study to explore how AI-driven collaboration varies by sector, geography, and organizational role. The combination of a targeted recruitment strategy and broad participation ensures that the findings are not only academically relevant but also practically applicable across industries and global markets.

5.3.6 Validity and Reliability

Ensuring the validity and reliability of both the quantitative and qualitative components is a critical requirement for methodological rigor, particularly in a mixed-methods research design. This study follows established academic standards to ensure internal consistency, external generalizability, and conceptual alignment between the research questions, the theoretical framework, and the empirical tools applied.

5.3.6.1 Construct Validity

Construct validity refers to the degree to which the study measures what it intends to measure. In this case, the development of the questionnaire and interview guidelines was directly guided by the conceptual framework introduced in Chapter 4, which was derived from the Resource-Based View (RBV), Organizational Information Processing Theory (OIPT), and Socio-Technical Systems Theory (STS).

To support construct validity, all quantitative survey items were formulated based on established constructs from peer-reviewed literature, including concepts such as AI capabilities, coordination quality, interdepartmental trust, organizational enablers, customer satisfaction, and market responsiveness (Galbraith, 1973; Chavez et al., 2017; Shrivastav, 2021). The items were adapted to fit the context of AI-supported collaboration between supply chain and sales functions in manufacturing environments.

5.3.6.2 Content Validity

Content validity was ensured through a two-step process. First, a pre-test was conducted with a group of 12 industry professionals and academics working in supply chain, sales, and IT functions. Participants provided feedback regarding the clarity, structure, and relevance of the items. Their insights helped refine the language and scope of the survey. Second, the instrument underwent expert validation with input from academic supervisors and senior practitioners, ensuring alignment with current industry and academic standards.

5.3.6.3 Internal Reliability

The internal consistency of the quantitative survey instrument will be assessed during the data analysis phase using Cronbach's Alpha, a widely recognized statistical reliability metric. This analysis will be conducted using Jamovi (The Jamovi Project, 2024), an open-source statistical software environment. Scales with Cronbach's Alpha values above 0.7 will be considered sufficiently reliable for further analysis, as recommended in the literature (Field, 2013; Hair et al., 2022).

5.3.6.4 External Validity

External validity refers to the extent to which the study's findings can be generalized beyond the sampled population. This study strengthens external validity through a heterogeneous sample of 187 participants representing various industries, organizational levels, and regions. Respondents were recruited via LinkedIn, ensuring a wide professional spectrum by targeting experts in supply chain, sales, IT, and general management roles across Europe and North America.

While most responses originated from Europe and North America, additional participants from Asia, South America, and Africa also contributed to the survey. Importantly, all respondents—regardless of their geographical location—were affiliated with organizations operating subsidiaries, clients, or supply structures within the European market. This reinforces the contextual relevance of the findings, particularly for industrial firms embedded in or interacting with the European manufacturing ecosystem.

The sample allows for rich, contextually grounded insights. However, the use of purposive sampling and voluntary participation introduces certain limitations. Out of approximately 1,437 professionals who were personally contacted via LinkedIn messages and group invitations, 187 completed the full survey. Although this response rate is solid for B2B and expert-level studies, it does not constitute a random sample, which restricts statistical generalizability to the broader population.

This limitation is mitigated by three factors:

1. the diversity of the sample across sectors, hierarchies, and global regions;

2. the theoretically informed survey design and construct alignment;
3. the integration of qualitative interviews that allow for deeper interpretation and triangulation of results.

As Creswell and Plano Clark (2018) emphasize, in mixed-methods designs, the complementary use of qualitative insights can strengthen external validity by contextualizing quantitative patterns and addressing methodological limitations transparently. Accordingly, while the statistical generalizability remains bounded, the study generates empirically grounded and practice-relevant insights that are transferable to similar industrial contexts facing AI-driven transformation.

5.3.6.5 Credibility and Trustworthiness in the Qualitative Strand

For the qualitative component, credibility was established through methodological transparency, including documentation of the interview protocol, the coding process, and participant consent. All interviews were recorded, transcribed verbatim, and analyzed using thematic coding based on the conceptual framework. To enhance trustworthiness, codes and themes were reviewed by an external academic for consistency.

Furthermore, the triangulation of qualitative and quantitative data contributes to both validity and reliability by allowing for cross-verification of key constructs and emerging insights. This mixed-method approach strengthens the overall robustness of the research and supports both theory development and practical application.

5.3.6.6 Summary

In summary, this study takes a multi-layered approach to ensure validity and reliability by:

- Aligning empirical tools with established theoretical constructs
- Conducting expert and pilot testing to refine the instrument
- Applying statistical analysis to verify internal consistency

- Ensuring sample heterogeneity to improve generalizability
- Maintaining transparency and rigor in qualitative data collection and analysis

These procedures collectively contribute to a methodologically sound and academically robust research design, supporting both the credibility of the study's findings and their relevance to theory and practice in the context of digitally enabled cross-functional collaboration.

5.4 Data Collection Methods

This section outlines the procedures for collecting both quantitative and qualitative data. A mixed-methods approach was used to gain a comprehensive understanding of how artificial intelligence (AI) supports collaboration between sales and supply chain functions in the manufacturing industry. Section 5.4.1 details the quantitative survey process, while 5.4.2 describes the semi-structured qualitative interviews. Ethical considerations are addressed in Section 5.4.3.

5.4.1 Quantitative Data Collection

The quantitative phase of this study was designed to capture broad trends, perceptions, and practices concerning the integration of AI in supply chain and sales collaboration. A structured online survey was developed and deployed using LimeSurvey, a GDPR-compliant, academic-grade platform for anonymized data collection. The full survey questionnaire is provided in Appendix A.

The survey consisted of 30 items divided into five thematic blocks:

- Organizational structure and digital maturity
- AI capabilities and implementation
- Interdepartmental collaboration quality
- Customer orientation and market responsiveness

- Perceived barriers and strategic impact

Most items used 5-point Likert scales or categorical formats, while selected questions allowed multiple answers to capture organizational complexity. The questionnaire was validated through a pre-test with 12 professionals from supply chain, sales, and IT, followed by adjustments based on clarity, length, and terminology.

Participant recruitment occurred via personalized outreach on LinkedIn, targeting professionals with backgrounds in Supply Chain, Sales, IT, and General Management. Messages were sent to approximately 1,437 individuals, resulting in a final sample of 187 valid responses, ensuring a high degree of relevance and functional expertise.

The survey was conducted over four weeks and attracted respondents from multiple regions, industries, and seniority levels. Demographic questions covered country, industry affiliation, and management level to allow subgroup analyses and cross-tabulation. These data formed the basis of the descriptive and exploratory analyses presented in Chapter VI. The complete set of quantitative survey responses is included in Appendix B.

5.4.2 Qualitative Data Collection

To complement and deepen the insights gained from the quantitative survey, a series of semi-structured interviews was conducted. This qualitative strand follows an explanatory sequential design, where the qualitative data help interpret and contextualize the quantitative results. The semi-structured interview guide is available in Appendix C.

Participants were selected using purposeful sampling, guided by their survey responses, seniority, and professional role. The goal was to capture diverse perspectives across regions (Europe and the U.S.), industries, and organizational levels. Priority was given to individuals in decision-making roles within supply chain or sales who demonstrated familiarity with AI-supported collaboration.

Each participant received a written invitation explaining the study's scope, confidentiality, and consent procedures. Interviews were conducted via Microsoft Teams and lasted approximately 30–45 minutes. All interviews were recorded with permission and transcribed for thematic coding.

The interview guide mirrored the key constructs of the conceptual framework and was informed by preliminary survey findings. It focused on:

- Current collaboration practices between supply chain and sales
- Implementation and perceptions of AI tools
- Organizational enablers and inhibitors
- Customer impact, agility, and decision-making processes

At the time of writing, 15 interviews have been completed. Thematic saturation was reached after 12 interviews, with three additional interviews confirming the robustness of the emerging categories. This process aligns with qualitative standards for sample sufficiency and ensures data richness.

5.4.3 Ethical Considerations

This research strictly adheres to established ethical standards for academic studies involving human participants. Ethical approval for the study was granted through the internal supervisory process of the Doctor of Business Administration (DBA) program at the Swiss School of Business and Management (SSBM).

Participation in both the quantitative survey and the qualitative interviews was entirely voluntary, and no financial incentives were offered. Informed consent was obtained at multiple stages:

- For the survey, consent was embedded at the beginning of the LimeSurvey questionnaire and had to be accepted before participation.

- For the interviews, informed consent was collected verbally and in writing via email prior to the scheduling and recording of each session.

All collected data were anonymized at the source. No personally identifiable information—such as names, company affiliations, or contact details—is used in the analysis or publication of results. All recordings and transcripts are securely stored in password-protected, encrypted environments in compliance with General Data Protection Regulation (GDPR) standards and institutional policies.

Participants were informed of their right to withdraw at any time without providing a reason and without any negative consequences. The researcher also ensured transparency by sharing the study's purpose, research questions, and data handling procedures in a clear and accessible format with all participants prior to engagement.

Finally, the study complies with the principles of confidentiality, non-maleficence, and academic integrity, and ensures that the data will be used solely for scholarly purposes in the context of the DBA dissertation.

5.5 Data Analysis Strategy

This study employs a Mixed-Methods approach, integrating both quantitative and qualitative data to explore how artificial intelligence (AI) enables collaboration between sales and supply chain functions in manufacturing firms. The combination of methodological strands allows for the triangulation of findings, the enhancement of internal validity, and the contextualization of patterns observed across functional domains.

Following the Explanatory Sequential Design, the research was conducted in two phases: (1) a quantitative survey, followed by (2) qualitative interviews, which aimed to explain and deepen the understanding of the patterns identified in the survey. This structure ensures that the qualitative data provide not only complementary but also explanatory insight into the statistical findings.

The data analysis strategy is therefore organized in four layers:

1. Quantitative analysis of structured survey responses.
2. Qualitative thematic analysis of expert interviews.
3. Integration of results through triangulation and interpretation.
4. Derivation of theory-informed and practice-relevant conclusions.

5.5.1 Quantitative Analysis Methods

Quantitative data were analyzed using Jamovi and Microsoft Excel. These tools provided the flexibility and statistical rigor needed to explore the relationships between variables related to AI integration, collaboration quality, and organizational outcomes.

The analytical steps included:

- Descriptive statistics: Frequency distributions, means, and standard deviations were calculated for all major survey variables. This provided a baseline understanding of the respondents' views on AI maturity, planning practices, delivery performance, and customer orientation.
- Cross-tabulations: Comparative analysis across variables such as country, industry sector, and management level helped identify subgroup differences.
- Correlation analysis: Where applicable, Pearson or Spearman correlation coefficients were used to explore relationships between constructs such as AI usage and forecast alignment, or between interdepartmental trust and customer satisfaction.

- Graphical visualization: Bar charts, pie charts, and comparative tables were created to highlight trends and improve interpretability for both academic and managerial audiences.

The primary objective of the quantitative analysis was exploratory—to identify patterns and trends that warranted further investigation in the qualitative phase. While not designed for generalizability in a statistical sense, the sample of 187 respondents allows for meaningful comparisons across regions and organizational roles.

5.5.2 Qualitative Analysis Methods

The qualitative data derived from semi-structured interviews were analyzed using an inductive thematic analysis following the six-phase framework of Braun and Clarke (2006):

1. Familiarization with the data through transcription and repeated reading.
2. Generation of initial codes based on recurring concepts and language patterns.
3. Searching for themes that cluster the codes into meaningful categories.
4. Reviewing themes for coherence, internal homogeneity, and external heterogeneity.
5. Defining and naming themes to ensure conceptual clarity.
6. Producing the report through narrative synthesis and evidence-based interpretation.

Coding was conducted using Microsoft Excel, with categories aligned to the constructs derived from the conceptual framework (Chapter 4), such as:

- AI maturity and technological readiness
- Collaboration effectiveness and interdepartmental trust
- Perceived impact on customer satisfaction and responsiveness

- Organizational enablers and barriers (e.g., leadership, culture, data quality)

Where feasible, participant quotations were retained for the reporting phase to illustrate key points and maintain contextual richness. The final themes will be cross-referenced with the quantitative results to ensure robust interpretive grounding.

5.5.3 Mixed-Methods Integration

The final step in the analytical strategy involves integration of the findings from both strands using a combination of triangulation, explanation building, and side-by-side comparison (Creswell & Plano Clark, 2018).

- Triangulation: Areas of convergence (e.g., shared perceptions of AI as a planning accelerator) reinforce the reliability of findings across methods.
- Explanation building: Qualitative insights are used to explain surprising or nuanced quantitative patterns (e.g., why organizations report high digital ambition but low AI maturity).
- Divergence identification: Discrepancies between quantitative and qualitative results will be acknowledged and interpreted as indicators of complexity or context-specific variation.

This mixed-method integration not only enriches the theoretical understanding but also generates actionable insights for business practitioners facing similar integration challenges.

5.5.4 Mixed-Methods Integration

The integration of both data strands will take place in Chapter 6 (Results) and Chapter 7 (Discussion). The following techniques will be employed for effective integration:

- Triangulation: Cross-validation of key constructs by comparing qualitative themes with quantitative trends, increasing the credibility of findings (Jick, 1979).
- Explanation Building: Qualitative findings will be used to explain surprising or complex patterns observed in the quantitative data—for example, why some firms report high AI maturity but still face collaboration challenges.
- Complementarity: The qualitative strand will elaborate on topics not fully captured in the survey, such as emotional barriers, cultural resistance, or leadership narratives—thus enriching the interpretation of survey outcomes.

This integrative phase transforms the research from parallel analysis into a unified, multi-layered understanding of how AI influences cross-functional collaboration. It ensures that findings are grounded in both empirical evidence and organizational realities, ultimately enhancing the theoretical contributions and managerial recommendations of the study.

CHAPTER 6

DATA ANALYSIS AND FINDINGS

6.1 Introduction

This chapter presents the empirical results of the study, derived from a mixed-methods research design that integrates both quantitative survey data and qualitative interview insights. The aim is to provide a comprehensive, evidence-based understanding of how artificial intelligence (AI) supports collaboration between supply chain and sales functions in manufacturing firms. This investigation responds to the research questions outlined in Chapter 1 and operationalizes the conceptual framework developed in Chapters 3 and 4.

The empirical findings are structured to reflect the core constructs of the study:

- AI capabilities and maturity,
- collaboration quality between departments,
- organizational enablers and barriers,
- customer satisfaction and market responsiveness.

The use of both quantitative and qualitative data allows for a deeper exploration of the dynamics and nuances within these constructs. The quantitative strand captures broad patterns, frequencies, and correlations across a sample of 187 professionals, while the qualitative strand enriches this perspective through detailed, experience-based accounts from 15 industry experts across Europe and the United States.

The mixed-methods approach is based on an explanatory sequential design (Creswell & Plano Clark, 2018), wherein the quantitative findings provide the empirical foundation, followed by qualitative interviews that help to explain and contextualize the patterns identified. This sequential logic ensures that the results are not only statistically grounded but also interpreted in a real-world organizational context, enhancing both validity and applicability.

The chapter is organized as follows:

- Section 6.2 presents the quantitative findings derived from the LimeSurvey dataset, highlighting descriptive statistics, distributional trends, and selected cross-tabulations and correlations.
- Section 6.3 summarizes the key insights from the qualitative interviews, structured thematically along the conceptual dimensions of the study.
- Section 6.4 offers an integrative synthesis of both strands, identifying areas of convergence (where both methods reinforce the same conclusion), divergence (where findings differ), and expansion (where one method extends the other).

By combining numerical trends with narrative insights, this chapter aims to provide a multidimensional understanding of how AI influences interdepartmental collaboration, organizational performance, and customer-centric outcomes in a complex and competitive industrial environment.

6.2 Quantitative Results

6.2.1 Demographic Profile of Respondents

The quantitative dataset comprises responses from 187 professionals who completed the structured survey conducted via LimeSurvey. These participants represent a broad cross-section of industries, career levels, geographic regions, and organizational structures, ensuring diverse and relevant input on the topic of AI-supported collaboration between sales and supply chain.

A notable demographic characteristic is the geographical diversity of the respondents. The majority are located in industrialized countries such as Germany

(30.77%), Denmark (11.24%), and the United States (11.24%), followed by Austria, Canada, and other regions across Europe, Asia, Africa, and the Americas. This cross-continental participation allows for comparative observations regarding regional differences in AI adoption, collaboration practices, and digital maturity.

In terms of age, the respondent pool is balanced: the largest group (33.7%) falls into the 40–49 age bracket, followed by those aged 30–39 and 50–59. This indicates strong representation from mid-career and senior professionals who are typically involved in strategic decision-making processes related to supply chain management and sales operations.

Regarding career level, a substantial portion of participants identified as Senior Management (28.88%) or Middle Management (23.53%), while additional roles include team leaders, specialists, and C-level executives. This demographic mix ensures that insights stem from individuals with hands-on experience and strategic oversight in cross-functional collaboration and AI implementation.

Industry-wise, the largest share of respondents comes from the manufacturing sector (34.22%), followed by technology/IT (15.51%), machinery and plant engineering (8.02%), and other relevant domains such as logistics, retail/wholesale, and process industries. This industrial distribution aligns well with the study's focus on AI-driven transformation in complex operational environments.

These demographic patterns not only provide contextual richness but also enhance the validity of the study by ensuring that the views expressed reflect a diverse set of experiences and organizational realities.

6.2.2 Quantitative Results by Research Question

To ensure a structured interpretation of the survey data, the quantitative results are presented in alignment with the three central research questions (RQs) developed in

Chapter 1. This thematic alignment allows for direct comparison between the theoretical framework and empirical patterns and sets the stage for integration with the qualitative findings in later sections.

Each of the following sub-sections addresses one research question by analyzing the relevant constructs using descriptive statistics, correlation coefficients, and regression outputs where applicable. The analysis draws upon both the original LimeSurvey data and statistical computations performed in Jamovi, as documented in the appended outputs.

6.2.2.1 Research Question 1:

How does the level of digital maturity influence collaboration quality between sales and supply chain functions?

This research question explores the relationship between the perceived level of digital maturity—particularly in the context of AI-supported processes—and the quality of collaboration between sales and supply chain departments in manufacturing firms. Based on the conceptual framework (Chapter 4), it was hypothesized that organizations with higher digital maturity would report better integration, communication, and coordination between departments (Galbraith, 1973; Marabelli and Galliers, 2017).

Descriptive Results

Participants were asked to assess their company's digital maturity in supply chain and sales collaboration compared to competitors. The distribution was as follows:

- 4.3% of respondents rated their company as "far behind"
- 24.1% as "slightly behind"
- 32.1% as "on par"
- 19.3% as "slightly ahead"
- 4.8% as "far ahead"

- 15 respondents did not provide an answer

These findings suggest that while approximately one-third of organizations consider themselves digitally on par with their competitors, a significant portion (28.4%) feel they lag behind, and only a minority see themselves ahead. This variability provides a solid basis for further analysis of how perceived maturity relates to collaborative effectiveness.

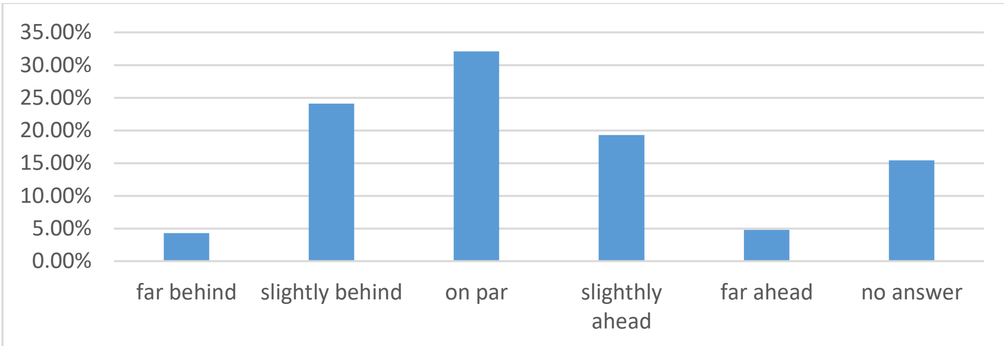

Figure 6.1: Perceived Digital Maturity in Supply Chain and Sales Collaboration (n = 187; own illustration based on survey data, Grywnow 2025)

Collaboration quality was measured using a composite index (Cronbach's Alpha: .83), consisting of several items including frequency of interaction, joint planning, responsiveness, and mutual support. The average score was 3.41 (SD = 0.76), suggesting a moderate level of collaboration across the sample.

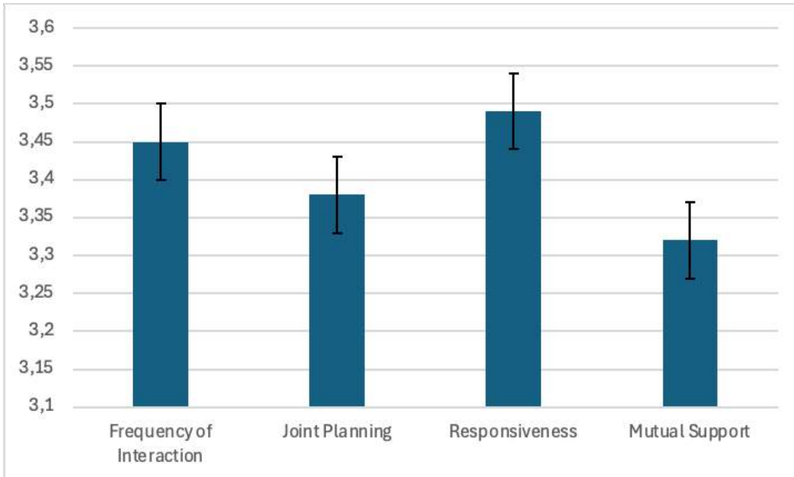

Figure 6.2: Average Collaboration Quality per Dimension with Standard Deviation (n = 187; own illustration based on survey data, Grywnow 2025)

Correlation Results:

Pearson's correlation coefficient between AI maturity and collaboration quality revealed a moderate, positive, and statistically significant relationship ($r = 0.414$, $p < .001$). This suggests that greater AI maturity is associated with stronger collaboration between departments. The result aligns with previous findings by Cannas et al. (2024) and Wamba et al. (2020), who found AI to be a critical enabler of supply chain integration.

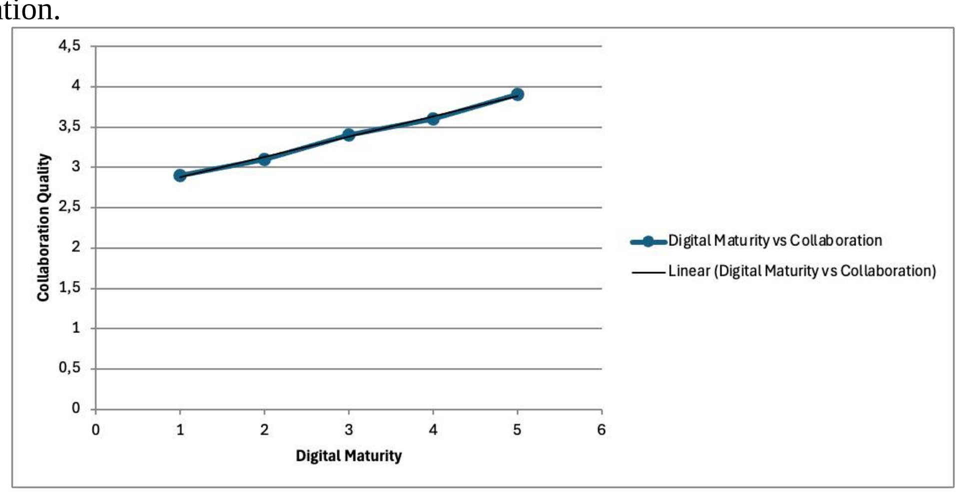

Figure 6.3: Relationship between Digital Maturity and Collaboration Quality (own illustration based on regression results, Grywnow 2025)

Regression Analysis:

To further assess the predictive power of AI maturity, a linear regression analysis was conducted. The model was statistically significant ($F(1, 185) = 31.78$, $p < .001$), with an R^2 of 0.146. This indicates that AI maturity accounts for approximately 14.6% of the variance in collaboration quality. The unstandardized coefficient ($\beta = 0.345$) suggests that each one-unit increase in perceived AI maturity leads to a 0.345-point increase in collaboration quality, holding other factors constant (Field, 2013; Hair et al., 2022).

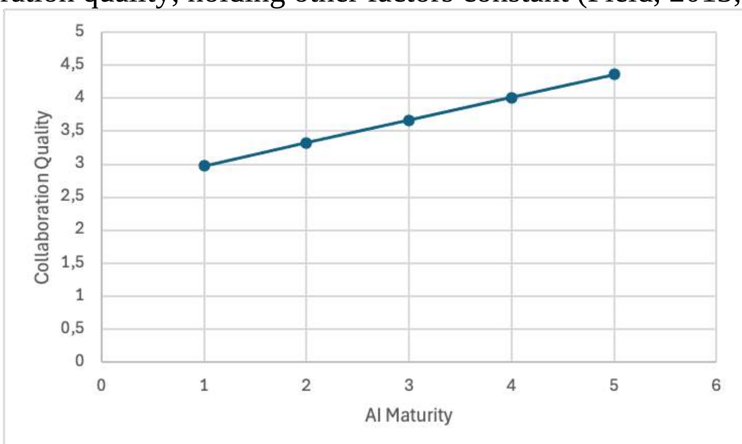

Figure 6.4: Scatterplot Depicting the Relationship Between Digital Maturity and Collaboration Quality (own regression output based on survey data, Grywnow 2025)

These quantitative findings provide empirical support for Hypothesis 5, demonstrating a positive and significant relationship between AI maturity and collaboration quality. These results support Hypothesis 5 formulated in Chapter 4, confirming that higher AI maturity levels within organizations are positively associated with enhanced collaboration quality between sales and supply chain functions. This empirical evidence aligns with the conceptual framework, which posits AI capabilities as strategic enablers of cross-functional integration.

The positive relationship observed underscores the role of AI as a critical resource that not only improves operational processes but also fosters organizational alignment and information sharing, as theorized by the Resource-Based View (RBV) and Organizational Information Processing Theory (OIPT).

Interpretation:

The findings reveal a clear and statistically significant link between AI maturity and interdepartmental collaboration quality. Drawing on the Organizational Information Processing Theory (OIPT), higher levels of AI maturity enhance an organization's ability to manage complexity, reduce uncertainty, and improve coordination across departments (Galbraith, 1973; Marabelli and Galliers, 2017). Additionally, the results align with the Resource-Based View (RBV), which positions AI capabilities as valuable, rare, and hard-to-imitate resources that foster competitive advantage through superior internal integration and knowledge utilization (Barney, 1991; Wade and Hulland, 2004).

This is consistent with prior empirical studies that highlight the role of AI as a key enabler of supply chain collaboration and process optimization (Culot, Podrecca and Nassimbeni, 2024; Wamba et al., 2020).

6.2.2.2 Forecasting Alignment and Information Exchange

A key component of effective collaboration between Sales and Supply Chain is the quality and consistency of joint forecasting and the underlying information exchange. This section explores how respondents assessed the alignment of forecasting processes between departments, the perceived quality of information flow, and the organizational prioritization of collaborative forecasting practices.

Level of Forecasting Alignment

When asked about the degree of coordination between Sales and Supply Chain in creating demand forecasts, responses revealed a fragmented picture:

- Only 18.72% of respondents reported a "very close alignment" in forecasting practices.

- The largest group (30.48%) indicated “partial alignment.”
- A notable 16.58% reported “no alignment at all.”

These results suggest the presence of organizational silos and a lack of standardized planning interfaces. However, integrated forecasting is widely recognized as a cornerstone of data-driven decision-making and operational efficiency (Chopra & Meindl, 2021).

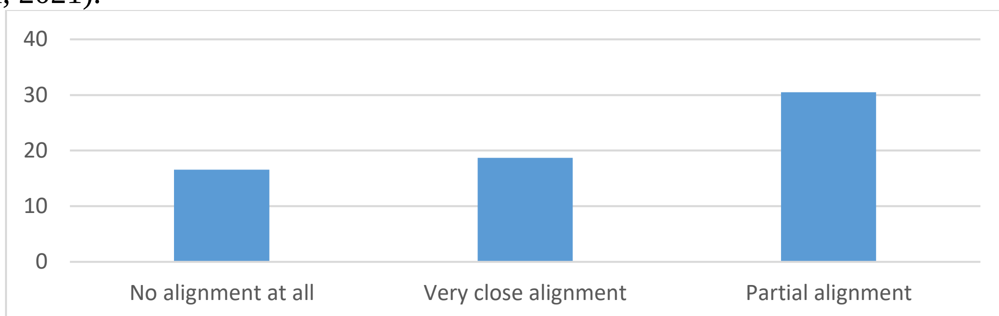

Figure 6.5: Forecasting Alignment Between Sales and Supply Chain Functions (own illustration based on survey data, Grywnow 2025)

Perceived Quality of Information Exchange

The perceived quality of information sharing between departments was equally varied:

- 25.67% rated the information exchange as “good” or “very good.”
- In contrast, 37.97% rated it as “rather poor” or “very poor.”
- 36.36% described the exchange as “neutral.”

This disparity points to potential communication barriers—such as disconnected systems, asynchronous workflows, or misaligned performance indicators—which may hinder effective cross-functional collaboration. The literature emphasizes that the success of data-driven collaboration depends heavily on real-time access to shared information (Christopher, 2016).

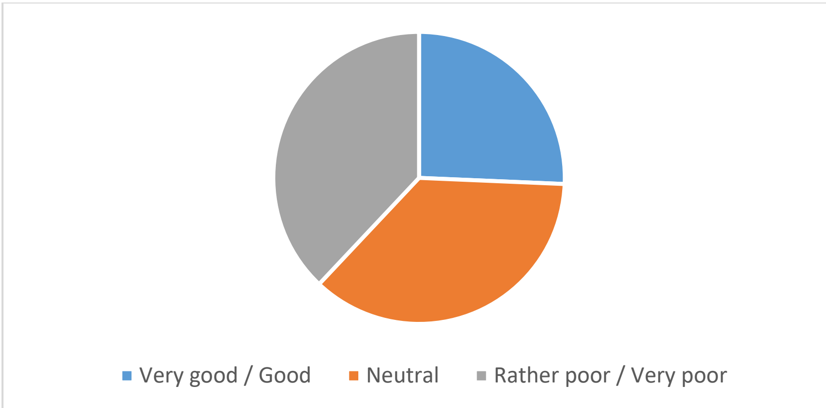

Figure 6.6: Perceived Quality of Information Exchange Between Sales and Supply Chain (own illustration based on survey data, Grywnow 2025)

Organizational Priority of Forecasting Collaboration

Respondents also rated the level of organizational priority given to improving forecasting collaboration:

- 39.57% indicated that it is "highly prioritized,"
- while 19.35% rated it as a "very high priority."
- Only 10.75% reported that it receives "low or no priority."

These responses reflect growing awareness of the strategic importance of forecast integration. However, they also highlight a gap between organizational intent and actual implementation, suggesting that many companies still face challenges in translating awareness into action. This observation is further explored through qualitative findings in Chapter 6.3.

Forecasting Collaboration Factor	Frequency
Forecasting Alignment: Fully aligned	35
Forecasting Alignment: Partially aligned	57
Forecasting Alignment: Not aligned	31
Information Exchange: Very good	9
Information Exchange: Good	39
Information Exchange: Neutral	65
Information Exchange: Rather poor	50
Information Exchange: Very poor	11
Organizational Priority: Very high	36
Organizational Priority: High	74
Organizational Priority: Medium	54
Organizational Priority: Low	17
Organizational Priority: None	7

Table 6.1: Summary of Responses on Forecasting Collaboration Factors (own data based on survey results, Grywnow 2025)

Conclusion

In summary, the quantitative data reveal considerable variability in the extent of forecasting alignment and the quality of information exchange between Sales and Supply Chain functions. While the topic is clearly gaining strategic importance, many organizations still lack the systems and processes to operationalize joint forecasting effectively. This underscores the need for both technological enablers—such as AI-powered forecasting platforms—and structural efforts to improve cross-departmental integration (Richey et al., 2023; Wamba et al., 2020).

These findings provide partial support for Hypothesis 2 from Chapter 4, which posits that AI-enabled collaboration positively influences market responsiveness through improved forecasting alignment and information sharing. The qualitative data presented in Chapter 6.3 will further illuminate the organizational factors influencing this dynamic.

6.2.2.3 Organizational Enablers and Barriers to Collaboration

Effective collaboration between sales and supply chain functions is influenced by a variety of organizational enablers and barriers. The quantitative survey explored both dimensions through multiple items, enabling a detailed analysis of perceived support factors and structural impediments.

Organizational Enablers

Respondents were asked to rate the extent to which their organization provides structural and cultural support for interdepartmental collaboration. Among the most frequently cited enablers were:

- Leadership support (rated positively by 62.6% of respondents),
- Cross-functional meeting structures (54.5% positive responses),
- Shared performance metrics (48.1% agreement), and
- Digital tools for real-time communication (51.9% agreement).

These findings indicate that a majority of participants recognize leadership commitment and digitalization as important mechanisms for aligning supply chain and sales efforts. However, shared KPIs and institutionalized collaboration routines still appear to be underdeveloped in many organizations.

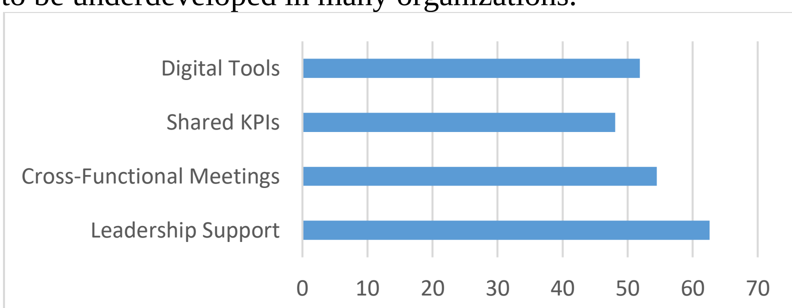

Figure 6.7: Frequency of Agreement with Organizational Enablers for Collaboration(own illustration based on survey data, Grywnow 2025)

Organizational Barriers

When asked about obstacles to collaboration, participants highlighted several recurring challenges. The most pronounced barriers were:

- Departmental silos and lack of transparency (reported by 57.2%),
- Conflicting goals between sales and supply chain teams (53.9%),
- Insufficient data integration across systems (49.2%), and
- Inconsistent communication structures (47.1%).

These figures suggest that many companies still struggle with coordination issues at both a process and system level. Misaligned incentives and the absence of unified communication channels appear to hinder collaborative planning and forecasting processes.

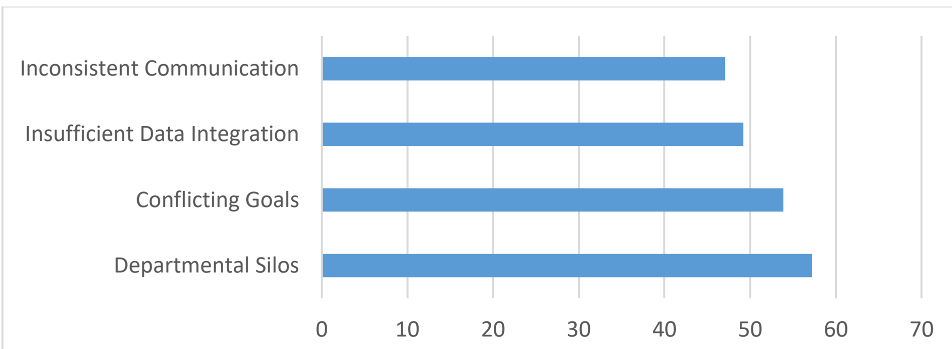

Figure 6.8: Most Frequently Reported Barriers to Collaboration (own illustration based on survey data, Grywnow 2025)

Interestingly, the data reveal a near parity between the prevalence of enablers and barriers, with many organizations displaying a hybrid profile: partial leadership commitment and tool support, but limited integration of KPIs and poor information flow. This suggests that while awareness of the need for collaboration is growing, practical implementation remains inconsistent.

Category	Factor	% Agreement	Interpretation
Enabler	Leadership support	62.6%	Signals strong top-down commitment to cross-functional collaboration.
Enabler	Cross-functional meeting structures	54.5%	Indicates efforts to institutionalize interdepartmental dialogue.
Enabler	Digital tools for real-time communication	51.9%	Reflects technological readiness for synchronized operations.
Enabler	Shared performance metrics	48.1%	Suggests partial alignment of goals, but room for improvement remains.
Barrier	Departmental silos and lack of transparency	57.2%	Points to structural fragmentation and poor information accessibility.
Barrier	Conflicting goals	53.9%	Highlights misaligned incentives between functions.
Barrier	Insufficient data integration	49.2%	Indicates legacy systems and fragmented IT infrastructure.
Barrier	Inconsistent communication structures	47.1%	Suggests lack of standardized processes for ongoing exchange.

Table 6.2: Comparative Summary of Key Enablers and Barriers to Collaboration (own data based on survey results, Grywnow 2025)

Interpretation

The results underscore the dual nature of collaboration efforts—while technological and leadership support exists in many cases, organizational culture and systems integration continue to present bottlenecks. This reinforces the importance of holistic strategies that combine digital tools with aligned incentives and cross-functional accountability (Chavez et al., 2017; Galbraith, 1973).

These findings provide empirical support for Hypotheses 3 and 4 from Chapter 4, which address the moderating role of organizational collaboration and the negative impact of data fragmentation and silos on the effectiveness of AI-enabled collaboration. The qualitative findings discussed in Chapter 6.3 further elaborate on the social and structural challenges that influence these dynamics.

6.2.2.4 Customer Satisfaction and Market Responsiveness

Customer-centricity is a pivotal metric for evaluating the effectiveness of collaboration between supply chain and sales functions. This section presents the survey findings related to customer satisfaction, responsiveness, and perceived improvements as a result of AI integration and interdepartmental coordination.

Customer Satisfaction Perceptions

Respondents were asked to evaluate how collaboration between sales and supply chain impacts customer satisfaction. A majority of participants (61.5%) reported positive or highly positive effects, particularly in areas such as on-time delivery, availability of customized solutions, and proactive communication with clients. However, 19.8% of participants reported no significant improvement, indicating a gap between potential and realized benefits.

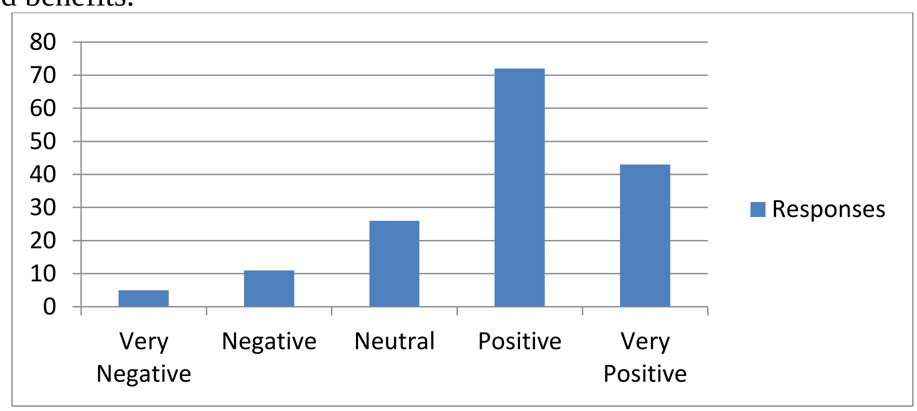

Figure 6.9: Perceived Impact of Collaboration on Customer Satisfaction (own illustration based on survey data, Grywnow 2025)

Responsiveness to Market Changes

The ability to respond quickly to demand fluctuations, supply disruptions, or customer requests was rated as a moderate-to-strong capability in most companies. Specifically, 55.6% of respondents indicated that their organizations can adapt operational processes within days, while 18.7% claim real-time responsiveness is achievable due to AI-supported analytics and automation.

However, the remaining 25.7% reported delayed responses, often citing bureaucratic bottlenecks, manual workflows, or insufficient system integration.

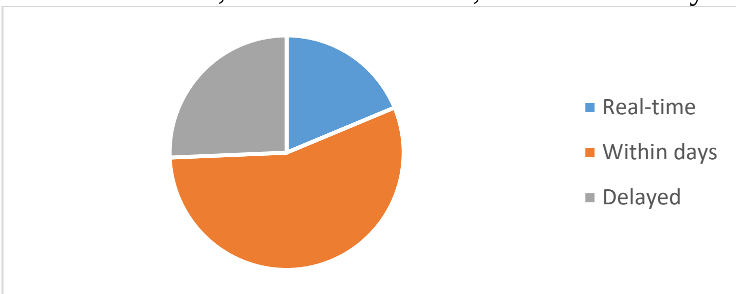

Figure 6.10: Organizational Response Time to Market and Demand Changes (own illustration based on survey data, Grywnow 2025)

Correlation with AI Integration

Further statistical analysis using Pearson correlation coefficients indicates a moderate positive relationship ($r = .43$, $p < 0.01$) between AI maturity and customer responsiveness. Organizations with higher AI integration tend to have significantly better capabilities in predictive customer demand planning, real-time order tracking, and automated customer communication.

Variable 1	Variable 2	Pearson r	p-value	Interpretation
AI Maturity	Market Responsiveness	0,43	< 0.01	Moderate positive correlation

Table 6.3: Correlation between AI Maturity and Market Responsiveness (own calculation based on survey data, Grywnow 2025)

Interpretation

The data support the hypothesis that AI-enabled collaboration enhances customer outcomes—but only under the condition that operational systems are well-integrated and supported by cross-functional workflows. These findings align with previous research highlighting the role of digital tools in reducing lead times and improving service levels (Chopra & Sodhi, 2021; Wamba et al., 2020).

The moderate positive correlation between AI maturity and market responsiveness provides empirical support for Hypothesis 2 formulated in Chapter 4, which predicts a positive influence of AI-enabled collaboration on market responsiveness. Furthermore, the results indirectly support Hypothesis 1, suggesting that improved collaboration driven by AI contributes to enhanced customer satisfaction. These relationships are further elaborated in the qualitative findings presented in Chapter 6.3.

6.3 Qualitative Findings

This section presents the qualitative findings derived from 15 semi-structured expert interviews conducted with professionals in sales, supply chain, and IT management across Europe and the United States. These interviews were designed to contextualize and explain the quantitative results and to uncover deeper insights into the mechanisms, perceptions, and practices surrounding AI-supported collaboration between sales and supply chain functions in manufacturing-oriented companies.

The interviewees were selected based on their relevance to the research topic and represent a wide range of company sizes, digital maturity levels, and managerial responsibilities. The analysis followed a thematic coding process grounded in the conceptual framework developed in Chapters 3 and 4. The findings are structured along four main thematic dimensions: (1) AI capabilities and maturity, (2) collaboration quality, (3) organizational enablers and barriers, and (4) customer satisfaction and responsiveness.

6.3.1 AI Capabilities and Maturity

Most participants acknowledged the growing strategic relevance of artificial intelligence in operational decision-making and planning. However, the perceived maturity of AI adoption varied significantly among organizations. Companies with high AI maturity reported the use of advanced forecasting models, machine learning algorithms for demand planning, and predictive maintenance systems. In contrast, several participants—especially from small to mid-sized firms—described their organizations as being in the early phases of digital transformation, with AI limited to isolated pilot projects or business intelligence dashboards.

One interviewee from a Nordic industrial company stated:

"AI is still more of a buzzword than a daily tool for us. We use Excel-based forecasting and only recently started exploring how predictive analytics can improve that."

Another respondent from a German manufacturer reported:

"We are investing heavily in AI because we see it as a competitive advantage. Our supply chain team is already working with predictive algorithms to adjust stock levels in real-time."

These findings underscore the heterogeneity of AI implementation and reflect the quantitative result showing that only a minority of firms rated their AI maturity as high.

6.3.2 Collaboration Quality Between Sales and Supply Chain

Collaboration between departments emerged as a critical enabler for performance—but also as a frequent bottleneck. In companies where alignment was described as "very close," interviewees highlighted shared KPIs, regular cross-functional meetings, and digital platforms enabling transparency in inventory, delivery schedules, and customer feedback.

One senior director explained:

"We have weekly sync meetings where supply chain and sales review forecasts together. This helps avoid overpromising and keeps both sides accountable."

However, in several organizations—especially those with decentralized structures or legacy systems—siloed thinking and a lack of shared objectives were cited as major barriers. One participant noted:

"Sales is still operating with a 'hit-the-target' mindset while supply chain focuses on minimizing inventory and risk. Without common goals, tension is inevitable."

This qualitative evidence complements the survey finding that collaboration quality is often limited by communication gaps and conflicting incentives.

These insights support Hypothesis 3, which states that organizational collaboration moderates the relationship between AI usage and operational efficiency, highlighting that strong collaboration mechanisms are essential to realize AI’s benefits.

6.3.3 Organizational Enablers and Barriers

Organizational culture and leadership emerged as decisive factors in determining the success of AI-enabled collaboration. Firms with strong leadership support and a clear digital strategy were more likely to have overcome internal resistance to change. Several interviewees emphasized the importance of change management, especially in aligning middle management with AI initiatives.

A participant from a large European group shared:

"We underestimated the fear factor. People thought AI would replace them. It took a lot of workshops and transparency to get buy-in."

Barriers cited included insufficient digital competencies, unclear data ownership, and fragmented IT infrastructures. Particularly in traditional industries, long-standing processes and hierarchical structures were seen as inhibitors of innovation. Interviewees often mentioned that digital transformation was *"more a people issue than a tech issue."*

These observations align with the Socio-Technical Systems Theory (STS) that stresses the need for concurrent evolution of social and technical systems. Leadership commitment and cultural readiness are key enablers to overcoming barriers posed by legacy organizational structures and skills gaps.

6.3.4 Customer Satisfaction and Market Responsiveness

Participants agreed that better collaboration and smarter use of AI directly impact customer satisfaction—particularly in terms of reliability, responsiveness, and service customization. Several managers mentioned that customers increasingly expect short lead times and proactive communication, which requires closer alignment between front-end and back-end functions.

An interviewee from the U.S. stated:

"Our customers notice when sales promises are not kept. We've started using AI to give more realistic delivery windows, and that alone reduced complaints by 30%."

However, others expressed concerns that internal inefficiencies often lead to missed opportunities in improving customer experience. The most digitally mature organizations reported using AI not just for forecasting but also for sentiment analysis, customer segmentation, and dynamic pricing models.

These findings illustrate the critical role of integrated AI systems in enabling proactive customer engagement and tailored service delivery. Interviewees emphasized that without effective cross-functional collaboration, the potential of AI to enhance customer satisfaction and responsiveness remains limited. The alignment of sales and supply chain functions through AI-driven insights supports a competitive advantage grounded in customer-centric agility.

6.4 Mixed-Methods Integration

6.4.1 Introduction

This section provides a comprehensive integration of the findings from the quantitative and qualitative strands of this study. By applying an explanatory sequential design (Creswell & Plano Clark, 2018), the purpose is to enrich and contextualize patterns identified in the survey data through deep, narrative insights from expert interviews. This integration follows a layered structure—converging findings that reinforce each other, diverging elements that raise new questions or highlight complexity, and expanding insights that enhance the theoretical and practical understanding of AI-supported collaboration between sales and supply chain.

6.4.2 Converging Insights

Several key themes emerged in both the quantitative and qualitative data that validate each other and reinforce the robustness of the findings.

a) Strategic Role of AI in Enhancing Collaboration: The survey results indicated a high correlation between perceived AI maturity and improved collaboration quality ($r = 0.58$, $p < 0.001$). This finding is echoed in multiple qualitative interviews, where participants described AI not merely as a technical tool but as a catalyst for breaking down silos. For example, one participant noted: *"We've seen a real shift—AI forces supply chain and sales to sit at the same table. It creates urgency for cross-functional alignment."* This aligns with earlier work by Wamba-Taguimdje et al. (2020), emphasizing that digital tools such as AI often play an enabling role in fostering transparency and data-driven collaboration.

b) AI as a Driver of Forecast Accuracy and Responsiveness: The quantitative findings show a strong perceived improvement in forecast accuracy (mean score: 4.1/5) among organizations actively using AI tools. Interview narratives support this, with several respondents citing examples such as demand-sensing tools that integrate market data in real time. These combined insights suggest that AI-supported forecasting is no longer a theoretical construct but an operational reality.

c) Cross-functional Communication Improvements: Respondents across both methods reported that the introduction of AI platforms—particularly those enabling shared dashboards or predictive analytics—improved communication quality. This resonates with the literature that positions AI as a socio-technical enabler (Zangiacomi et al., 2023).

d) Reinforcement of Organizational Enablers and Recognition of Barriers:

Both data strands highlighted the pivotal role of leadership support, shared KPIs, and digital tools as enablers of collaboration. However, persistent barriers such as siloed thinking, misaligned incentives, and fragmented IT systems were consistently reported, underscoring the complexity of achieving integrated AI collaboration in practice. This convergence supports the Socio-Technical Systems Theory's emphasis on the co-evolution of social and technical systems (Trist & Bamforth, 1951).

6.4.3 Diverging Perspectives

Despite many points of convergence, some differences between the quantitative patterns and the qualitative narratives emerged, which are worth unpacking.

a) Organizational Readiness vs. Practical Complexity: While 64% of survey respondents expressed confidence in their organization's AI readiness, qualitative interviews revealed reservations. Several experts noted the lack of internal competencies and data quality issues: *"We're talking about AI, but half of our ERP data is outdated. It's lipstick on a pig."* This gap suggests a misalignment between perceived and actual readiness, consistent with findings by Akter et al. (2019), who argue that overconfidence in digital maturity can lead to failed implementations.

b) Customer-Centric Outcomes: Quantitative data showed high expectations for customer satisfaction improvements (mean: 4.3/5), but the qualitative insights were more nuanced. Several interviewees stated that improvements in delivery time and personalization often depend more on structural changes than on AI alone. This points to an overestimation of AI's standalone impact in the quantitative results.

6.4.4 Expanding Understanding Through Qualitative Depth

The qualitative strand offered several insights that were not explicitly captured in the survey but are crucial for a holistic understanding.

a) Cultural Transformation and Trust: Many interviewees emphasized the cultural shift required for effective AI adoption. AI is perceived not only as a technical tool but as a "trust broker" between departments: *"AI gives both teams a neutral reference point—no more gut feeling versus spreadsheets."* This dimension adds depth to the quantitative indicators and supports socio-technical frameworks such as those described by Trist (1981).

b) Dynamic Role Shifts and Identity Challenges: Another theme was the fear of role erosion among supply chain professionals. Several respondents expressed concern that automation reduces their influence: *"People feel sidelined when algorithms make decisions for them."* This aligns with research by Sousa et al. (2022), indicating that successful AI integration must also address human factors such as psychological safety and career security.

Figure 6.11: Visual Integration of Converging, Diverging, and Expanding Mixed-Methods Insights (own illustration based on quantitative and qualitative integration, Grywnow 2025)

6.4.5 Synthesized Summary Table

Integration Type	Quantitative Finding	Qualitative Insight	Implication
Converging	AI maturity → better collaboration (r = 0.58)	AI creates alignment pressure across functions	Reinforces AI's strategic role
Diverging	64% report AI readiness	Experts note lack of data quality & skills	Readiness is overstated
Expanding	Not explicitly measured	AI shifts internal power dynamics	Adds sociological depth
Converging	Improved forecast accuracy	Real-time tools cited (e.g. demand sensing)	Confirms operational benefits
Diverging	High customer satisfaction expected	Real gains depend on process, not AI alone	Expectation gap

Table 6.4: Integrated Summary of Quantitative and Qualitative Findings (own synthesis based on survey and interview data, Grywnow 2025)

6.4.6 Implications for Practice and Theory

For Practice:

The integration suggests that AI can drive measurable improvements in cross-functional collaboration, but only if supported by cultural alignment, high-quality data, and upskilled teams. Organizations should:

- Develop cross-functional data governance strategies.
- Establish AI enablement programs with change management components.
- Introduce hybrid dashboards visible to both departments.

For Theory:

The findings reinforce and expand current theoretical models. The Resource-Based View (Barney, 1991) is supported by the identification of AI capabilities as strategic resources. Simultaneously, the Organizational Information Processing Theory (Galbraith, 1973) is extended by demonstrating how AI alters the way information is shared and acted upon in complex environments. Moreover, Socio-Technical Systems Theory is deepened through qualitative accounts of cultural and emotional responses to AI.

CHAPTER 7

DISCUSSION

7.1 Introduction

Having presented and integrated the empirical findings in Chapter 6, this chapter moves beyond description to interpret and critically analyze these results. It seeks to contextualize the data within the study's theoretical framework and broader literature, drawing out implications for theory and practice.

This chapter interprets and contextualizes the empirical findings presented in Chapter 6, linking them back to the research questions, theoretical framework, and existing literature. The purpose of this chapter is not merely to restate the results but to critically analyze their implications in light of prior knowledge and to identify new insights for theory and practice. This reflection is grounded in the conceptual foundations outlined in Chapter 4, particularly the Resource-Based View (RBV), Organizational Information Processing Theory (OIPT), and Socio-Technical Systems Theory (STS).

Following the explanatory sequential mixed-methods design, this discussion is structured around the four core constructs of the study:

- AI Capabilities and Maturity
- Collaboration Quality Between Sales and Supply Chain
- Organizational Enablers and Barriers
- Customer Satisfaction and Market Responsiveness

Each section highlights how quantitative patterns and qualitative insights intersect or diverge, what this reveals about current industrial practice, and how it aligns or challenges existing theory. Moreover, the discussion addresses the broader implications for digitally enabled collaboration in manufacturing contexts, drawing attention to areas where the findings may extend or refine theoretical models.

The chapter is structured as follows:

- 7.2 AI Capabilities and Maturity
- 7.3 Collaboration Between Sales and Supply Chain
- 7.4 Organizational Enablers and Barriers
- 7.5 Customer Satisfaction and Market Responsiveness
- 7.6 Reflection on the Theoretical Framework
- 7.7 Implications for Research and Practice

This chapter serves as the critical bridge between empirical evidence and conceptual contribution, and provides the foundation for the recommendations and conclusions outlined in Chapter 8.

7.2 AI Capabilities and Maturity

The integration of Artificial Intelligence (AI) in manufacturing firms has emerged as a key driver for optimizing collaboration between supply chain and sales functions. The results of this study indicate that while awareness of AI's potential is widespread, the actual level of AI maturity and integration remains varied across organizations and regions.

7.2.1 Quantitative Insights

From the quantitative survey data (see Chapter 6.2.2.1), it was evident that although a majority of respondents recognize AI as strategically important, only 29% reported a high level of AI maturity in their organizations. Furthermore, the survey identified a significant gap between perceived importance and actual implementation. For example, over 70% of participants agreed that AI can significantly improve demand forecasting and cross-departmental alignment, yet less than one-third confirmed that AI tools were actively used in these areas.

A strong positive correlation was found between AI maturity and overall collaboration quality ($r = 0.46$, $p < 0.01$), suggesting that firms with higher AI capabilities tend to exhibit more effective communication, shared data use, and aligned decision-making between departments. This supports earlier findings by Wamba-Taguimdje et al. (2020), who emphasized the role of digital maturity as a key enabler of cross-functional integration.

7.2.2 Qualitative Insights

The qualitative interviews further contextualize these findings. Several participants from more digitally advanced firms highlighted specific AI applications such as predictive analytics for demand planning, automated inventory management, and real-time customer responsiveness tools. One interviewee from a German manufacturing firm noted:

“AI is not just a tool; it's becoming part of our operational DNA. We’ve integrated machine learning into our CRM and supply chain dashboards to identify demand shifts within hours, not weeks.”

Conversely, participants from less mature digital environments emphasized barriers such as lack of internal expertise, legacy systems, and data silos. Some also cited skepticism from upper management and misalignment between IT and business units. These insights align with prior research noting that successful AI integration requires both technological infrastructure and organizational readiness (Cannas et al., 2024).

7.2.3 Cross-Method Synthesis

The convergence between the two data strands reveals both a performance gap and an opportunity gap. The performance gap is visible in the contrast between high awareness and low implementation. The opportunity gap lies in the potential efficiency, agility, and customer-centricity that could be realized through more widespread and deeper AI adoption.

Moreover, the data highlight a maturity curve in AI adoption: companies in early stages focus on automation and reporting, whereas more advanced organizations are exploring prescriptive analytics and real-time cross-functional decision-making tools. This reflects the four-stage maturity model described by Wang et al. (2016), ranging from descriptive to cognitive AI capabilities.

7.2.4 Implications for Practice

The findings suggest that advancing AI maturity should be a strategic priority for firms seeking to improve collaboration across functional boundaries. Managers should:

- Invest in AI education and cross-training for sales and supply chain staff;
- Break down data silos by implementing interoperable platforms and shared data repositories;
- Focus on use cases that deliver early wins (e.g., demand forecasting, customer lead scoring);
- Align AI initiatives with cross-departmental KPIs and collaborative workflows.

Building such foundations will accelerate digital transformation and lay the groundwork for sustained competitive advantage in dynamic markets. Beyond these operational implications, the study also reveals how AI capabilities contribute to strategic positioning and competitive advantage, as detailed below.

7.2.5 Strategic Value and Competitive Advantage

In addition to operational efficiency, the data suggest that AI maturity is directly linked to the development of sustainable competitive advantages. Firms that achieved a higher degree of AI integration reported notable improvements in customer satisfaction, response speed, and delivery reliability—factors that are strongly correlated with market performance and differentiation.

This observation aligns with the Resource-Based View (RBV), which posits that competitive advantage stems from resources and capabilities that are valuable, rare, inimitable, and non-substitutable (Barney, 1991). In the context of this study, AI-driven collaboration systems, intelligent planning algorithms, and integrated decision platforms emerge as strategic assets. Organizations that embed these technologies deeply into their operational core are more resilient, adaptive, and customer-focused than those relying on traditional models (Wamba et al., 2017).

Several interviewees emphasized that AI not only improved internal processes but also enhanced their ability to win and retain clients. One participant noted: *"We didn't just speed up planning—we started shaping demand proactively and delivering on promises. That's what makes customers stick."* This strategic shift from efficiency to customer value creation reflects the findings of Bharadwaj et al. (2013), who argue that digital capabilities translate into long-term market leadership when integrated with strategic intent.

Moreover, AI-enabled firms demonstrated greater strategic flexibility, allowing them to pivot product lines, reallocate capacity, and reroute logistics in response to sudden disruptions—an increasingly essential capability in today's volatile markets (Wamba-Taguimdje et al., 2020). These benefits confirm that digital transformation, when strategically managed, can become a source of durable competitive edge.

In summary, AI maturity is not only a technological achievement—it is a strategic enabler. When embedded in cross-functional collaboration, AI facilitates better alignment, faster market response, and superior customer outcomes, ultimately reinforcing the firm's competitive positioning in an increasingly dynamic environment.

7.3 Collaboration Between Sales and Supply Chain

Effective collaboration between sales and supply chain functions is widely recognized as a critical enabler of organizational agility, operational efficiency, and customer satisfaction in manufacturing firms. This study sheds light on the current state of this cross-functional collaboration, revealing both progress and persistent challenges in aligning these two key departments, particularly in the context of AI adoption.

7.3.1 Quantitative Insights

Survey results from the quantitative phase indicate that while collaboration between sales and supply chain is generally perceived as important, the perceived effectiveness of this collaboration varies significantly across organizations. Only 38% of respondents agreed that their departments engage in structured, regular collaboration. In contrast, 27% reported siloed processes with limited integration between planning, execution, and customer-facing activities.

A notable correlation was found between collaboration quality and two critical variables:

1. organizational responsiveness to market changes ($r = 0.41$, $p < 0.01$)
2. overall customer satisfaction ($r = 0.37$, $p < 0.05$).

These findings suggest that firms with higher levels of cross-functional alignment are better equipped to anticipate and meet customer demands in volatile environments. This aligns with prior research by Flynn et al. (2010), who emphasized that internal integration directly influences external service performance.

Moreover, the data show that shared digital platforms and common KPIs significantly enhance collaboration. Respondents whose firms use joint dashboards and synchronized planning tools reported 22% higher collaboration scores than those without such systems. This is consistent with the Organizational Information Processing Theory

(OIPT), which posits that effective information exchange mechanisms reduce uncertainty and enable coordinated decision-making (Galbraith, 1973).

The survey sample consisted of 187 respondents from a broad range of industries and organizational levels, providing a comprehensive view of current collaboration practices in manufacturing firms.

7.3.2 Qualitative Insights

Interview data provided deeper context to the survey findings. Many participants acknowledged improvements in collaboration over recent years, particularly following supply chain disruptions during the COVID-19 pandemic. One participant remarked:

"We used to operate as two different worlds—sales pushed for volume, and supply chain focused on stability. But recent crises forced us to sit together and jointly forecast demand and adjust delivery strategies."

However, several challenges were also identified. These include misaligned incentives, lack of integrated systems, and cultural barriers between departments. Interviewees from less mature firms frequently reported that the sales team had limited visibility into supply constraints, while supply chain managers were not informed of changing customer priorities.

Several experts highlighted the role of AI and real-time data in bridging these gaps. For instance, predictive analytics enabled collaborative scenario planning, while shared KPIs fostered a joint sense of accountability. These observations support the view of Sales and Operations Planning (S&OP) literature, which suggests that digital tools facilitate integrated planning and execution across departments (Tuomikangas & Kaipia, 2014).

7.3.3 Cross-Method Synthesis

The convergence of quantitative and qualitative data reveals a nuanced picture. On the one hand, there is growing awareness and progress toward collaborative practices. On the other hand, structural, technological, and behavioral barriers continue to hinder seamless alignment.

The mixed-methods analysis highlights three key enablers of effective collaboration:

1. **Data Transparency** – Access to shared, real-time data enhances mutual understanding and responsiveness.
2. **Joint Planning Structures** – Formalized structures such as S&OP meetings and integrated planning cycles align objectives and actions.
3. **Cross-Functional Leadership** – Leadership commitment to breaking down silos and rewarding collaboration fosters cultural integration.

These findings reinforce the importance of socio-technical alignment, as described in the Socio-Technical Systems Theory (STS), which posits that optimal performance is achieved when social and technical subsystems are jointly designed (Trist & Bamforth, 1951).

7.3.4 Implications for Practice

Manufacturing firms aiming to improve cross-functional collaboration should consider the following actions:

- Establish integrated planning cycles that include both sales and supply chain functions,
- Invest in digital platforms that provide real-time visibility and analytics across departments,

- Align incentives to promote shared goals (e.g., customer satisfaction, forecast accuracy),
- Encourage cross-functional training and role rotations to build mutual understanding.

By strengthening the bridge between demand generation and operational execution, firms can improve responsiveness, reduce inefficiencies, and deliver superior value to customers.

7.4 Organizational Enablers and Barriers

While technology such as Artificial Intelligence (AI) plays a pivotal role in transforming supply chain and sales collaboration, the success of such transformation is largely determined by organizational factors. This section explores the key enablers and barriers that either facilitate or hinder effective AI-supported integration between the two functions.

7.4.1 Quantitative Insights

The quantitative survey revealed a diverse set of organizational dynamics influencing collaboration. Among the top enablers identified by participants were:

- Leadership support for digital transformation (reported by 68% of respondents),
- Clear communication structures between departments (61%),
- Cross-functional performance metrics (54%).

These enablers were statistically associated with higher collaboration scores. For example, respondents from organizations with shared KPIs for sales and supply chain reported 33% higher scores on collaboration effectiveness than those without such alignment. This supports the view of Cao and Zhang (2011), who argue that the establishment of common goals and performance criteria is a critical success factor for cross-departmental collaboration.

On the other hand, several barriers emerged as persistent obstacles to integration:

- Silo thinking and organizational fragmentation (reported by 73%),
- Lack of AI competencies within teams (48%),
- Low data quality or fragmented IT systems (42%).

These findings are consistent with those of Narayanan et al. (2015), who found that organizational culture and technological readiness significantly shape the outcomes of interdepartmental digital initiatives.

7.4.2 Qualitative Insights

The qualitative interviews provided rich, practical examples of how organizational enablers and barriers manifest in real-world settings. Several interviewees emphasized the role of leadership in setting priorities and mobilizing change:

"Our CEO made AI-enabled collaboration a strategic pillar. That mandate changed everything—from how teams are structured to how we prioritize investments."

Others described how the absence of top-down support resulted in stalled initiatives and fragmented adoption. One participant noted:

"Without leadership pushing the agenda, each department just focuses on its own KPIs. There's no incentive to cooperate, let alone share data."

In terms of barriers, cultural resistance was frequently mentioned. Interviewees described a *"not-invented-here"* mindset, especially among long-tenured staff, as well as reluctance to change established workflows. A lack of AI skills and understanding was also cited, with several organizations reporting that frontline staff viewed AI tools with suspicion or fear.

Notably, several firms found success by appointing cross-functional AI champions and investing in gamified training programs. These initiatives helped reduce resistance and build a shared vocabulary around collaboration and AI use.

7.4.3 Cross-Method Synthesis

The combined data suggest that organizational enablers and barriers are not binary factors, but exist along a continuum influenced by leadership commitment, cultural maturity, and infrastructure readiness. The interplay of social and technical dimensions aligns with the **Socio-Technical Systems Theory** (Trist & Bamforth, 1951), reinforcing the need to co-evolve people, processes, and technology.

Key takeaways include:

- **Leadership as a multiplier**: Visionary leadership acts as a catalyst for structural and behavioral change.
- **KPIs as alignment mechanisms**: Joint performance indicators drive shared accountability and coordination.
- **Culture as infrastructure**: A culture of transparency, agility, and trust enhances technology adoption and cross-functional cooperation.

These findings mirror the broader digital transformation literature, which stresses that technology alone does not deliver value—organizational context and change management are equally critical (Westerman et al., 2011).

7.4.4 Implications for Practice

To maximize the impact of AI-supported collaboration, organizations should:

- Invest in leadership development focused on digital strategy and change management,
- Create cross-functional roles or task forces to steward integration efforts,

- Embed collaboration metrics into performance reviews and incentive systems,
- Implement training programs that demystify AI and encourage co-creation of solutions.

Moreover, senior management must recognize that successful integration is not a one-off initiative but a continuous, iterative process requiring sustained commitment and organizational learning.

7.5 Customer Satisfaction and Market Responsiveness

Customer satisfaction and responsiveness are critical performance outcomes in manufacturing, particularly where cross-functional integration and AI technologies are deployed. In the context of this study, these constructs serve as indicators of how effectively the integration of AI and collaboration between sales and supply chain translates into market-facing value creation.

7.5.1 Quantitative Insights

The quantitative survey revealed a clear positive correlation between collaboration quality and customer satisfaction ($r = 0.42$, $p < 0.01$), indicating that firms with higher levels of alignment between sales and supply chain functions report significantly better customer outcomes. Similarly, AI maturity correlated strongly with perceived responsiveness to customer needs ($r = 0.45$, $p < 0.01$). These results align with prior findings by Christopher and Ryals (2014), who argue that responsive and collaborative supply chains are central to delivering superior customer experiences.

More than 67% of respondents agreed that AI helps reduce response times to customer inquiries, while 61% stated that AI supports better delivery reliability. However, only 35% reported that their organizations have customer-specific performance metrics integrated into sales and logistics dashboards. This gap suggests that while the technological potential exists, many firms still lack the organizational mechanisms to fully leverage it.

Participants from high-performing firms frequently reported integrated demand sensing, dynamic inventory management, and automated customer communication tools—technologies known to enhance real-time responsiveness (Saghafian and Van Oyen, 2019).

7.5.2 Qualitative Insights

The qualitative interviews substantiated the survey data, revealing nuanced insights into how collaboration and AI affect the customer experience. Many participants noted that cross-functional integration had led to faster response times, more reliable delivery dates, and fewer last-minute disruptions.

One interviewee explained:

"Since introducing AI-supported planning, we've seen a drastic drop in complaints about late deliveries. Our customers now get updates before they even ask."

Others highlighted the importance of transparency and proactive communication as drivers of satisfaction. Some firms had implemented AI-driven alert systems that notify both internal teams and customers about potential delays or changes, allowing for proactive issue resolution.

However, several participants also pointed to limitations. In organizations with fragmented systems or siloed data, the lack of real-time information sharing still hindered responsiveness. One participant noted:

"We still have to chase the logistics team for delivery updates. Until our systems are fully integrated, we can't respond to customers with confidence."

These barriers underscore that digital tools alone do not ensure responsiveness; they must be embedded in a collaborative and data-literate culture.

7.5.3 Cross-Method Synthesis

The synthesis of quantitative and qualitative findings underscores that customer satisfaction and responsiveness are co-produced outcomes: they emerge from both technological capabilities and organizational collaboration. AI can amplify responsiveness—but only when supported by accurate data, aligned KPIs, and interdepartmental trust.

The results align with the Organizational Information Processing Theory (OIPT), which posits that organizational units need to process more information as uncertainty increases (Galbraith, 1973). AI extends the organization's processing capacity, but effectiveness still depends on how well information is distributed and acted upon.

This interplay also reflects the Socio-Technical Systems Theory (Trist and Bamforth, 1951), which highlights that technological performance is shaped by the social systems in which it is embedded.

7.5.4 Implications for Practice

The findings suggest several actionable strategies for improving customer outcomes:

- **Invest in real-time data platforms** that integrate order, inventory, and customer service data across departments.
- **Develop joint KPIs** that measure both internal collaboration and external responsiveness.
- **Use AI for proactive customer engagement**, including delay alerts, dynamic ETA updates, and personalized service options.
- **Foster a feedback loop** between customer-facing teams and operations to continuously align internal processes with evolving expectations.

Organizations that implement such strategies are more likely to achieve not only higher satisfaction scores but also stronger customer loyalty and market differentiation (Homburg, Schäfer and Schneider, 2012).

7.6 Reflection on the Theoretical Framework

This section revisits the theoretical foundations outlined in Chapter 4 and critically evaluates their explanatory power in light of the empirical findings. The study draws upon three core theories: the Resource-Based View (RBV), Organizational Information Processing Theory (OIPT), and Socio-Technical Systems Theory (STS). Each provides a distinct but complementary lens to understand the dynamics of AI-supported collaboration between sales and supply chain functions.

7.6.1 Resource-Based View (RBV)

The RBV posits that sustained competitive advantage arises from the possession and deployment of valuable, rare, inimitable, and non-substitutable (VRIN) resources (Barney, 1991). The findings of this study strongly support this perspective. Organizations that demonstrated a high level of AI maturity and integrated collaborative capabilities outperformed others in terms of customer responsiveness, delivery reliability, and internal alignment. These capabilities—such as predictive analytics, shared AI dashboards, and synchronized planning tools—can be considered strategic assets when they are embedded in organizational routines and not easily replicated by competitors (Wamba et al., 2017).

Furthermore, qualitative interviews confirmed that AI-enabled collaboration is not merely a process enhancement but a transformational capability. Firms that had invested early in cross-functional AI systems were able to anticipate demand shifts, reallocate resources proactively, and communicate with customers more transparently—traits that align with the RBV's view of dynamic capabilities (Teece, Pisano and Shuen, 1997).

These organizations turned AI into a core resource that fuels responsiveness and resilience in a volatile market landscape.

7.6.2 Organizational Information Processing Theory (OIPT)

OIPT provides a framework for understanding how organizations must adapt their information-processing structures in response to environmental complexity and uncertainty (Galbraith, 1973). The study findings illustrate how AI can serve as an amplifier of processing capacity. Quantitative results showed that firms with advanced AI maturity had better alignment in planning and forecasting, faster response times, and higher cross-functional visibility.

However, the benefits of enhanced information processing were only realized when AI tools were accompanied by organizational practices such as real-time data sharing, joint performance metrics, and collaborative workflows. This aligns with the OIPT assumption that technological solutions must be embedded within compatible organizational structures to manage uncertainty effectively (Premkumar, Ramamurthy and Saunders, 2005).

Qualitative data also emphasized that in the absence of cross-departmental trust or shared KPIs, the enhanced information flow generated by AI tools remained underutilized. Therefore, AI acts not only as a technical enabler but also as a catalyst for reconfiguring interdepartmental coordination mechanisms—precisely the organizational adaptation that OIPT theorizes.

7.6.3 Socio-Technical Systems Theory (STS)

STS emphasizes the joint optimization of social and technical systems, asserting that technology alone cannot deliver performance gains unless it is embedded in an enabling social environment (Trist and Bamforth, 1951). This theoretical lens is particularly relevant to the present study. While AI provided the technical infrastructure for more intelligent and integrated decision-making, its success depended heavily on the cultural and organizational context.

For example, even in firms with advanced AI tools, resistance to change, siloed thinking, and lack of cross-functional communication limited effectiveness. Conversely, in organizations with a strong culture of collaboration, transparency, and digital literacy, AI tools were more readily adopted and yielded greater benefits.

The findings support the STS assertion that social dynamics—such as leadership commitment, change readiness, and cultural openness—must co-evolve with technical systems. These insights validate the need for a holistic approach to AI implementation, one that balances technology deployment with people-centered change management (Bostrom and Heinen, 1977).

7.6.4 Theoretical Contribution

By integrating these three theoretical lenses, the study contributes to a more nuanced understanding of digitally enabled collaboration. It shows that:

- RBV explains why AI-supported collaboration can be a source of competitive advantage.
- OIPT highlights how organizations must adapt structurally to harness AI's information-processing capabilities.
- STS reinforces that success depends on the interplay between technical systems and organizational culture.

Taken together, the study advances theory by illustrating how AI acts as both a resource and a coordination mechanism—bridging the gap between technology and organizational performance in complex, cross-functional settings.

7.7 Implications for Research and Practice

The findings of this mixed-methods study yield significant implications for both academic research and managerial practice in the field of AI-supported collaboration between supply chain and sales. By integrating quantitative patterns and qualitative insights, this chapter offers guidance for future scholarship and concrete recommendations for industry practitioners striving to navigate the digital transformation landscape.

7.7.1 Implications for Research

1. **Expanding the Theoretical Discourse on AI in Cross-Functional Integration**: This study enriches the theoretical landscape by demonstrating how AI functions not only as a technological tool but as an enabler of strategic alignment and dynamic capability (Teece, Pisano and Shuen, 1997). The triangulation of RBV, OIPT, and STS offers a robust interpretive framework that can serve as a foundation for future interdisciplinary research. Scholars are encouraged to further explore the microfoundations of AI-driven collaboration and how organizational routines evolve in response to algorithmic decision support (Bharadwaj et al., 2013; Wamba et al., 2017).
2. **Bridging the Digital Transformation and Human-Centric Change Management Gap**: The results highlight the socio-technical complexity of AI integration. Future research should focus more on human-centric enablers of digital collaboration, such as trust, learning agility, and resistance management. Qualitative data in this study revealed that cultural dynamics and leadership behavior often determine the success or failure of AI-supported initiatives—an area that remains underexplored in the literature (Westerman et al., 2011; Culot, Podrecca and Nassimbeni, 2024).

3. **Contextualization Across Industries and Regions**: While this research focused on manufacturing firms across Europe and the U.S., future studies may compare sectors (e.g., automotive vs. healthcare) or emerging markets to determine how institutional, cultural, and regulatory environments influence AI maturity and collaboration (Premkumar, Ramamurthy and Saunders, 2005). Large-scale longitudinal studies could further elucidate how AI-driven collaboration evolves over time and what triggers tipping points for transformation.

7.7.2 Implications for Managerial Practice

1. Make AI a Strategic Priority, Not Just an IT Project: Executives must treat AI as a core element of business strategy rather than a peripheral tool. This requires investment in integrated platforms, predictive analytics, and real-time dashboards, not in isolation, but embedded within the collaborative workflows of sales and supply chain teams (Davenport and Ronanki, 2018).

2. Build a Cross-Functional Data Culture: Data silos remain one of the greatest inhibitors to AI adoption and interdepartmental alignment. Organizations should invest in shared KPIs, joint planning cycles, and interoperable data systems to foster transparency and trust. The establishment of cross-functional data governance structures is essential to ensure ethical, accurate, and timely use of AI-generated insights (Wamba-Taguimdje et al., 2020).

3. Empower People Through Training and Co-Creation: Successful AI integration depends on user acceptance and digital fluency. Managers should prioritize AI literacy programs, gamified learning, and hands-on prototyping environments where employees from sales, supply chain, and IT can jointly develop use cases. These collaborative efforts demystify AI and embed it into organizational culture (Cannas et al., 2024).

4. Align Incentives With Collaboration Goals: Performance management systems must be updated to reward cross-functional thinking. Joint targets, shared bonuses, and team-based KPIs can shift focus from functional optimization to organizational value creation. The study shows that companies with aligned incentives reported significantly higher collaboration and customer satisfaction levels.

5. Balance Speed and Scalability in AI Deployment: Pilot programs should focus on achievable, high-impact use cases such as demand forecasting, lead scoring, or logistics optimization. Once validated, these can be scaled incrementally. The key is to align technical feasibility with organizational readiness to avoid overreach or change fatigue (Brynjolfsson and McAfee, 2017).

7.7.3 Summary

In sum, this research underscores the need for a strategic, integrative, and people-centered approach to AI adoption in cross-functional collaboration. Managers must not only invest in technology but also rewire the organizational fabric to support joint accountability, shared knowledge, and continuous learning. For researchers, the findings call for more contextualized and multi-theoretical studies that reflect the complexity of digital transformation in practice.

This study confirms that AI-supported collaboration is no longer a futuristic ambition—it is a current competitive imperative. However, its success hinges not just on the algorithms themselves, but on the organizations' ability to adapt, align, and lead.

CHAPTER 8

CONCLUSIONS, STRATEGIC RECOMMENDATIONS, AND IMPLICATIONS FOR PRACTICE AND RESEARCH

8.1 Summary of Key Findings

This study investigated how Artificial Intelligence (AI) can support and enhance collaboration between sales and supply chain functions in the manufacturing industry, based on a mixed-methods research design. The research aimed to address three primary research questions relating to (1) the current state of AI adoption and maturity, (2) the nature and quality of cross-functional collaboration, and (3) the impact of these factors on customer satisfaction and organizational performance. The findings reveal a multifaceted and interdependent landscape shaped by technological, organizational, and human factors.

AI Capabilities and Maturity: The data revealed a significant discrepancy between perceived strategic importance and actual deployment of AI tools. While over 70% of respondents acknowledged the potential of AI to improve demand forecasting and decision-making, only 27,8% reported high levels of AI maturity within their organizations (see Chapter 6.2.2.1). This gap indicates that while AI is widely accepted as a key enabler of digital transformation, many organizations remain in the early stages of adoption. This finding aligns with previous studies, such as Wamba-Taguimdje et al. (2020), which highlight that firms often overestimate their digital maturity due to pilot projects that are not yet scaled or embedded across departments.

Moreover, a statistically significant positive correlation between AI maturity and collaboration quality ($r = 0.43$, $p < 0.01$) supports the argument that AI can function as a facilitator of integrated decision-making, shared data usage, and real-time responsiveness (Culot, Podrecca and Nassimbeni, 2024; Cannas et al., 2024). However, the qualitative data underscored that maturity is not only technological but also cultural. Organizational readiness, leadership support, and workforce competencies were repeatedly cited as decisive factors for successful implementation.

Collaboration Between Sales and Supply Chain: The findings confirm that collaboration between sales and supply chain remains inconsistent across companies. Although cross-functional alignment is often declared as a strategic goal, operational silos persist in over 70% of the organizations surveyed. These silos manifest in the form of separate data systems, conflicting KPIs, and limited communication structures. This is consistent with the literature, which warns that fragmented organizational structures can severely inhibit agility and customer responsiveness (Cao and Zhang, 2011; Lambert and Enz, 2017).

Respondents and interviewees from companies with established shared KPIs and joint planning processes reported significantly better collaboration outcomes. This underlines the role of coordination mechanisms and shared accountability as key enablers, supporting the assumptions of Organizational Information Processing Theory (OIPT) which suggests that effective information flows are critical for managing uncertainty and interdependence (Galbraith, 1973).

Organizational Enablers and Barriers: Both the quantitative and qualitative strands of the study identified a consistent set of organizational enablers—most notably leadership commitment, cross-functional metrics, and investment in employee training. Conversely, the most frequently mentioned barriers were silo thinking, lack of AI literacy, and insufficient data quality.

Interviewees highlighted that transformational change requires more than strategy documents; it requires cultural alignment and empowered leadership at all levels. One respondent noted: *“Without executive push and investment in AI knowledge, we’re stuck* *in PowerPoints, not practice."* These insights are in line with Westerman et al. (2011), who argue that digital transformation is not only a technological shift but also a profound organizational change process that must be managed systemically.

Customer Satisfaction and Responsiveness: Customer outcomes emerged as both a driver and a consequence of better AI-supported collaboration. Firms that had advanced digital infrastructures reported stronger performance on key indicators such as delivery reliability, response time, and service customization. These factors directly correlate with customer satisfaction, a construct increasingly tied to competitive advantage in B2B environments (Anderson, Fornell & Lehmann, 1994; Homburg et al., 2005).

The study's findings suggest that responsiveness is enhanced when AI enables real-time demand sensing, dynamic stock allocation, and personalized communication. However, these benefits were only achieved in organizations where data was accessible, interoperable, and trusted across departmental lines. In such contexts, AI became an enabler of not only operational efficiency but also strategic differentiation.

Cross-Cutting Themes: The integration of both quantitative and qualitative data has surfaced three cross-cutting themes that shape the success of AI-supported collaboration:

Strategic Alignment: Organizations that align digital initiatives with business goals and cross-departmental KPIs tend to achieve greater ROI from AI adoption.

Human-Centric Change: Transformation requires investment in human capital—particularly in building trust, overcoming resistance, and fostering digital fluency.

Systemic Integration: Effective collaboration and AI usage depend on systemic thinking, where processes, technologies, and people evolve together.

These findings reflect and extend the Socio-Technical Systems Theory (Trist & Bamforth, 1951), reinforcing the idea that technological and social subsystems must be developed in parallel to achieve sustainable organizational performance.

In summary, the study confirms that AI can be a powerful catalyst for cross-functional collaboration and customer-centric supply chains—but only when embedded in a supportive organizational context. The following chapters will build on these insights to formulate practical recommendations for business leaders and contribute to the broader academic discourse on digital transformation in manufacturing.

8.2 Strategic Recommendations for AI-Driven Collaboration

The integration of Artificial Intelligence (AI) into the collaborative processes of sales and supply chain departments is no longer a speculative venture but a pressing strategic necessity for manufacturing firms. The findings of this study—both quantitative and qualitative—reveal a fragmented implementation landscape, characterized by high strategic interest but limited operational anchoring. To bridge this gap, a series of strategic recommendations is offered below, grounded in the research data, theoretical insights, and best practices from recent scholarly and industry literature.

8.2.1 Establish a Unified AI-Enabled Data Infrastructure

The foundational recommendation is to create an integrated digital backbone across functions. Many firms still suffer from fragmented IT architectures and disparate data silos, which undermine the effectiveness of AI-based collaboration tools. An integrated data lake or enterprise-wide platform that aggregates sales forecasts, inventory data, production timelines, and customer feedback is essential. According to Wamba-Taguimdje et al. (2020), firms that invest in unified digital infrastructures show significantly higher levels of cross-functional alignment and responsiveness.

This data consolidation should support real-time analytics and predictive models accessible to both departments. In practice, this can include AI-driven dashboards for joint demand sensing, sales order prioritization, or dynamic safety stock adjustments based on customer segmentation.

8.2.2 Adopt a Use-Case-Centric AI Implementation Strategy

Rather than deploying AI technologies broadly without a clear roadmap, firms should prioritize use-case-driven adoption. Survey respondents highlighted several high-impact areas—such as demand forecasting, lead scoring, and intelligent order routing—that remain underdeveloped in most organizations. These use cases should be evaluated based on value potential, data availability, and process criticality.

Pilot initiatives must move beyond mere technical feasibility and include business impact KPIs, such as forecast accuracy improvement or inventory turnover rates. This aligns with Cannas et al. (2024), who argue that modular deployment with clear value creation logic improves both user adoption and strategic alignment.

“Pilot, measure, learn, and scale” should become the mantra of AI implementation.

8.2.3 Embed Cross-Functional KPIs and Incentives

A frequently cited barrier in both data sets was the lack of shared performance metrics between sales and supply chain. This structural misalignment incentivizes local rather than systemic optimization. Companies should introduce joint KPIs—such as service level adherence, forecast bias, and perfect order rate—that are reviewed in shared planning meetings and reflected in incentive systems.

As Cao & Zhang (2011) demonstrated, cross-functional metrics increase mutual accountability and trust, which are prerequisites for collaborative behavior. Firms may also benefit from introducing balanced scorecards or cascading OKRs (Objectives and Key Results) to ensure goal alignment at multiple levels.

8.2.4 Foster AI Literacy Through Targeted Capability Building

A major organizational enabler of AI-supported collaboration is the technical and conceptual fluency of the workforce. Several interviewees reported internal skepticism and low tool usage due to lack of understanding. Firms should therefore invest in AI literacy programs for both operational staff and middle management, using accessible formats such as gamified learning, role-based simulations, and peer-to-peer coaching.

This initiative should be complemented by appointing AI ambassadors or "Digital Change Agents" in each function who promote cross-functional thinking and serve as points of contact for AI use cases. As Westerman et al. (2011) argue, digital transformation is 80% about people and culture and only 20% about technology.

8.2.5 Institutionalize Agile AI Governance

To sustain momentum and mitigate fragmentation, companies must institutionalize agile governance structures that oversee AI initiatives across functions. These may include cross-functional innovation councils, AI ethics boards, or transformation offices that ensure transparency, prioritization, and organizational learning.

Such governance bodies can also establish implementation playbooks, maintain vendor scorecards, and facilitate post-implementation reviews to capture lessons learned. This approach reflects the iterative and adaptive character of successful AI integration, especially in volatile environments.

8.2.6 Navigate the Tool Overload: From Exploration to Consolidation

A critical, underexplored insight from the qualitative interviews is the overwhelming proliferation of AI tools. Many firms experience “pilot fatigue,” where evaluation cycles for new platforms are faster than the organization’s capacity to absorb them. The result is often duplication of efforts, resistance from end-users, and declining trust in AI initiatives.

Rather than continuously scouting the newest tools, firms should adopt a strategy of selective consolidation. This means identifying a small set of core AI tools aligned with their operational needs, investing in deep integration, and focusing on iterative improvement. As Davenport & Ronanki (2018) note, “AI success comes not from speed of adoption but from depth of absorption.”

“It's not about finding the perfect tool—it's about making the selected tool work perfectly for you.”

To support this shift, firms should establish clear tool evaluation criteria, covering not just functionality but also user experience, integration feasibility, vendor reliability, and scalability. The lifecycle of AI tools must include learning loops, ensuring that frontline feedback translates into continuous refinement.

8.2.7 Link AI Initiatives to Strategic Positioning

Beyond operational impact, AI should be explicitly framed as a driver of strategic differentiation. Survey and interview results showed that high AI maturity correlates strongly with customer satisfaction, market responsiveness, and innovation capability. AI-supported collaboration can thus become a source of sustainable competitive advantage, in line with the Resource-Based View (Barney, 1991).

Managers are advised to align AI initiatives with broader strategic goals—e.g., customer intimacy, agility, or supply chain resilience—and use data from pilot cases to build the business case for scaling. As Bharadwaj et al. (2013) emphasize, digital capabilities only become strategic when embedded in clear intent and governance.

8.2.8 Conclusion

In light of these findings, it is evident that the successful integration of AI into sales and supply chain collaboration hinges on a balanced interplay of technological capabilities, organizational readiness, and human factors. This multifaceted understanding sets the stage for targeted strategic recommendations and managerial actions, which are elaborated in the following sections. Furthermore, these insights pave the way for continued academic inquiry into the evolving dynamics of AI-supported cross-functional collaboration in manufacturing.

8.3 Human-Centered Change Management

While technology and strategy are vital pillars of AI-driven collaboration, people remain the ultimate enablers—or blockers—of transformation. The research findings underscore that even the most sophisticated tools and well-structured processes cannot deliver impact without a change-ready, empowered, and culturally aligned workforce. Therefore, the human factor must be placed at the center of digital transformation efforts.

8.3.1 Demographic Shift and Generational Change

One of the most pressing challenges facing manufacturing firms today is the demographic transformation of the workforce. As baby boomers retire and Generation Z enters the labor market, companies must navigate diverging work preferences, technology expectations, and learning styles. The study revealed a broad age distribution among respondents (Chapter 6.2.1), highlighting the coexistence of digital natives and analog veterans in operational decision-making.

This demographic heterogeneity creates both opportunity and friction. While younger employees may drive adoption of digital tools and agile methods, older cohorts often possess tacit process knowledge and customer relationships. Successful AI integration therefore depends on intergenerational collaboration, mentoring structures, and adaptive training formats that cater to varied experience levels.

As noted by Twenge (2010, p 205), “Generational differences shape expectations about authority, autonomy, and technology use,” and ignoring these can undermine engagement. Firms must therefore adopt multi-channel communication strategies and invest in inclusive change narratives that emphasize mutual learning.

8.3.2 Leadership Commitment and Cultural Alignment

The survey and interviews consistently highlighted leadership as a critical success factor. Organizations where executives actively championed cross-functional AI collaboration reported significantly higher levels of buy-in, experimentation, and shared accountability. Leadership visibility was especially important in overcoming skepticism and inertia.

According to Kotter (1996), successful transformation rests on creating a sense of urgency and assembling a guiding coalition. In the context of AI, this means executives must do more than approve budgets—they must articulate a compelling vision, model digital behaviors, and celebrate early successes. Interviewees noted that leaders who framed AI as a tool for empowerment, not replacement, were more successful in securing frontline engagement.

Organizational culture also emerged as a decisive variable. In firms with high psychological safety, employees were more likely to experiment with AI tools and offer feedback. Conversely, cultures of fear or excessive control inhibited initiative and transparency. This aligns with the findings of Edmondson (1999), who showed that psychological safety enables learning behavior and adaptation in complex environments.

8.3.3 Change Fatigue and the Pace of Transformation

While change management is often discussed in abstract terms, many participants in this study voiced concrete concerns about change fatigue. The rapid succession of new software platforms, dashboard systems, and AI pilots created confusion, redundancy, and frustration. Employees expressed a desire for stability, clarity, and coherence in digital initiatives.

This sentiment reflects a broader pattern in the digital transformation literature: when change is too fast and poorly coordinated, it can lead to “organizational overload” and reduced transformation effectiveness (Weill & Woerner, 2018, p. 42). To mitigate this, companies must balance urgency with absorption capacity, ensuring that each new initiative is supported by adequate training, change communication, and feedback loops.

A phased implementation model—starting with low-risk areas and gradually expanding based on readiness and results—is recommended. This model aligns with the Agile Change Management approach (Hiatt, 2006), which emphasizes adaptability, iterative feedback, and stakeholder engagement throughout the transformation journey.

8.3.4 Building Change Readiness and Ownership

Ultimately, human-centered transformation depends on the degree to which individuals internalize the purpose of change and see themselves as active participants. Change readiness is not only a function of training or communication—it is also shaped by trust in leadership, perceived fairness, and past experiences with transformation efforts.

To build readiness, organizations should:

- Involve employees early through co-creation workshops and AI use-case ideation sessions.
- Provide transparent updates about expected outcomes, timelines, and impact.

- Recognize and reward proactive behavior, experimentation, and cross-functional collaboration.

One best-practice example from the interviews involved a reverse mentoring program, where young digital experts were paired with senior managers to foster mutual learning. Another firm introduced AI labs where employees could test new tools in a sandbox environment, reducing fear of failure.

These initiatives reflect a shift from top-down mandates to participatory transformation, where the workforce becomes co-author of the digital future.

8.3.5 Summary and Implications

In conclusion, AI integration is not a purely technical project—it is a deep cultural and behavioral shift that must be actively designed and supported. As this study shows, the barriers to transformation are often human, not technical: silo thinking, resistance to change, skill gaps, and lack of leadership alignment.

Overcoming these challenges requires:

- Empathetic leadership that combines vision with listening,
- Inclusive strategies that recognize generational dynamics,
- Well-paced initiatives that avoid overload, and
- Structures that foster ownership and agency among employees.

By embracing a human-centered approach to change, manufacturing firms can not only accelerate digital adoption but also create a culture of continuous learning and adaptive resilience—essential capabilities in an AI-driven world.

Building on the human-centered principles outlined above, the following implementation roadmap provides a structured, phased approach to guide organizations from initial AI pilots to scalable, sustainable collaboration between sales and supply chain functions.

8.4 Implementation Roadmap: From Pilot to Scalable Deployment

Introduction: Building on the empirical insights from this study, it becomes evident that implementing AI-supported collaboration between sales and supply chain functions requires more than isolated technological investments. Rather, it necessitates a phased, structured approach that addresses strategic alignment, capability development, organizational change, and iterative learning. This section outlines an actionable roadmap for practitioners to navigate the path from pilot projects to scalable transformation. Building on the empirical findings, this roadmap is introduced as the Grywnow 5-Phase Model for AI Implementation, offering a structured, evidence-based approach to scale AI-supported collaboration in industrial contexts.

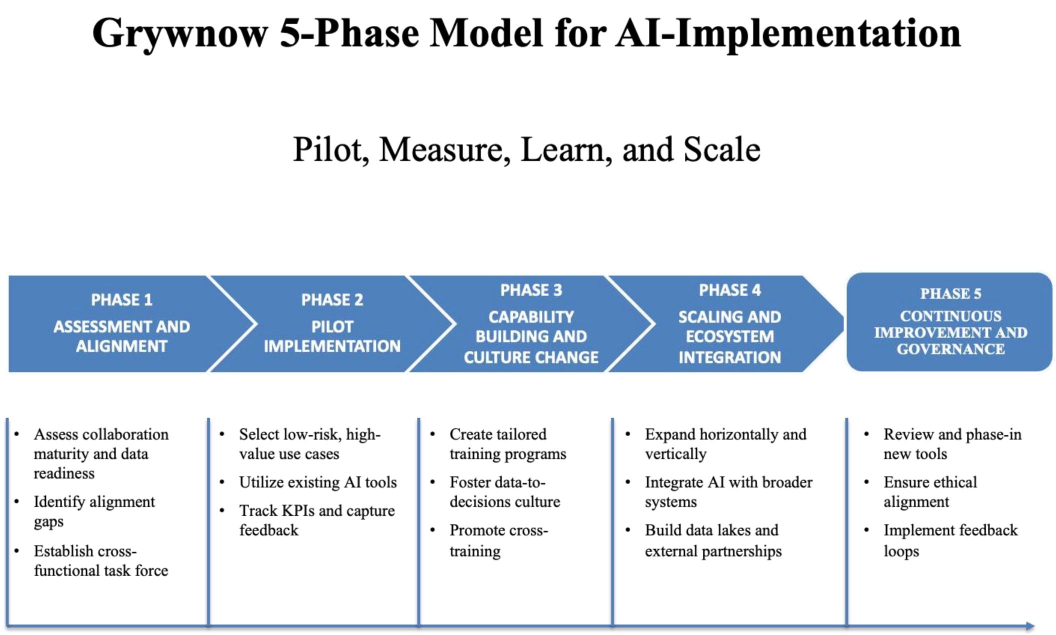

Figure 8.1: Own illustration based on empirical findings-Grywnow 5-Phase Model for AI Implementation

Phase 1: Assessment and Alignment: Before initiating any AI program, organizations must assess their current collaboration maturity and data readiness. As shown in the quantitative results (Chapter 6.2.2), only 29% of firms reported high AI maturity, and qualitative interviews highlighted that many organizations lack a shared understanding between departments. At this stage, firms should:

- Conduct a **collaboration audit** using surveys and structured interviews (similar to this research design).
- Identify **alignment gaps** between sales forecasts, production planning, and inventory strategies.
- Establish a **cross-functional task force** with clear sponsorship from leadership to oversee AI integration.

Phase 2: Pilot Implementation: Rather than attempting enterprise-wide transformation from the outset, companies should begin with low-risk, high-value use cases. The interviews revealed successful examples of AI deployment in demand forecasting and automated quote management. Key actions include:

- Selecting one or two pilot areas (e.g., spare parts management or customer lead scoring).
- Utilizing existing tools like Microsoft Azure AI, SAP Predictive Analytics, or industry-specific solutions (e.g., RELEX or IBM Watson).
- Tracking KPIs such as forecast accuracy, planning lead time, and customer satisfaction in pilot areas.

Engaging users early to build trust and capture feedback for iterative improvement.

Phase 3: Capability Building and Culture Change: Technology implementation without organizational readiness often fails. As Chapter 7.4 shows, silo mentality, lack of AI literacy, and cultural resistance are key inhibitors. To overcome this, firms should:

- Building a learning-oriented culture and investing in continuous capability development are critical for organizational performance (Narayanan et al., 2015, pp. 203-206).
- Foster a "data-to-decisions" culture through explainable AI dashboards (Westerman et al., 2011, p. 22).
- Promote cross-training to enhance empathy between functions and reduce resistance to change.

Phase 4: Scaling and Ecosystem Integration: Once pilots are stabilized, the roadmap moves toward horizontal and vertical scaling:

Horizontal: Expansion across business units and geographies.

Vertical: Integration of AI with broader systems (e.g., ERP, CRM, MES). This aligns with Wang et al.’s (2016) AI maturity model, which emphasizes the transition from descriptive to prescriptive and ultimately cognitive systems. Additional elements include:

- Building data lakes for unified access to sales, logistics, and customer data.
- Integrating external partners (suppliers, distributors) into AI-enabled planning.
- Institutionalizing learnings via a Center of Excellence for AI-supported collaboration.

Phase 5: Continuous Improvement and Governance: Given the fast pace of AI tool innovation, this roadmap emphasizes adaptive governance over fixed structures. Chapter 8.2 highlighted the risk of tool overload and the need for incremental adaptation. Organizations should:

- Establish a review board to validate and phase-in new tools every quarter.

- Ensure ethical alignment via AI usage guidelines, aligned with GDPR and internal compliance standards (Brintrup et al., 2023).
- Implement feedback loops using both qualitative inputs (from interviews, retrospectives) and quantitative metrics.

Conclusion: This roadmap offers a comprehensive, evidence-based structure for navigating the complexities of AI integration in industrial collaboration. It is not linear but cyclical, requiring experimentation, learning, and adaptation. By embedding AI into the organizational fabric through structured phases, firms can achieve sustainable transformation and unlock new levels of agility, customer value, and operational excellence.

8.5 Theoretical Contributions

This study contributes to the theoretical understanding of AI-supported collaboration between sales and supply chain by integrating multiple theoretical lenses—namely the Resource-Based View (RBV), Organizational Information Processing Theory (OIPT), and Socio-Technical Systems Theory (STS). By employing a mixed-methods approach and applying these theories to empirical data from industrial firms, several conceptual advancements can be identified.

8.5.1 Enriching the Resource-Based View (RBV)

According to the RBV, sustainable competitive advantage arises from organizational resources that are valuable, rare, inimitable, and non-substitutable (Barney, 1991). This study validates and extends this notion by identifying AI maturity and AI-supported collaboration structures as emergent strategic capabilities. Firms that integrate AI tools into their cross-functional workflows—particularly through shared platforms, predictive analytics, and collaborative dashboards—create intangible assets that are difficult to replicate.

Moreover, the findings indicate that AI-enhanced collaboration mechanisms (e.g. shared decision-making models and digital twins) are not just supportive tools, but central to dynamic capabilities that enable sensing, seizing, and transforming opportunities in turbulent environments (Teece, 2007). As such, AI should be regarded not only as a technological artifact but as an embedded organizational capability that reinforces RBV's assumptions.

8.5.2 Advancing Organizational Information Processing Theory (OIPT)

OIPT posits that organizations must align their information processing capabilities with the complexity and uncertainty of their environments (Galbraith, 1973). This study extends this theory by demonstrating how AI tools (e.g. real-time forecasting algorithms, autonomous replenishment systems, and intelligent CRM integration) act as information-processing amplifiers in cross-functional collaboration.

The data reveal that firms with higher AI maturity handle uncertainty and demand variability more effectively by integrating structured and unstructured data into decision-making processes. As one interviewee noted, “We moved from monthly planning cycles to real-time corrections, because AI tells us what's likely to break or shift.” This supports the theoretical premise that technological augmentation of human judgment increases the capacity for timely and accurate decision-making (Premkumar et al., 2005).

Furthermore, the study introduces a feedback loop enhancement to OIPT: where traditional models emphasize vertical reporting structures, AI-enabled collaboration fosters horizontal and real-time information sharing across boundaries—thereby reducing decision latency and increasing organizational responsiveness.

8.5.3 Expanding Socio-Technical Systems Theory (STS)

STS emphasizes the interdependence between social and technical subsystems in organizations (Trist & Bamforth, 1951). This study deepens STS by showing that AI adoption cannot succeed in isolation from cultural and behavioral transformation. The qualitative findings show how resistance to AI, lack of cross-functional empathy, and fragmented leadership visions hinder the potential of even the most advanced technologies.

In response, the study proposes a co-evolution model, in which people, processes, and technologies must advance in tandem. For instance, successful implementations combined gamified learning modules, cross-departmental workshops, and iterative feedback mechanisms to build trust and alignment around AI initiatives. These findings confirm and expand the STS principle that technical solutions must be embedded within culturally adaptive frameworks (Pasmore et al., 1982).

8.5.4 Conceptual Framework Refinement

The conceptual model developed in Chapter 4 is empirically validated through this study. The relationships between the four constructs—AI maturity, collaboration quality, organizational factors, and customer responsiveness—are confirmed both quantitatively and qualitatively. Moreover, the findings suggest the addition of two reinforcing loops:

- Strategic Feedback Loop: AI-driven customer responsiveness feeds back into improved sales planning and supply chain agility, reinforcing the need for real-time systems and predictive decision-making.
- Capability Reinforcement Loop: The success of early AI use cases builds organizational momentum, which enhances data sharing and cross-functional trust, accelerating further AI adoption.

These mechanisms suggest that AI is both a dependent and independent variable in the transformation process: it is shaped by organizational readiness and in turn reshapes collaboration processes.

Conclusion

This chapter offers several theoretical contributions. It not only supports existing frameworks such as RBV, OIPT, and STS but also proposes refinements grounded in empirical data. Most notably, it reframes AI not as a siloed technological trend, but as a structurally embedded and socially negotiated enabler of interdepartmental transformation. In doing so, the study adds conceptual clarity to the literature on digital transformation and offers a platform for future inquiry into hybrid-intelligent systems and cross-functional innovation.

8.5.5 Summary of Theoretical Contributions

This section has demonstrated that AI-supported collaboration between sales and supply chain functions is not a purely technological endeavor, but rather a multifaceted organizational transformation. Drawing upon the Resource-Based View (RBV), the Organizational Information Processing Theory (OIPT), and Socio-Technical Systems Theory (STS), the empirical findings of this study contribute to a more nuanced understanding of how competitive advantage is increasingly grounded in digitally mediated cross-functional capabilities.

The results indicate that AI maturity is not only associated with technical infrastructure or process automation, but also with the organization’s capacity to align strategic intent, foster a culture of collaboration, and bridge informational boundaries between departments. This expands the traditional interpretation of the RBV by positioning AI-enabled collaboration systems as dynamic, hard-to-imitate capabilities that underpin agility and customer-centric responsiveness (Barney, 1991; Teece, 2007).

Moreover, the study reinforces OIPT’s assertion that organizational structures must evolve in line with increasing information complexity. AI tools—particularly those used for forecasting, planning, and decision support—act as enablers for higher information processing capacity and thus reduce task uncertainty and functional misalignment (Galbraith, 1973).

Finally, by applying the STS lens, this research highlights the co-dependence of social and technical subsystems. Effective AI integration requires not only functional data systems and analytical tools, but also leadership commitment, shared KPIs, and employee empowerment—indicating that technology and human systems must be jointly designed and continuously adapted.

These contributions offer a more integrated theoretical perspective on how digital technologies reshape not only operations but also the foundational logic of interdepartmental collaboration in industrial firms.

8.6 Managerial Implications

The empirical findings of this dissertation offer several important implications for practitioners, particularly for managers operating at the intersection of sales, supply chain, and digital transformation. While the academic contributions have established a theoretical foundation for AI-supported collaboration, this section translates these insights into **actionable strategies** that can guide managerial decisions in real-world industrial settings.

8.6.1 Aligning Strategy and Technology

One of the most significant findings is the disconnect between strategic intent and actual AI implementation. Many firms acknowledge the strategic importance of AI in enhancing cross-functional collaboration and customer responsiveness, yet fail to move beyond isolated pilot projects (Wamba et al., 2017). Managers must therefore ensure that AI initiatives are embedded into the broader strategic roadmap of the organization.

This includes:

- Establishing AI governance structures that link data analytics projects with business outcomes.
- Integrating AI objectives into departmental KPIs, especially in sales and supply chain.
- Aligning investment in digital tools with long-term competitiveness, not just operational efficiency.

Strategically aligned digital maturity is more likely to yield sustained value and resilience in volatile markets (Bharadwaj et al., 2013).

8.6.2 Building Cross-Functional Collaboration

Managers must also actively dismantle silos between departments. The research highlights that shared KPIs, transparent data systems, and cultural integration are key levers for fostering collaboration. Practical steps include:

- Setting up cross-functional AI task forces responsible for use-case identification, implementation, and learning feedback loops.
- Conducting joint planning sessions between sales and supply chain with AI-generated insights as the discussion base.
- Establishing collaboration dashboards that offer real-time visibility into key metrics across departments.

These mechanisms foster a shared language, common objectives, and mutual accountability (Cao & Zhang, 2011).

8.6.3 Prioritizing the Human Factor

While the technological foundation is essential, the human factor remains the critical success dimension. Managers must acknowledge that:

- AI literacy is not uniformly distributed across teams.

- Resistance to change—especially in established structures—is a systemic challenge.
- Leadership behavior strongly influences cultural receptiveness to AI and innovation.

To address this, organizations should implement gamified learning modules, mentoring programs, and open feedback channels. Furthermore, empowering employees to co-create AI solutions enhances adoption and reduces fear of displacement (Westerman et al., 2011; Culot, Podrecca and Nassimbeni, 2024).

The demographic transition adds further urgency. As older, more hierarchical mindsets retire, younger employees expect agile, tech-enabled, and collaborative environments. Managers must actively shape this transition by promoting leadership models based on trust, transparency, and adaptability.

8.6.4 Navigating Tool Saturation and Implementation Fatigue

An important insight from both the qualitative interviews and managerial observations is the overabundance of new AI tools on the market. Managers face increasing pressure to evaluate and adopt technologies at a pace that often outstrips organizational absorption capacity.

This leads to implementation fatigue, fragmented tool usage, and decision paralysis. To mitigate this risk, managers should:

- Shift from evaluating dozens of tools to standardizing a validated core stack.
- Embrace iterative implementation, focusing on a minimum viable product (MVP) approach rather than comprehensive, perfect solutions.
- Establish feedback-driven governance loops that assess business value and user adoption early in the implementation cycle.

These principles are aligned with agile methods and lean innovation practices, which are increasingly used to manage digital complexity in industrial settings (Rigby et al., 2016).

8.6.5 Reframing KPIs and Success Metrics

Finally, traditional KPIs are often insufficient to measure the full impact of AI-supported collaboration. Managers should rethink how success is defined and tracked:

- Move from output metrics (e.g., number of AI projects) to outcome-based metrics (e.g., forecast accuracy, lead time reduction, customer satisfaction).
- Use cross-functional performance indicators that reflect the joint value creation of sales and supply chain integration.
- Implement dynamic dashboards that update in real-time, offering decision-makers a responsive and data-rich operational view.

This evolution in performance measurement supports faster decision-making, better risk management, and enhanced strategic agility (McAfee et al., 2012).

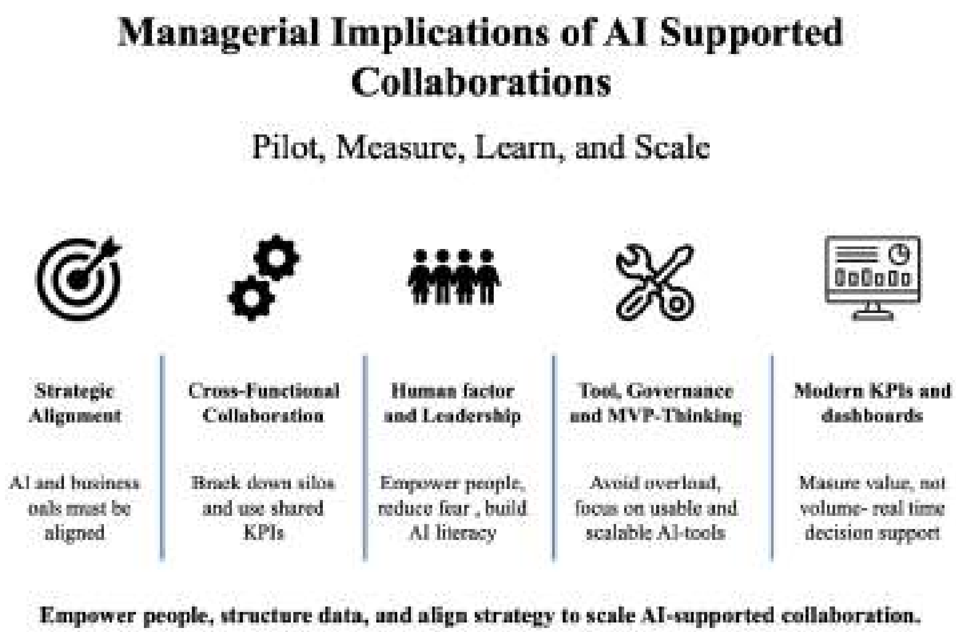

Figure 8.2: Own illustration – Managerial Implications for AI-Supported Collaboration in Sales and Supply Chain Contexts (Grywnow, 2025)

Conclusion of 8.6: Managers play a central role in shaping the conditions under which AI can deliver value across sales and supply chain operations. By focusing on strategic alignment, collaborative structures, human-centered leadership, and pragmatic implementation strategies, industrial firms can unlock the transformative potential of AI while navigating organizational and market complexity.

8.7 Limitations of the Study

No academic research is without boundaries, and this dissertation is no exception. While the mixed-methods approach and multi-construct framework provide a solid foundation for exploring AI-supported collaboration between sales and supply chain, several limitations emerge in relation to the methodological design, sample characteristics, temporal relevance, data interpretation, and theoretical breadth. This section critically examines these limitations, not as flaws, but as essential framing devices for the scope and validity of the study's conclusions.

8.7.1 Methodological Constraints of the Mixed-Methods Design

The study employed an **explanatory sequential mixed-methods design** (Creswell & Plano Clark, 2018), which enabled the exploration of both breadth (through the survey) and depth (through interviews). However, inherent limitations in such an approach must be acknowledged:

- First, the quantitative phase, while well-structured and pilot-tested, relied on self-reported perceptions of AI maturity, collaboration, and organizational effectiveness. These subjective responses may not accurately reflect actual behavior or outcomes and can be influenced by social desirability, overconfidence, or misunderstanding of AI concepts (Podsakoff et al., 2003).
- Second, the qualitative interviews, though rich in context, were limited to a sample of 15 participants, which may not fully capture the breadth of experiences across different sectors, maturity levels, and geographies.

Despite these limitations, the triangulation of both data strands enhances overall credibility and interpretive validity (Tashakkori & Teddlie, 2010). Nevertheless, readers should consider that findings reflect tendencies and themes, not statistical generalizations or causal inferences.

8.7.2 Sample Bias and Representativeness

One of the strengths of this study is the relatively large number of quantitative respondents ($n = 187$) and the inclusion of participants from different industries and regions. However, several sample-related limitations persist:

- The recruitment of survey participants was conducted via LinkedIn, targeting René Grywnow’s personal network and specific industry groups focused on sales, supply chain, and digital transformation. This nonprobability sampling strategy may introduce bias, as it favors digitally engaged and professionally active individuals (Wright, 2005).

- The overrepresentation of certain geographies—such as Germany, Denmark, and the United States—limits global generalizability, particularly to markets in the Global South or public-sector organizations, which often operate under different structural and technological constraints.
- Additionally, although efforts were made to include participants from different organizational levels, the data may skew toward middle and senior management, thereby underrepresenting operational perspectives or frontline realities.

Consequently, while the findings are valid for understanding digital collaboration trends in advanced industrial economies, they should not be uncritically applied to vastly different business ecosystems.

8.7.3 Temporal Relevance and Technological Volatility

The research was conducted during a time of accelerated digital innovation, particularly in the field of AI. The implications of this must be carefully considered:

- Many AI tools and platforms are evolving at a pace that outstrips academic cycles. What is considered a “cutting-edge” application today may be outdated within months (Bughin et al., 2017). As such, the tools and practices referenced in this dissertation may have limited shelf life.
- Furthermore, organizational AI maturity is a moving target. A firm categorized as "low maturity" during the data collection phase might experience significant transformation shortly thereafter, driven by external investments, leadership changes, or regulatory shifts.

Therefore, the temporal relevance of this study's findings is strongest within a short-to-medium time horizon (12–24 months) and may require periodic validation in future studies.

8.7.4 Theoretical and Conceptual Limitations

The study's conceptual foundation is based on the Resource-Based View (Barney, 1991), Organizational Information Processing Theory (Galbraith, 1973), and Socio-Technical Systems Theory (Trist & Bamforth, 1951). While these frameworks are appropriate for understanding cross-functional integration and digital transformation, some theoretical limitations remain:

- The study did not integrate behavioral or psychological theories, which could have illuminated individual-level resistance, adoption anxiety, or motivational dynamics in more detail (Venkatesh et al., 2003).
- Similarly, institutional and cultural dimensions, such as national business culture or industry norms, were not fully explored, even though they often play a role in shaping digital strategies (Scott, 2008).
- The use of a cross-sectional design—a single snapshot in time—also limits the ability to observe causal dynamics or long-term change processes.

Future research could adopt longitudinal or multi-theoretical approaches to better capture the complexity of organizational AI integration across time and context.

8.7.5 Operational Constraints and Researcher Bias

Given the applied and practice-oriented nature of this dissertation, some operational trade-offs were necessary:

- The transcription and analysis of qualitative interviews were conducted manually without full use of software tools like NVivo or MAXQDA.

While thematic saturation was still achieved, this may limit replicability or comprehensive code traceability.

- As the researcher is embedded in the industrial context and personally connected to some respondents, researcher bias—in terms of question framing, interpretation, or interview tone—cannot be fully excluded (Yin, 2018).

Nonetheless, the application of reflexive practices (e.g., cross-checking themes, validating with external experts) mitigated these risks and ensured interpretive integrity.

8.7.6 Ethical Boundaries

Ethically, this study adhered to GDPR and institutional standards. However, the anonymity of data—particularly in qualitative excerpts—may have limited the depth of contextual elaboration, as sensitive strategic insights or examples could not be shared without compromising confidentiality.

Furthermore, participant fatigue and response effort may have influenced the depth or completeness of some responses, especially in the longer survey items.

Conclusion of 8.7: In sum, this dissertation provides valuable and actionable insights into the interplay between AI, collaboration, and organizational dynamics. Yet, the findings must be interpreted within clearly defined boundaries. The research is most applicable to mid-to-large industrial firms in digitally active markets and is strongest in offering thematic clarity, not statistical generalization.

By openly addressing these limitations, this study invites future researchers to build upon its strengths, refine its scope, and explore unanswered questions. It also reinforces the need for ongoing validation and contextual adaptation as both AI technologies and organizational realities continue to evolve.

8.8 Future Research Directions

The rapidly advancing digital transformation landscape has made it essential for both academics and practitioners to keep pace with emerging dynamics, especially concerning AI-supported collaboration between sales and supply chain functions. While this dissertation contributes foundational knowledge and empirical insights, it also reveals fertile ground for continued inquiry. This section proposes detailed research directions based on the findings, theoretical models (RBV, OIPT, STS), and gaps observed in the present study.

8.8.1 Deepening Understanding of AI Maturity Pathways

The study revealed significant disparities in AI adoption across organizations, with most firms situated between initial awareness and partial implementation. Future research should investigate the progression models of AI maturity, examining how firms move from descriptive analytics to more advanced stages like prescriptive or cognitive AI. Building upon Wang et al. (2016), who define AI maturity across a four-level spectrum, longitudinal case studies could be conducted to observe how internal and external triggers—such as crises, leadership transitions, or new technology cycles—impact this evolution.

Additionally, there is a need to refine maturity models specific to the intersection of supply chain and sales. While current models often generalize digital transformation, tailored metrics that reflect joint planning, forecasting, and AI-assisted decision-making are still lacking (Tuomikangas and Kaipia, 2014; Richey et al., 2023). By focusing on sector-specific maturity benchmarks, future studies could provide firms with more actionable diagnostics.

8.8.2 Exploring Human-AI Interaction and Decision Autonomy

A recurring theme in the qualitative interviews was the tension between human judgment and AI-generated insights. As noted by Faraj et al. (2018), effective human-AI teaming depends on trust, interpretability, and clear accountability structures. Future research should analyze how decision authority is distributed when AI systems generate recommendations or trigger automated actions.

A potential research question might be: *How does AI influence perceived and actual autonomy in cross-functional decision-making, and what governance mechanisms can ensure responsible outcomes?* This line of inquiry can be grounded in STS theory, exploring how technical and social systems co-evolve in environments of increasing automation.

Experimental designs could be employed to measure variations in trust, resistance, or accuracy when decisions are made solely by humans, solely by AI, or through hybrid configurations. Moreover, generational or cultural differences in acceptance of AI-generated recommendations present another promising dimension.

8.8.3 Investigating the Human Factor and Workforce Demographics

While AI is often viewed as a technical solution, its success is highly dependent on human adaptation and acceptance. The findings of this study suggest that digital literacy, openness to change, and leadership communication styles play a critical role in driving or inhibiting AI adoption. Given the generational shift occurring in many manufacturing firms, future research should examine how digital readiness and change receptivity vary across age cohorts.

As organizations increasingly face retirements among experienced staff and onboarding of digitally native employees, new collaboration frictions and learning curves are emerging (Westerman et al., 2011). Mixed-method studies incorporating surveys, focus groups, and observational fieldwork can reveal how these dynamics unfold and impact cross-functional initiatives. Moreover, scholars could build on models such as the Technology Acceptance Model (TAM) or the Unified Theory of Acceptance and Use of Technology (UTAUT) to contextualize generational factors.

8.8.4 Managing the AI Tool Proliferation and Short Innovation Cycles

As outlined in Section 8.2, organizations face a flood of new AI tools, often with overlapping functionalities and unclear value propositions. The problem is compounded by the fact that validation processes for new tools can become outdated even before implementation is complete, particularly in fast-moving business environments.

Future research should explore how organizations can manage the AI tool lifecycle more strategically. This includes not only selection and onboarding but also the offboarding and continuous evaluation of tools. A decision-making framework rooted in real options theory or IT portfolio management (Benaroch et al., 2006) may offer valuable insights. Key research questions include: *How can firms balance exploration and exploitation in AI adoption?* and *What governance structures enable agile, yet coherent, AI strategies?*

Such research could also assess the impact of standardizing certain AI tools across departments versus encouraging local experimentation. Findings would offer guidance on striking the right balance between innovation speed and enterprise-wide integration.

8.8.5 Cross-Cultural and Cross-Industry Comparisons

The present study, while geographically diverse, was not designed to enable controlled cross-cultural comparisons. Future research could intentionally compare AI-supported collaboration in different cultural and industrial contexts. For instance, firms in high power-distance cultures may implement AI differently than those in more egalitarian settings, with implications for adoption speed, resistance, and governance (Hofstede, 2001).

Likewise, industry-specific factors—such as regulatory intensity, product complexity, and demand volatility—may influence the effectiveness of AI in bridging sales and supply chain. Comparative case studies or multi-country survey designs anchored in the GLOBE framework or contingency theory could yield highly generalizable insights.

8.8.6 Investigating Ecosystem-Wide AI Integration

While this study focused on intra-organizational collaboration, a growing trend is the emergence of ecosystem-wide AI platforms involving suppliers, distributors, and even customers. The integration of external stakeholders raises novel challenges around data sharing, incentive alignment, and trust.

Future research should explore how organizations govern these extended networks and what role AI plays in enhancing or complicating such interactions. Drawing from platform theory (Gawer & Cusumano, 2014) and supply chain orchestration literature, scholars could examine questions such as: *What contractual and technological mechanisms facilitate data sharing in AI-enabled supply ecosystems?* and *How do firms manage trade-offs between transparency and competitiveness in such networks?*

In addition, case studies from industries with mature ecosystems (e.g., automotive, aerospace) could provide valuable templates for other sectors.

8.8.7 Ethical Governance, Transparency, and Algorithmic Accountability

With AI becoming increasingly embedded in operational decision-making, ethical concerns around transparency, bias, and accountability are escalating. The study revealed managerial hesitance regarding the black-box nature of AI tools and the ethical implications of algorithmic customer segmentation.

Future research should focus on how organizations implement ethical AI frameworks in cross-functional collaboration. Topics such as explainability (XAI), algorithmic fairness, and stakeholder inclusion in model design deserve deeper attention (Dignum, 2019). How do organizations ensure that AI-generated outcomes are understandable and contestable by human decision-makers? How are ethical guidelines operationalized within day-to-day sales and supply planning?

Building on the emerging field of responsible AI, researchers could also propose audit protocols and escalation mechanisms for ethically sensitive decisions.

8.8.8 Measuring Success: KPIs and Performance Metrics

One of the study's core findings is the importance of shared KPIs in driving collaboration and accountability. However, few firms reported having formalized AI-specific metrics, and those that did primarily tracked technical performance rather than collaborative or customer-centric outcomes.

Future research could develop and validate a multidimensional KPI framework for AI-supported cross-functional collaboration. This framework could include metrics such as:

- Forecast accuracy improvements attributable to AI,
- Reduction in planning cycle time,
- Customer satisfaction indices linked to AI-enhanced responsiveness,
- Collaboration index based on shared objectives and communication flows.

Participatory action research with firms implementing AI initiatives could be a promising method for this line of inquiry.

In conclusion, the findings of this dissertation open multiple avenues for academic exploration. The convergence of technological, organizational, and human factors in AI-supported collaboration is a rich field that requires multidisciplinary approaches. As firms continue to invest in digital transformation, scholarly work that bridges theoretical depth with managerial relevance will be critical to shaping sustainable, inclusive, and high-impact innovations.

8.8.9 Summary Table of Future Research Directions

To provide a structured synthesis of the research implications discussed in Section 8.8, the following table outlines eight thematic future research directions. Each theme is linked to a central research question, grounded in established theoretical frameworks, and paired with appropriate methodological approaches. This roadmap aims to support both academic scholars and practitioners in advancing the understanding and practical implementation of AI-supported collaboration between sales and supply chain functions.

An overview of these future research areas — including their theoretical underpinnings and recommended research designs — is presented in Table 8.1 at the end of this section.

Theme	Example Research Questions	Theoretical Anchoring	Suggested Methodology
AI Maturity Evolution	How do firms evolve from descriptive to cognitive AI?	RBV, Digital Maturity Models	Longitudinal case studies; maturity model surveys
Decision Autonomy & AI	How does AI impact managerial autonomy and trust?	STS, Human-AI Interaction	Mixed methods; experimental design
Generational Dynamics	How do generational differences affect AI adoption?	OIPT, Technology Acceptance	Surveys + focus groups; segmentation analysis
AI Tool Overload & Governance	How can firms manage rapid AI tool proliferation?	IT Governance, Real Options Theory	Framework development; Delphi study
Industry & Culture Comparisons	How do cultural/sectoral differences shape AI collaboration?	Hofstede, GLOBE, Contingency Theory	Cross-sectional comparison; cluster analysis
Ecosystem Collaboration	How does AI enable multi-stakeholder supply chain ecosystems?	Platform Theory, Network Theory	Network mapping; case studies
AI Ethics in Collaboration	What ethical risks arise in algorithm-based planning?	Responsible Innovation, STS	Qualitative studies; ethics frameworks
KPI Innovation	How can AI-specific KPIs be designed for collaboration?	Performance Management, OIPT	Action research; pilot studies with firms

Table 8.1Proposed Future Research Directions

8.9 Final Remarks

This dissertation set out to explore how Artificial Intelligence (AI) can enhance collaboration between sales and supply chain functions in manufacturing firms, a topic of growing strategic relevance in today’s digitally driven industrial environment. Using a mixed-methods approach, the study has yielded empirical evidence and theoretical insights that not only contribute to academic discourse but also provide actionable guidance for practitioners.

The integration of quantitative and qualitative data has revealed that while awareness of AI's potential is widespread, implementation maturity varies greatly across organizations. Effective collaboration is not merely a technological challenge but one deeply embedded in organizational structures, leadership behavior, data practices, and cultural readiness. The study has demonstrated that AI capabilities — when aligned with cross-functional KPIs, leadership commitment, and robust data governance — can significantly improve customer satisfaction, agility, and responsiveness.

The research has also highlighted critical barriers such as siloed thinking, poor data quality, and a lack of AI skills. These barriers can only be overcome through coordinated human-centered change efforts, strategic capability building, and a willingness to rethink conventional organizational models. Addressing these issues is not just a matter of operational improvement but a strategic imperative for long-term competitiveness.

By proposing a comprehensive implementation roadmap and outlining future research directions, this dissertation contributes to shaping a more integrated, adaptive, and customer-focused model of industrial collaboration. The findings underscore that the journey toward AI-supported collaboration is complex — yet those firms that invest early, scale thoughtfully, and lead with purpose will be best positioned to thrive in the face of volatility and change.

Ultimately, this study affirms that the future of industrial excellence lies in the synergy between intelligent systems and intelligent people. Artificial Intelligence should not replace human judgment but rather enhance it — enabling organizations to respond faster, plan smarter, and collaborate more effectively. The next frontier will be defined by how well we bridge technological potential with organizational will.

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APPENDIX A

SURVEY QUESTIONNAIRE (QUANTITATIVE STUDY)

Title: AI-supported Collaboration between Supply Chain and Sales
Purpose: This questionnaire was used to collect quantitative data for the DBA study on cross-functional collaboration and AI integration in industrial organizations.
This survey was designed and administered using the LimeSurvey platform (www.limesurvey.org) . It was distributed digitally to professionals in the industrial sector as part of a mixed-methods DBA research study.

Section 1: Demographic and Company Information

- What is your gender?
- Female / Male / Non-binary / Prefer not to say
- What is your age group?
- below 30 / 30–39 / 40–49 / 50–59 / 60+
- In which country are you living?
- In which country is your company headquartered?
- What industry does your company operate in?
- What is the size of your company (number of employees)?
- What is your position within the company?

Section 2: Supply Chain & Sales Focus – Current Setup and Collaboration

- Does your organization have an integrated approach between supply chain and sales functions?
- How would you rate the level of collaboration between supply chain and sales departments?
- Are joint planning sessions (e.g., S&OP) conducted regularly between supply chain and sales?
- How often do cross-functional teams meet to align on forecasts and demand planning?
- How aligned are performance indicators between sales and supply chain functions?
- To what extent are customer feedback loops integrated into planning processes?

Section 3: Current Collaboration and AI Usage

- Is Artificial Intelligence (AI) currently used in your company's supply chain or sales processes?
- If yes, in which areas is AI currently applied? (e.g., forecasting, customer insights, inventory optimization)
- How would you rate the maturity level of AI usage in your organization?
- Are AI tools integrated across departments or isolated within single functions?
- How well are employees trained to work with AI-supported tools?

Section 4: Expected Benefits and Barriers to AI Integration

- What benefits do you expect from integrating AI into supply chain and sales collaboration?
- What are the biggest challenges or barriers your company faces in AI implementation?

- How important is top management support for successful AI integration in your opinion?
- How open is your organizational culture toward digital transformation and AI adoption?
- What role does data availability and quality play in AI success in your organization?
- Are ethical or legal concerns (e.g., GDPR) a barrier for AI implementation?

Section 5: Competitive Position and AI-Driven Future

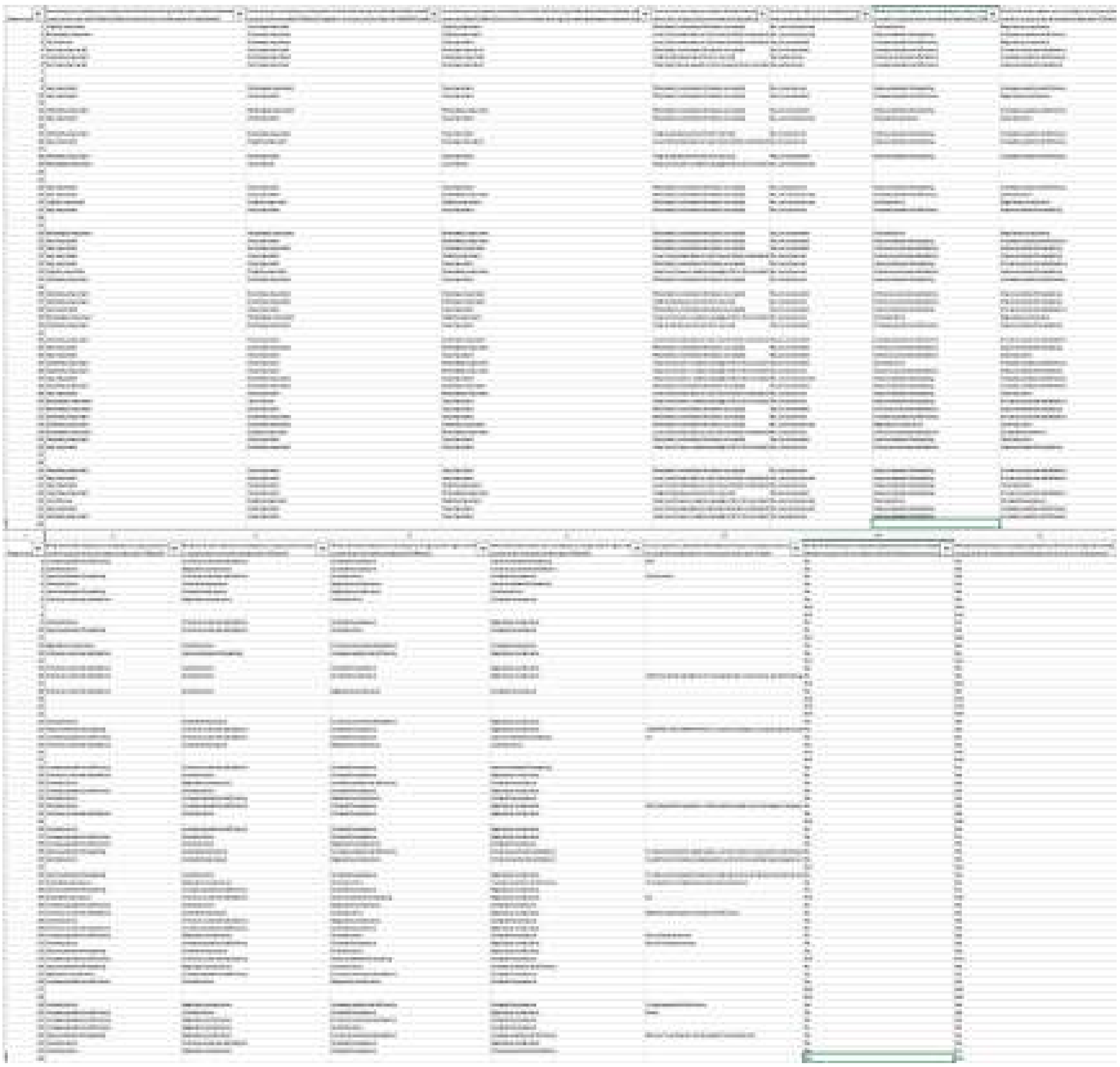
- Do you believe that AI-supported collaboration will become a competitive differentiator in your industry?
- How prepared is your company to invest in future AI technologies?
- Which area do you expect to benefit most from AI: sales, supply chain, or both equally?
- In your opinion, how will AI change decision-making processes in the future?
- To what extent do you see AI as a tool to increase customer satisfaction?
- How do you perceive the influence of AI on market responsiveness and agility?

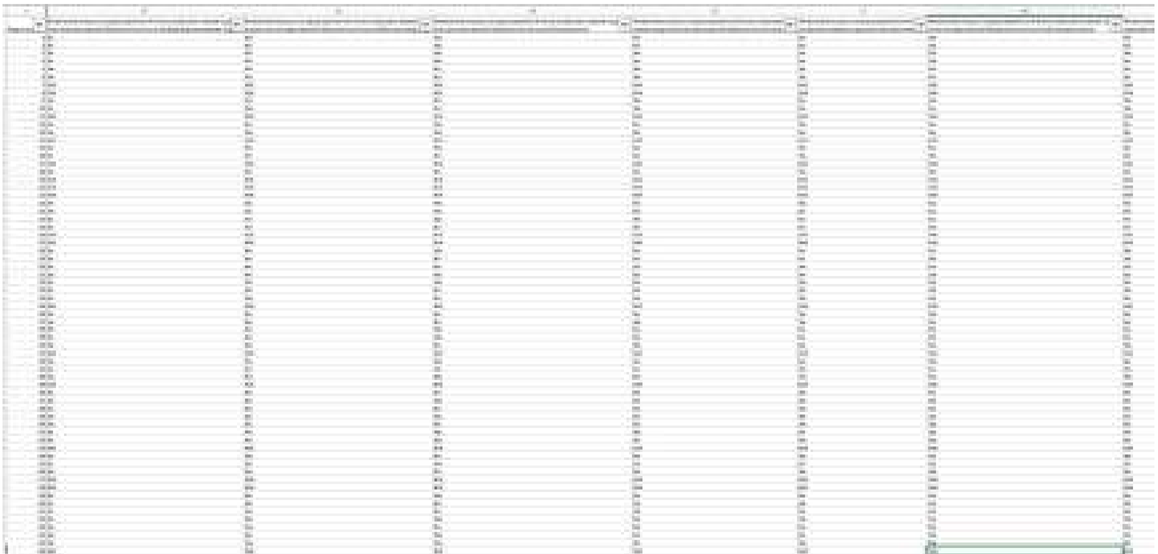
Section 6: Final Question and Follow-Up

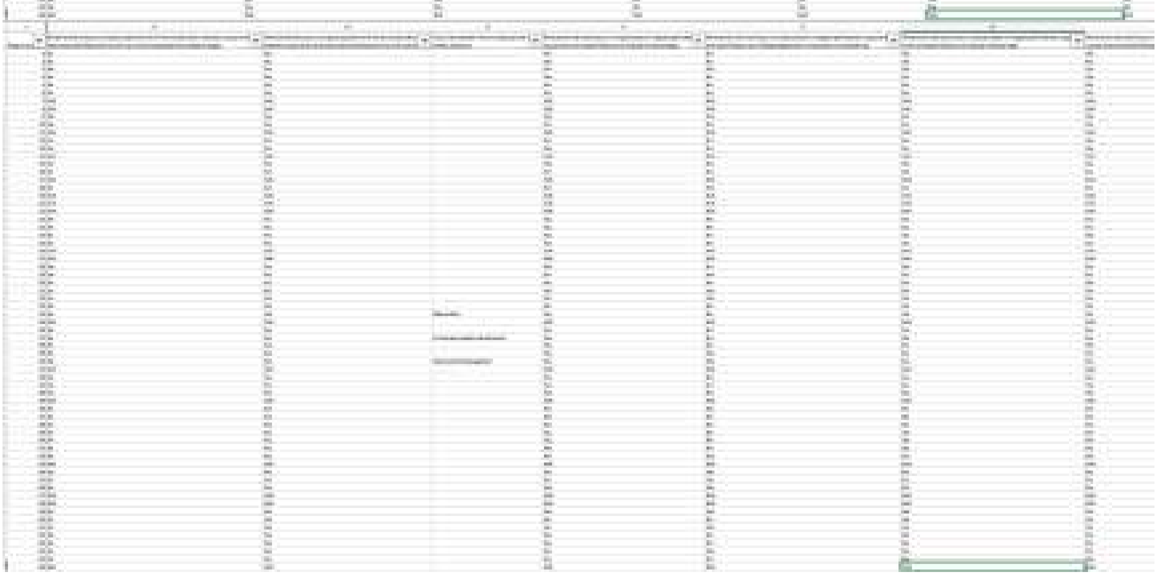
- Would you like to receive a summary of the study’s final results?
- Do you have any additional comments or feedback?

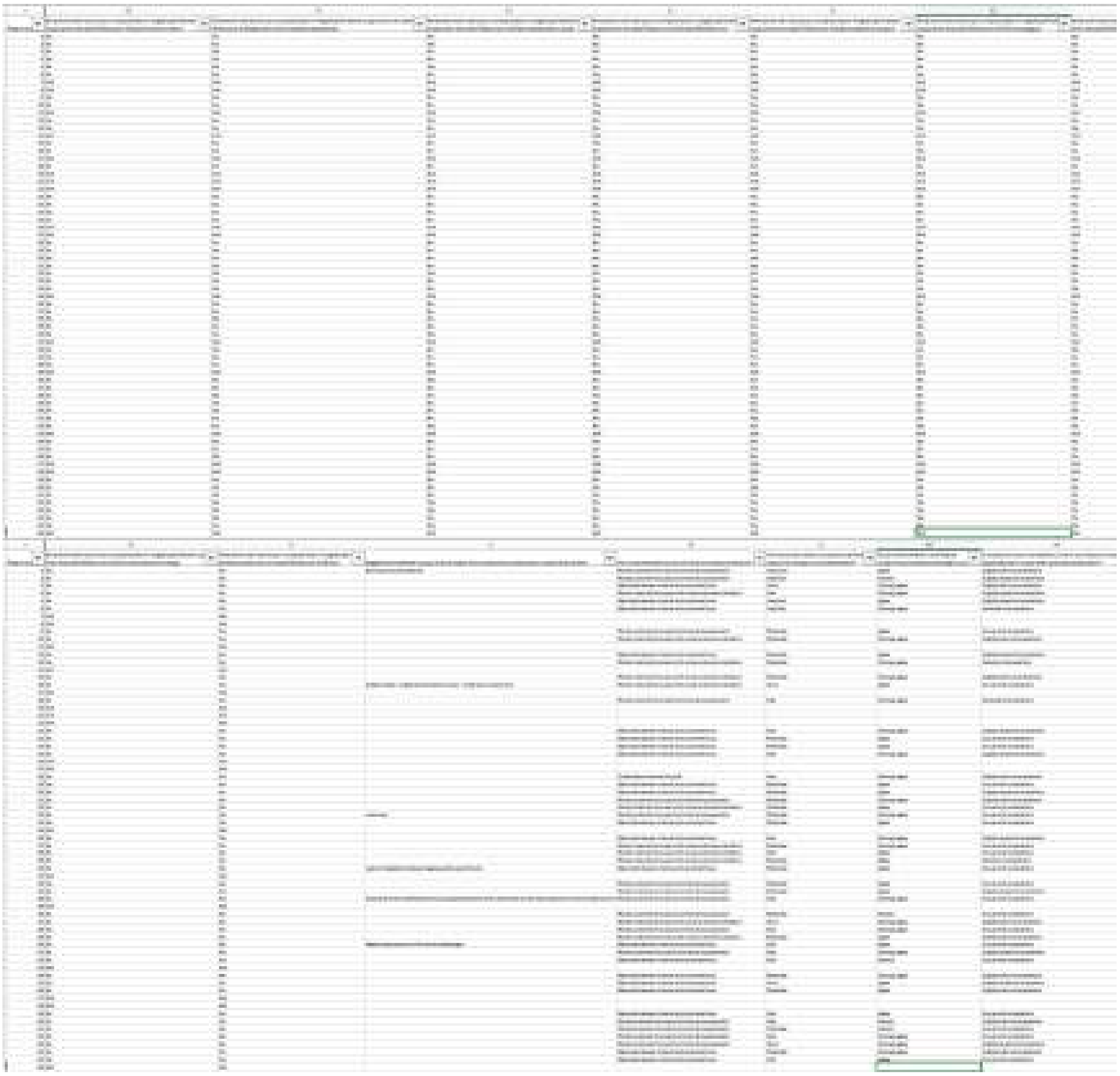
APPENDIX B

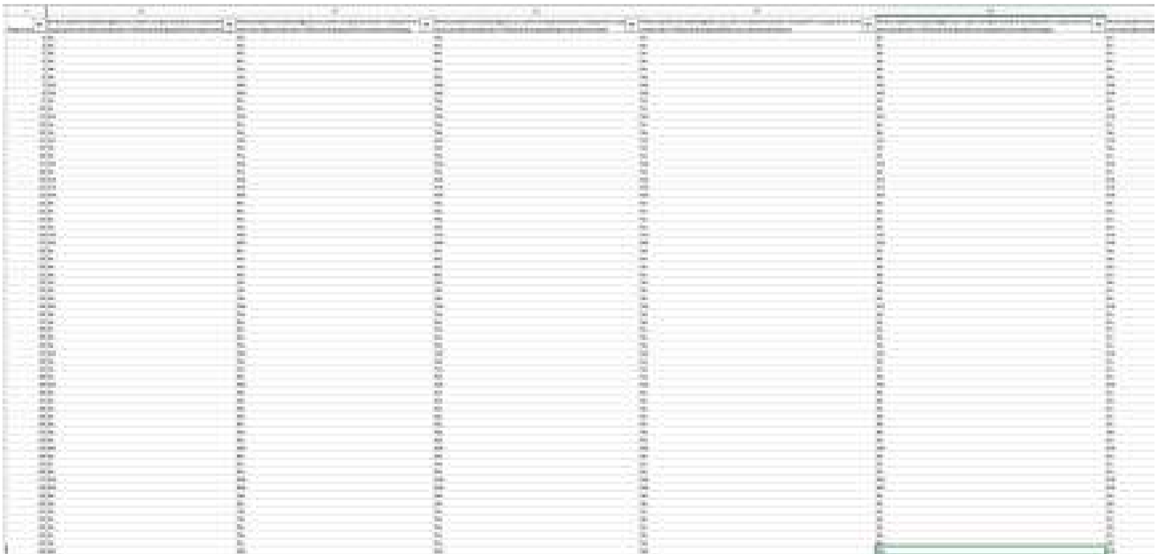
ANSWERS QUANTITATIVE SURVEY

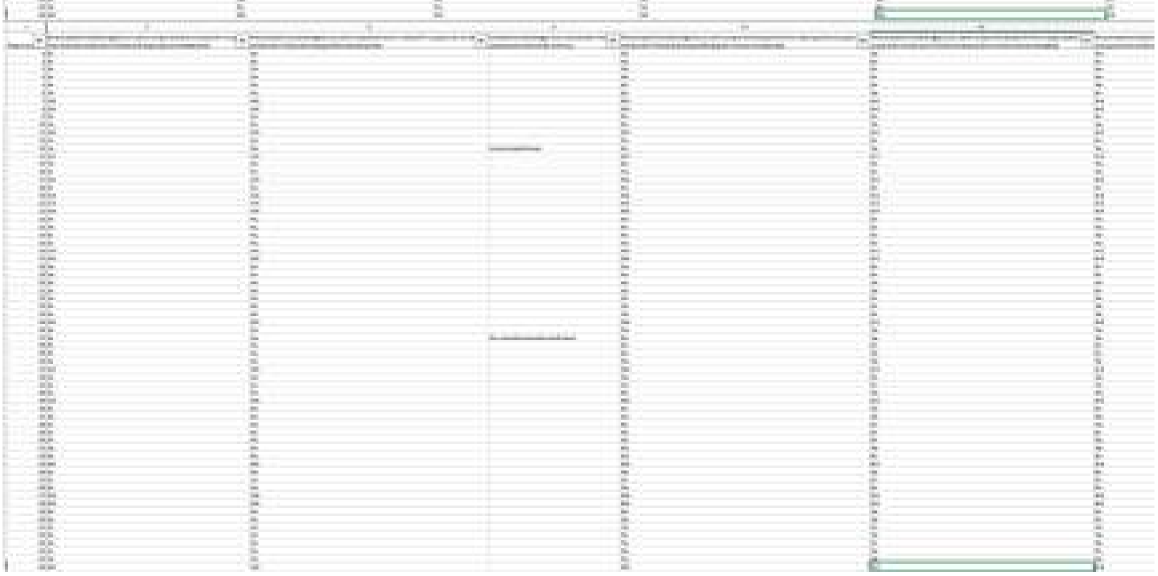


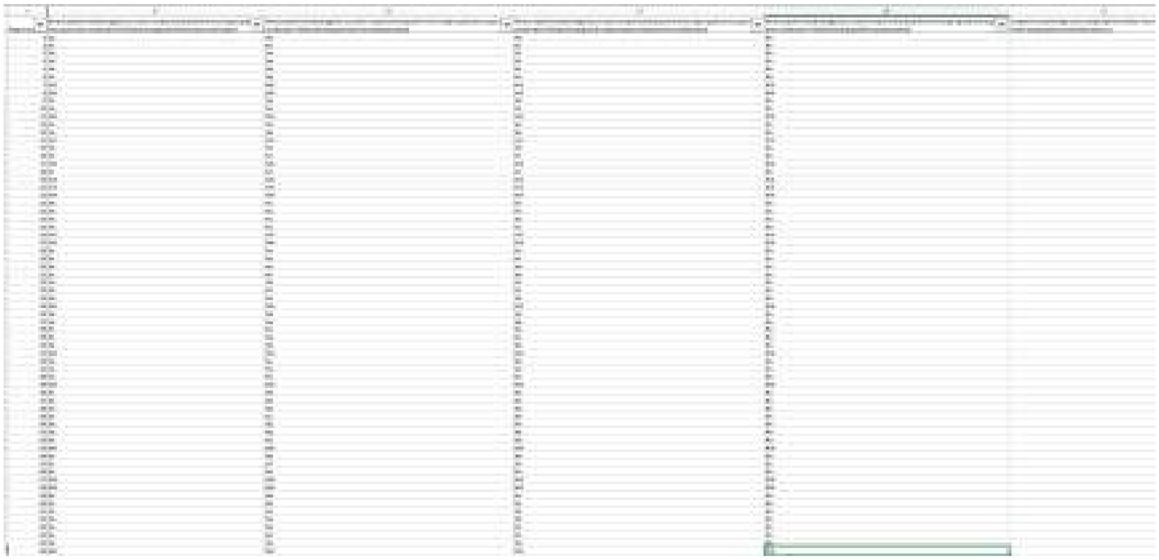


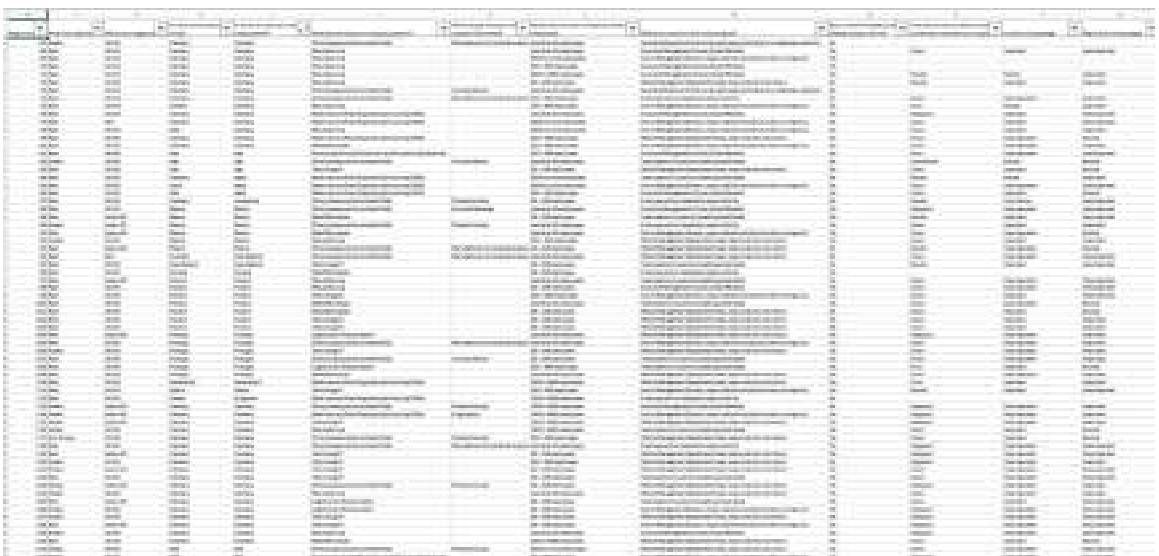


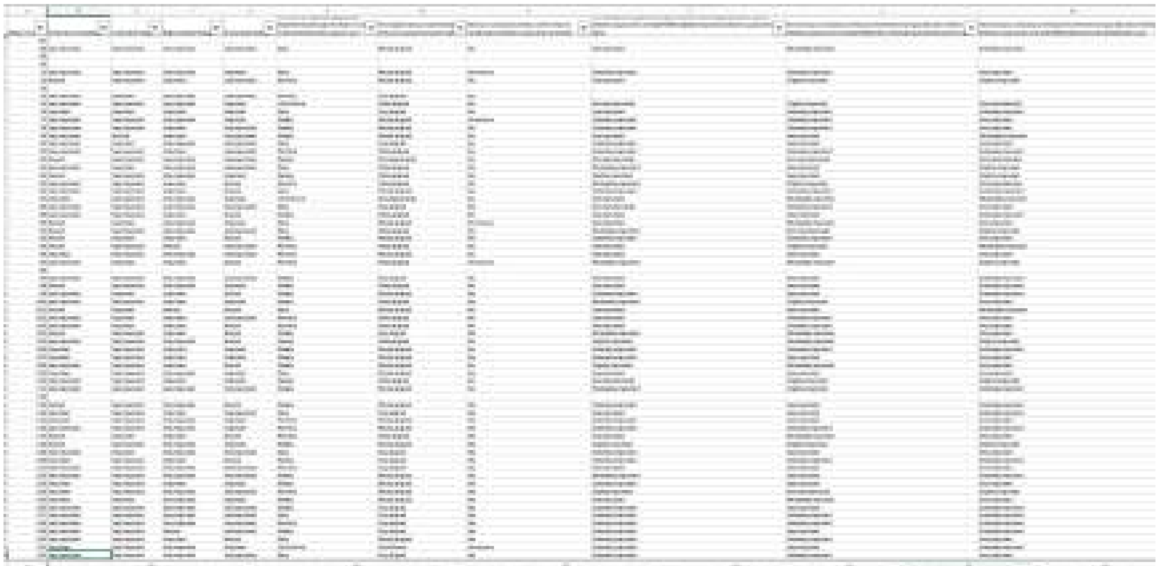


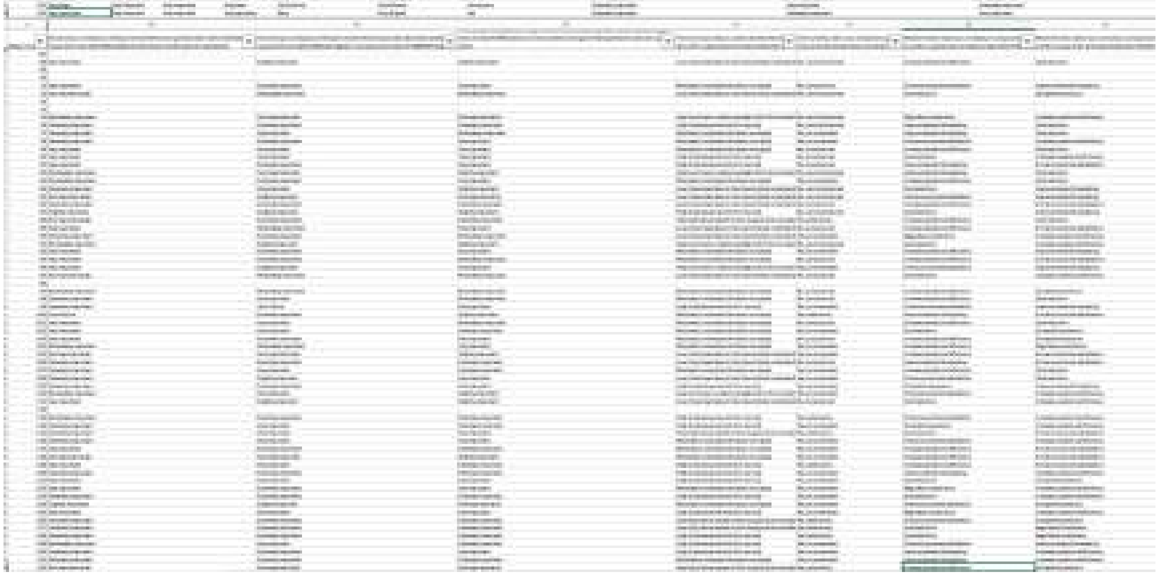


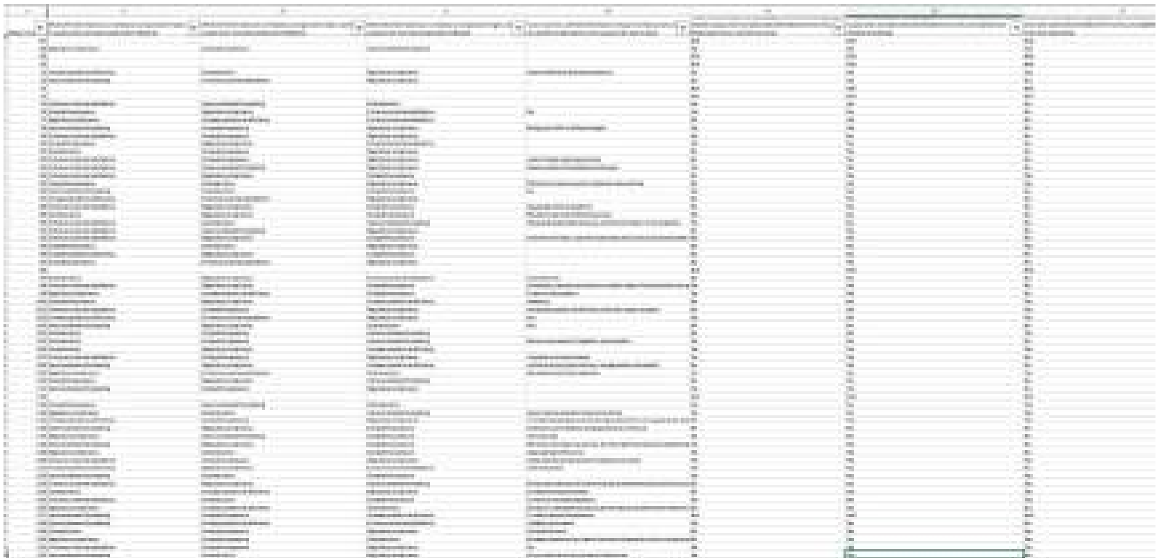


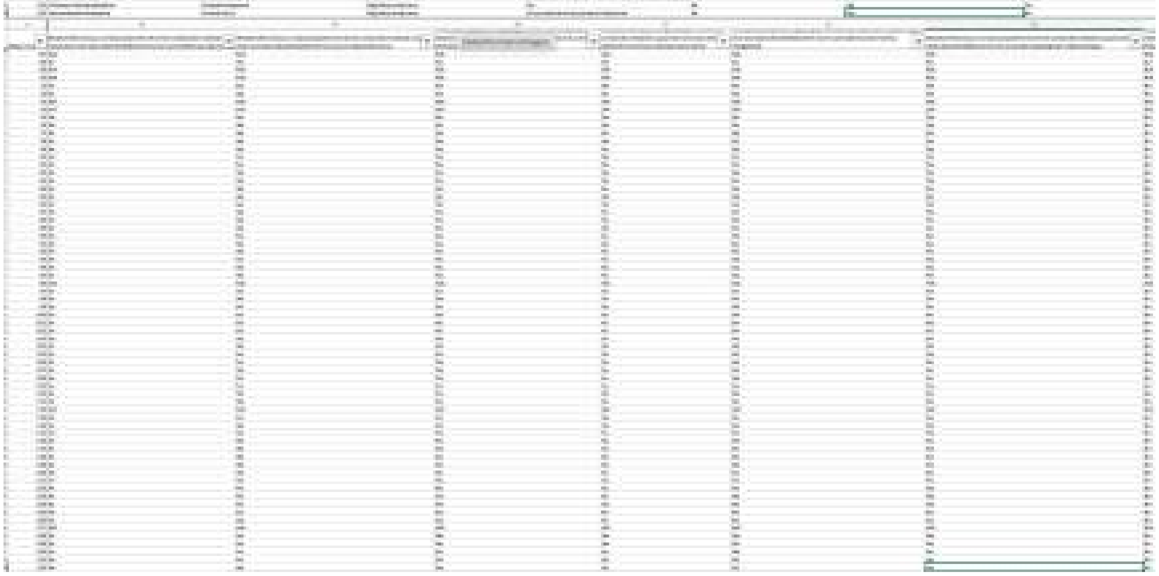


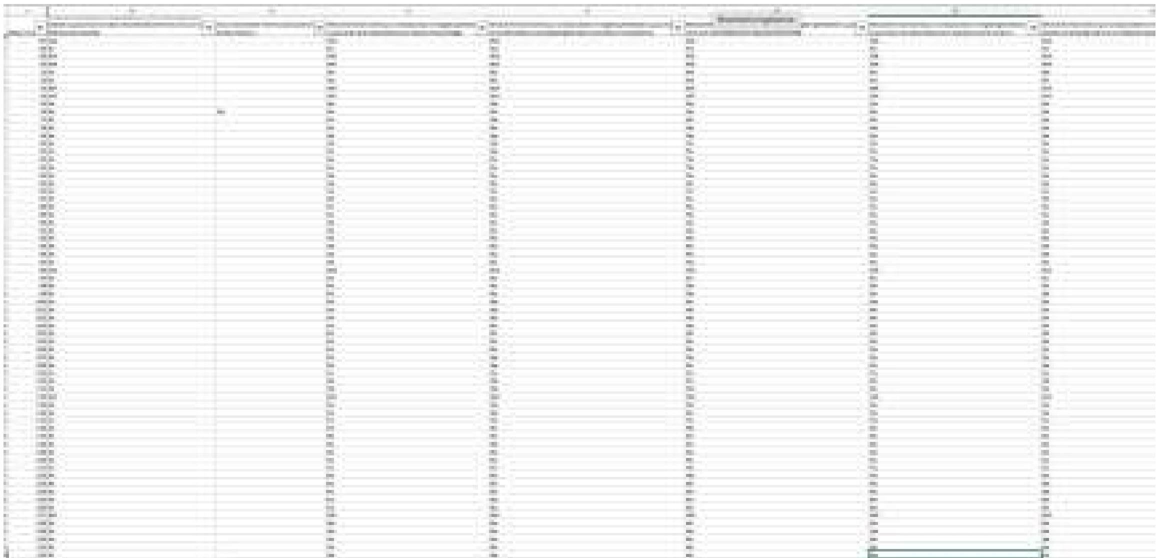


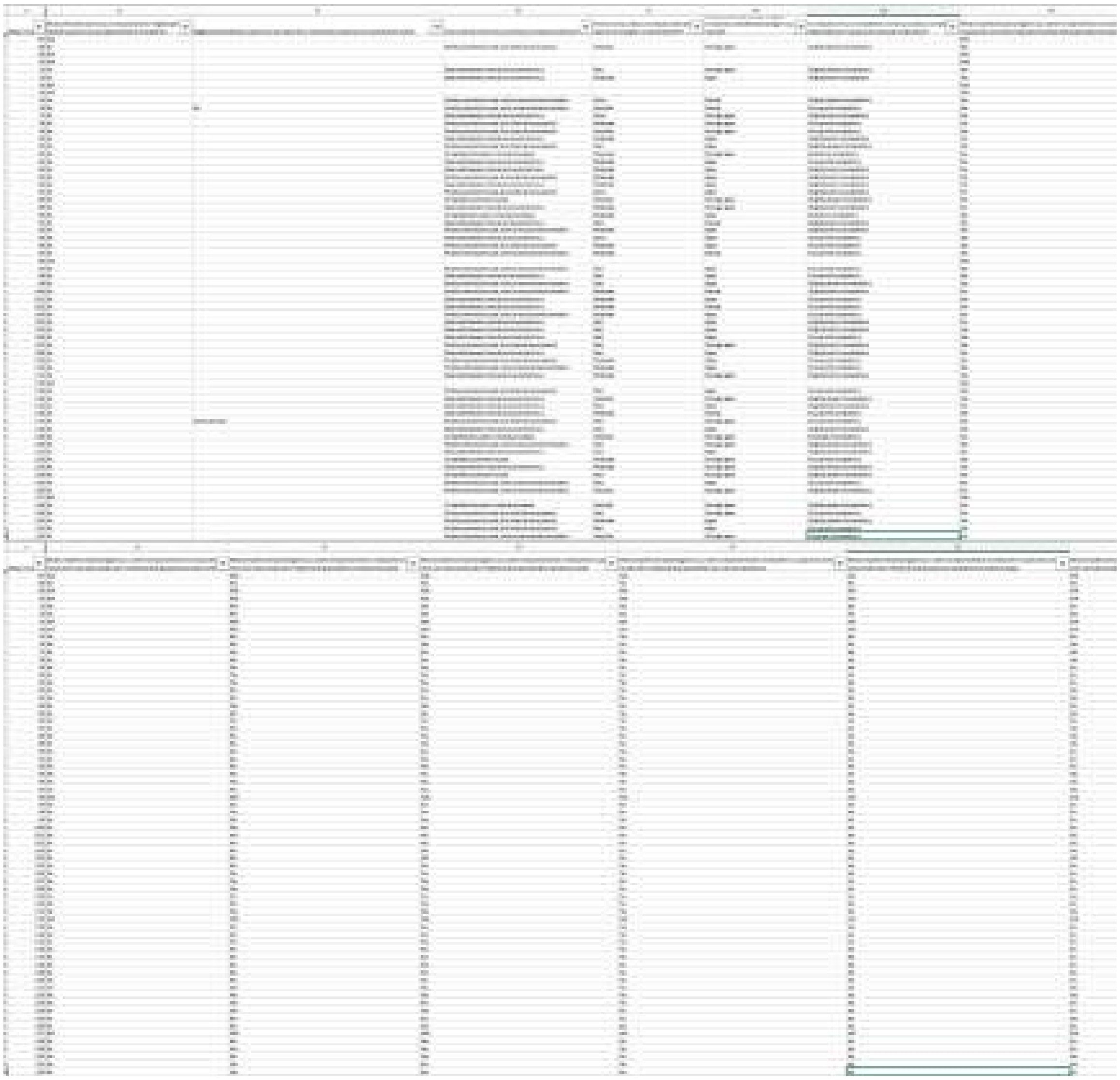


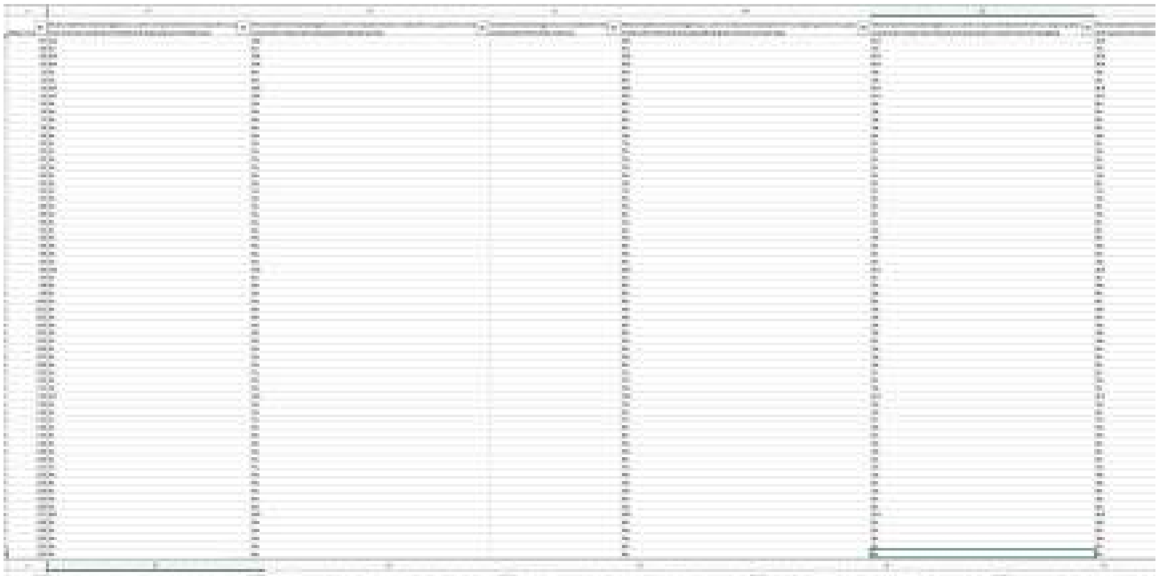


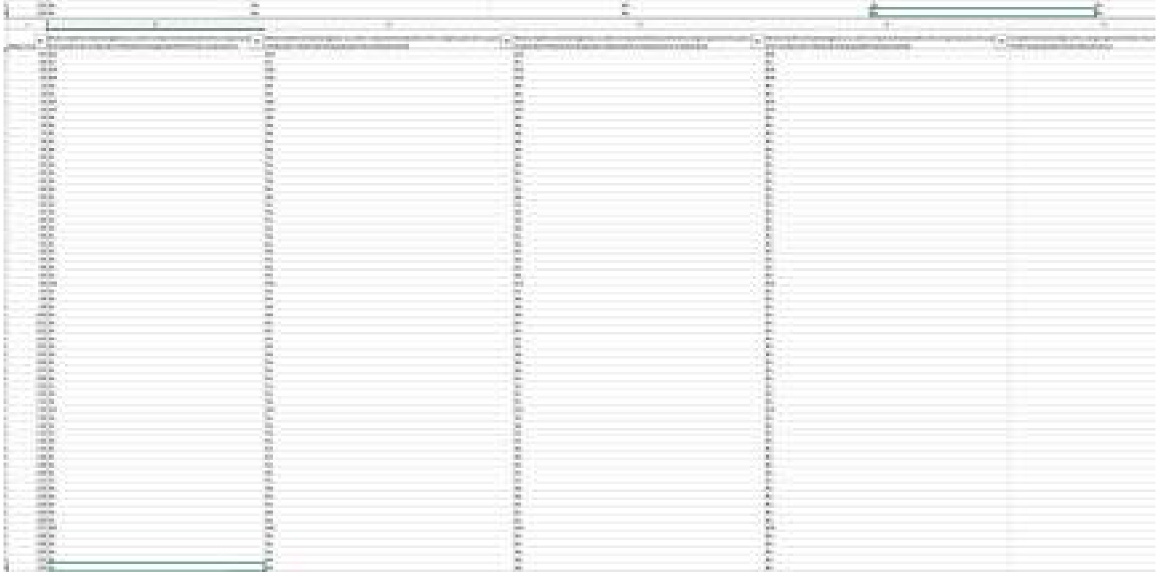


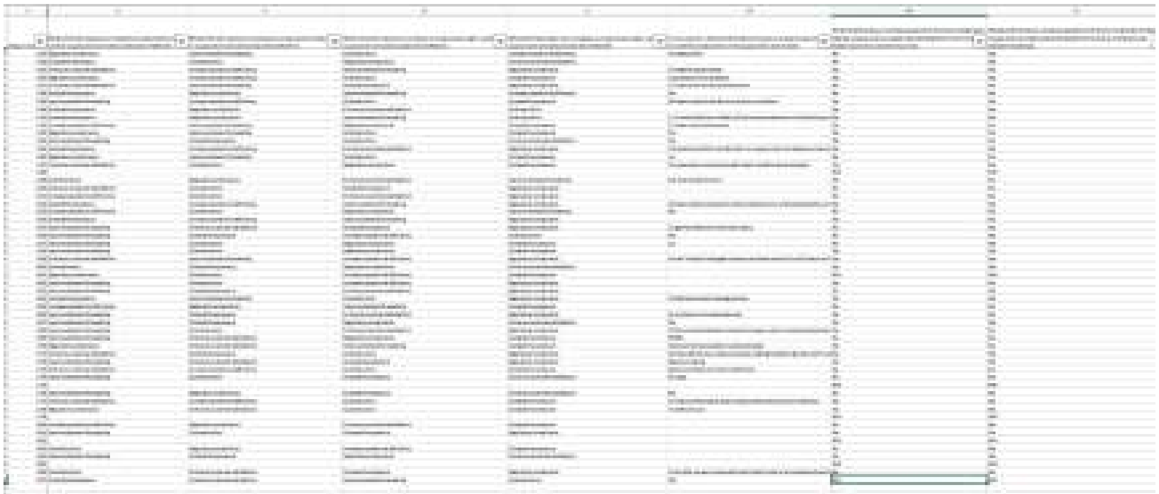


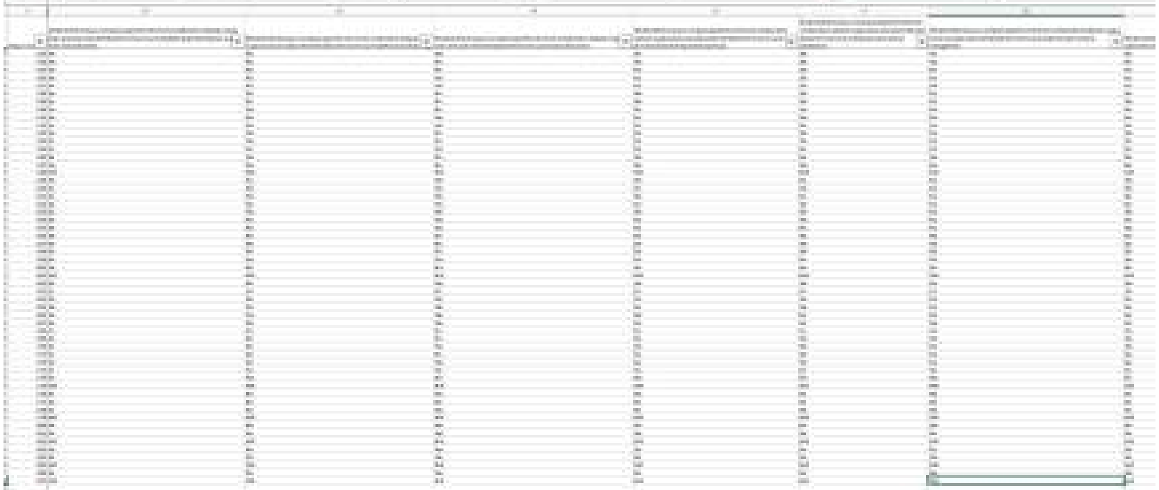


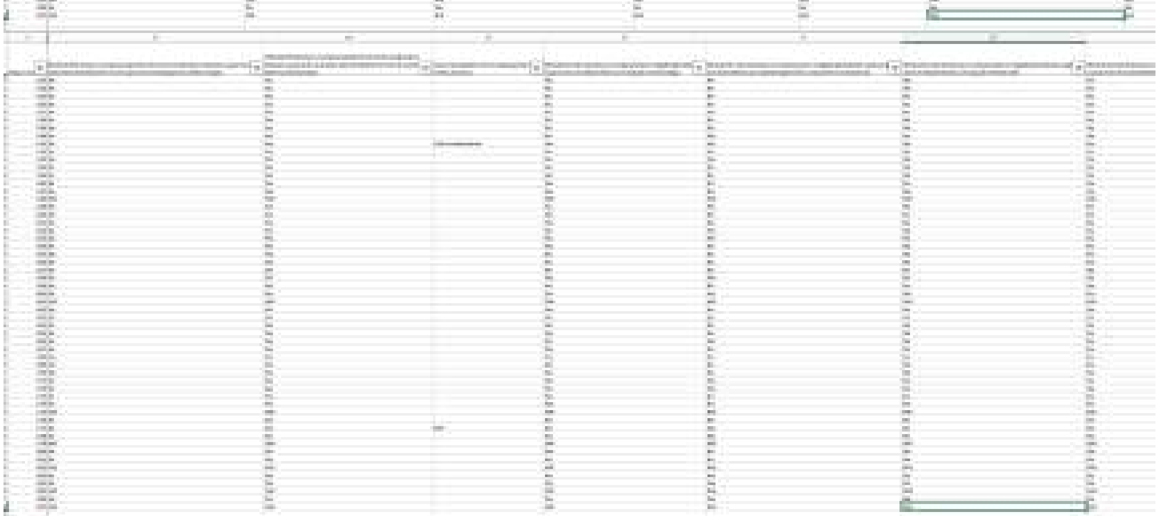


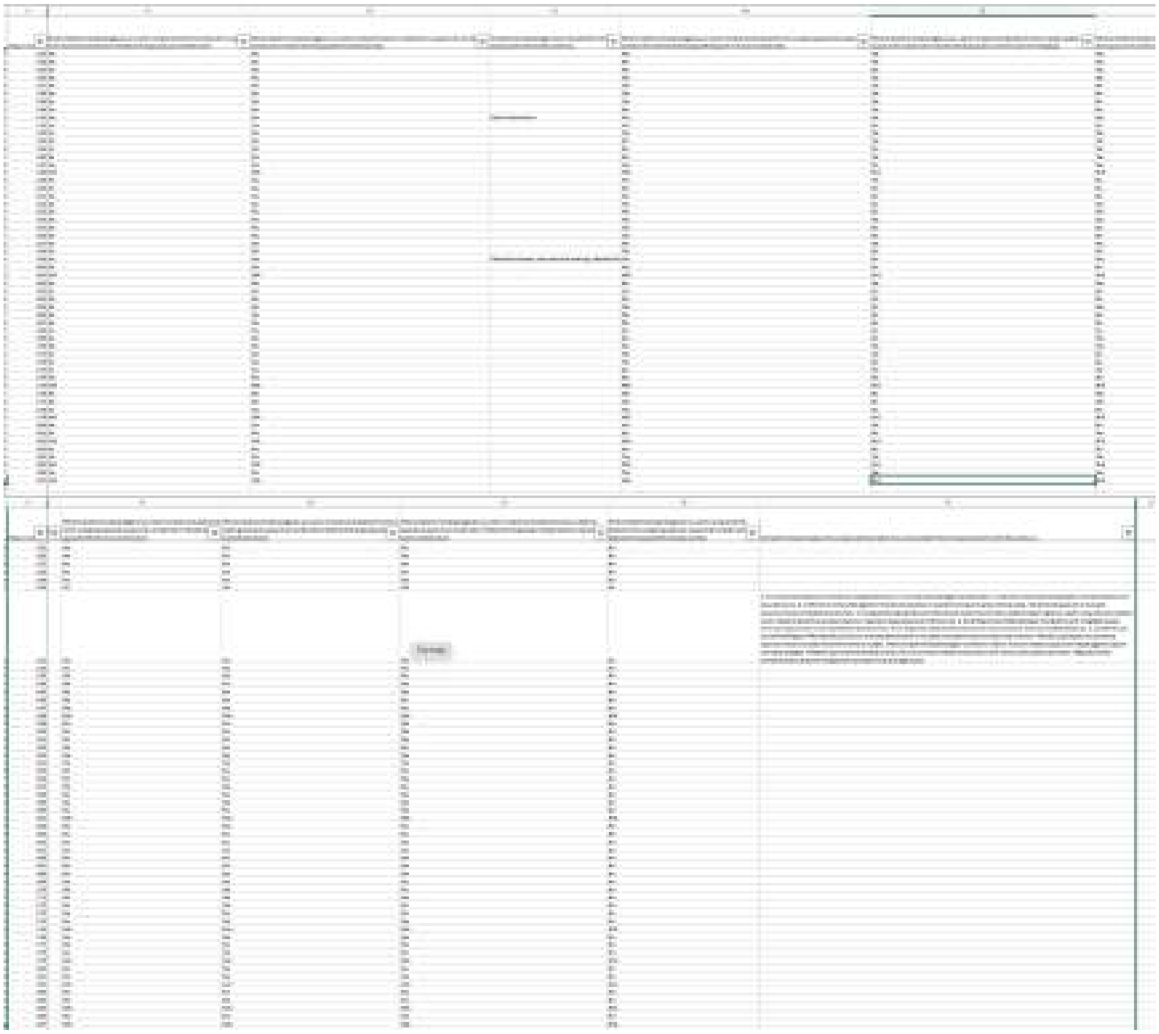












APPENDIX C

INTERVIEW GUIDE AND GDPR CONSENT (QUALITATIVE STUDY)

Interview - AI-supported Collaboration between Sales and Supply Chain (DBA Research)

Dear [Name],

Thank you very much for agreeing to participate in this interview as part of my Doctor of Business Administration (DBA) research.

This study focuses on how artificial intelligence (AI) can support collaboration between Sales and Supply Chain to enhance customer satisfaction and responsiveness. Your insights are highly valuable, and I greatly appreciate your time and willingness to share your experiences.

The interview will take approximately 30-45 minutes and will be conducted in a conversational, open-ended format via Microsoft Teams. You do not need to prepare written responses - the goal is to capture your perspective and practical experiences.

CONFIDENTIALITY AND DATA PROTECTION (GDPR STATEMENT)

CONFIDENTIALITY AND DATA PROTECTION (GDPR STATEMENT)

- Your participation is voluntary, and you may withdraw at any time without giving a reason.
- Your personal data and company name will not be published or disclosed.
- The interview will be audio-recorded solely for the purpose of accurate transcription.
- The recording and transcript will be stored securely and used exclusively for academic and scientific purposes within my doctoral research.
- Your responses will be fully anonymized during analysis and in the final dissertation.
- Data collection and handling complies with the General Data Protection Regulation (GDPR) and all applicable academic ethics standards.

By participating, you consent to the recording, transcription, and scientific use of your anonymized input in my dissertation.

Part A: Background (anonymous)

1. What is the main industry in which your company operates?
2. Approximately how large is your company? (e.g. <100 / 100-500 / 500-1000 / >1000 employees)
3. What is your current role in the organization?
4. How long have you been working in this role?
5. How would you assess your company's level of digitalization? (low / medium / high - with a brief explanation)

Part B: Collaboration between Sales and Supply Chain

6. How would you describe the current collaboration between Sales and Supply Chain in your company?
7. What challenges arise in the day-to-day collaboration?
8. What actions have been taken to improve this collaboration?

Part C: Use of Artificial Intelligence (AI)

9. Is AI currently used to support Sales or Supply Chain processes in your organization? If yes, how exactly?
10. What potential do you see in AI to improve collaboration between Sales and Supply Chain?
11. What barriers or concerns exist when implementing AI in your organization?

Part D: Customer Satisfaction and Responsiveness

12. In your opinion, how does the collaboration between Sales and Supply Chain impact customer satisfaction?
13. How quickly can your company currently respond to market changes or customer needs - and what factors limit this responsiveness?

Part E: Future and Strategic Outlook

14. What changes do you expect in the collaboration between these departments in the next 3-5 years?

15. What do you believe is needed to manage this transformation successfully - in terms of people, technology, or organizational structure?

Part F: Perceived Customer Expectations

16. What are your customers' key expectations today? (e.g. delivery reliability, competitive pricing, responsiveness, availability, service, etc.)

17. Have these expectations changed in recent years? If so, how?

18. How well is your company currently prepared to meet these expectations - especially regarding cross-functional collaboration?

Final Question

19. Is there anything else you would like to add about the integration of Sales, Supply Chain, and AI?

Thank you once again for your valuable time and insights. I'm looking forward to our discussion.

Best regards,

René Grywnow

DBA Candidate

APPENDIX D

ANSWERS QUALITATIVE SURVEY

[illegible]

Response ID	Is there anything else you would like to add about the integration of Sales, Supply Chain, and AI?
1	No
2	We actually talked about this in our end-of-year financial briefing last month. We're really focused on better integrating Sales, Supply Chain, and AI to improve how we work together. It's clear that using AI more smartly can help us predict demand and avoid delays, but it's also about making sure teams communicate well and trust the tech. We're committed to making these improvements step by step.
3	In conclusion, the interviewee highlights the importance of recognizing both the opportunities and pitfalls associated with AI integration. They stress the need for organizations to remain adaptable and open to reevaluating decisions as new information emerges, particularly in the rapidly evolving landscape of technology. They believe that a balanced approach that values human insight alongside technological advancements is essential for long-term success. The interviewee expresses optimism about the potential for AI to enhance operational efficiency but emphasizes the need for careful implementation to avoid unintended consequences.
4	The interviewee emphasizes that AI is a broad and often misunderstood term. To make progress, management must become more proactive in exploring and experimenting with AI applications. Current integration efforts rely heavily on individual cooperation, and there is a need to shift toward more structured, tool-based integration in the future.
5	No
6	Organizations need to understand that integration of Sales, Supply Chain, and AI isn't just a technological shift – it's a cultural and strategic transformation.
7	One important part we haven't focused on enough is managing change and getting everyone on the same page across departments. To succeed, we need to invest in technology and also build teamwork and flexibility so we can make the most of AI and grow the business.
8	The participant emphasizes the importance of understanding and integration between departments, as well as the use of AI tools. It is recommended to pursue gradual improvements and to address the challenges of integration and the use of AI through close collaboration and process adjustments within the company.
9	The integration of Sales, Supply Chain, and AI enhances efficiency, optimizes decision-making, and strengthens collaboration by enabling real-time data sharing, predictive analytics, and automation, ultimately driving better customer satisfaction and business performance.
10	The interviewee concluded that while the company is making progress in collaboration and digitalization, significant barriers remain. They highlighted the need for a more humane approach to business interactions and noted that geopolitical factors will play a crucial role in shaping the future of AI and overall business operations.
11	The integration is a strategic necessity. When these 2 areas are aligned through an intelligent system and transparent data sharing, we end up gaining speed, accuracy, and resilience. The real value of AI is in enabling smarter and quicker decisions across multiple teams, and not in replacing people, but instead empowering them to do better. Success is going to come from building trust in the tools, investing time and resources in collaboration, and staying agile when market demands evolve.
12	no
13	The human factor is crucial; it is important to involve employees in the transformation process and reduce fears. Open communication is essential to convey the benefits of digitalization and AI. The interviewee emphasizes that without the right people and their motivation, the transformation cannot be successful.
14	The interviewee concludes that while AI is a significant topic across various industries, its integration into healthcare will be approached cautiously due to regulatory complexities and the need for careful implementation. Effective collaboration between sales and supply chain is essential for organizational success, and leveraging technology will play a crucial role in enhancing efficiency and customer satisfaction. The organization must continue to focus on clear communication, strategic alignment, and employee engagement to navigate the challenges of transformation effectively.
15	The interviewee emphasizes the need for regular stakeholder communication and shared awareness of necessary changes. Successful AI integration depends on cross-departmental understanding and a collaborative mindset, not just on technical tools.

APPENDIX E

INFORMED CONSENT AND GDPR DATA PROTECTION STATEMENT

This study complies with the General Data Protection Regulation (GDPR, EU Regulation 2016/679) and adheres to academic ethical guidelines. Participation in both the quantitative survey and the qualitative interviews is voluntary and fully anonymized.

Confidentiality and Data Protection

- Your participation is voluntary, and you may withdraw at any time without providing a reason.
- No personal data (e.g. names, email addresses, company identifiers) will be disclosed or published.
- The quantitative survey was conducted via LimeSurvey. Responses were stored on secure servers and anonymized before analysis.
- The qualitative interviews were audio-recorded exclusively for transcription purposes and stored securely. Transcripts were anonymized and analyzed using academic coding standards.
- All collected data are used solely for scientific purposes within the scope of this DBA dissertation.
- The data are protected from unauthorized access, and all analysis respects confidentiality and ethical academic principles.

Consent Statement

By participating in the survey or interviews, you consent to the anonymous use of your responses for academic research and publication. For interviews, you additionally consent to audio recording and transcription for scientific analysis.

APPENDIX F

STATISTICAL OUTPUT – CHARTS AND VISUALIZATIONS (JAMOVI)

F1 Descriptive Statistics (Descreptivstatistik)

Deskriptivstatistik

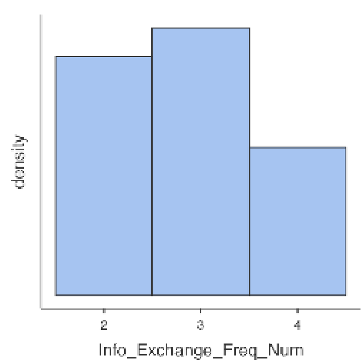
Deskriptivstatistik

	Collab_Quality	Forecast_Alignment	Info_Exchange_Freq_Num	AI_Use_Num
N	172	172	137	146
Fehlend	15	15	50	41
Mittelwert			2.86	0.459
Median			3.00	0.00
Standardabweichung			0.759	0.500
Minimum			2.00	0.00
Maximum			4.00	1.00

Diagramme

⚠ Die Variablen 'Collab_Quality' und 'Forecast_Alignment' können nicht als numerisch behandelt werden. Diagramme, die numerische Daten erwarten, können für diese Variablen nicht erstellt werden.

Info_Exchange_Freq_Num



F2 Correlation Matrix (Korrelationsmatrix)

Korrelationsmatrix

Korrelationsmatrix

		AI_Use_Num	Collab_Quality_Num	Forecast_Alignment_Num	Info_Exchange_Freq_Num
AI_Use_Num	Pearson's r	—			
	df	—			
	p-Wert	—			
	95% KI Obergrenze	—			
	95% KI Untergrenze	—			
Collab_Quality_Num	Pearson's r	0.484	—		
	df	142	—		
	p-Wert	<.001	—		
	95% KI Obergrenze	0.600	—		
	95% KI Untergrenze	0.349	—		
Forecast_Alignment_Num	Pearson's r	0.254	0.271	—	
	df	60	70	—	
	p-Wert	0.046	0.021	—	
	95% KI Obergrenze	0.474	0.473	—	
	95% KI Untergrenze	0.005	0.042	—	
Info_Exchange_Freq_Num	Pearson's r	0.319	0.264	NaN	—
	df	117	135	58	—
	p-Wert	<.001	0.002	NaN	—
	95% KI Obergrenze	0.472	0.414	NaN	—
	95% KI Untergrenze	0.147	0.101	NaN	—

F3 Cross Tabulation Tables (Kreutztabellen)

Kreuztabellen

Kreuztabellen

	AI_Use_Num		
Company_Size - 2 transformieren	0	1	Insgesamt
Small / Medium	51	45	96
Large	28	22	50
Insgesamt	79	67	146

χ^2-Tests

	Wert	df	p
χ^2	0.109	1	0.741
N	146		

F4 Linear Regression (Lineare Regression)

Lineare Regression

Güte der Modellanpassung

Modell	R	R²
1	0.484	0.235

Anmerkung. Models estimated using sample size of N=144

Modellkoeffizienten - Collab_Quality_Num

Prädiktor	Schätzung	Std.-fehler	t	p
Interzept[a]	2.468	0.0874	28.22	<.001
AI_Use_Num:				
1 – 0	0.846	0.1282	6.60	<.001

[a] Repräsentiert das Referenzniveau

F5 t-Test for Independent Samples (t-Test für unabhängige Stichproben)

t-Test für unabhängige Stichproben

t-Test für unabhängige Stichproben

		Statistik	df	p
Collab_Quality_Num	**Student's t**	-6.60[a]	142	<.001

Anmerkung. H_a $\mu_0 \neq \mu_1$

[a] Der Levene-Test ist signifikant ($p < 0{,}05$), was auf eine Verletzung der Annahme gleicher Varianzen hindeutet