AI in Supply Chains

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Dissertation submitted in partial fulfilment of requirements for the MSc in International Management, at the Universidade Católica Portuguesa, 02.01.2024.

Abstract

AI in SC is an application that has the potential to be a disruptive force, presenting avenues to reduce complexity in operations, better managerial choice making, and innovations in effectiveness. But despite this potential, AI is only marginally adopted because the barriers include siloed data systems, a fear of change, and worrying about ethics. With this study, we sought to explore the drivers and barriers to AI adoption in SCM interact and what are the implications for a transformative change in the sector.

We undertook a literature review of artificial intelligence and frameworks for consumer adoption of supply chain innovation, including the Technology Acceptance Model and Diffusion of Innovation. With the above, we aimed to identify underlying key concepts. The approach to primary data entailed expert interviews with industry professionals and a consumer survey. This allowed for triangulation against the secondary information available and fed into scenarios regarding possible adoption trajectories. The findings of AI capabilities in augmenting predictive analytics, automating processes, and enabling personalization can emerge as a foundational enabler of managing SCM challenges.

This study contributes to AI in SCM discourse by revealing actionable strategies that organizations can adopt to make effective use of its potential. Concluding the gradual evolution of AI adoption is likely, with transformative impact contingent upon foundational barriers being addressed, and technological capabilities aligned with organizational objectives.

Keywords: Supply Chain Management, Artificial Intelligence, Consumer Adoption, Predictive Analytics, Digital Transformation

Title: Unlocking AI’s Potential in Supply Chains: Drivers, Barriers, and Future Pathways

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Sumário

A IA na gestão da SCM é uma aplicação com potencial para ser uma força disruptiva, oferecendo oportunidades para reduzir a complexidade operacional, melhorar a tomada de decisões gerenciais e impulsionar inovações em eficiência. No entanto, apesar desse potencial, a adoção da IA ainda é marginal, devido a barreiras como sistemas de dados isolados, resistência à mudança e preocupações éticas. Este estudo busca explorar como os impulsionadores e barreiras para a adoção de IA na SCM interagem e quais são suas implicações para uma mudança transformadora no setor.

Foi realizada uma revisão da literatura sobre inteligência artificial e estruturas para a adoção de inovações na cadeia de suprimentos, incluindo o Modelo de Aceitação de Tecnologia e o Modelo de Difusão da Inovação. Essas informações permitiram triangulação com os dados secundários disponíveis e alimentaram a construção de cenários sobre possíveis trajetórias de adoção. Contudo, sua adoção em larga escala dependerá da superação de barreiras básicas, especialmente relacionadas à qualidade dos dados e à preparação da infraestrutura.

Este estudo contribui para o debate sobre IA na SCM, revelando estratégias práticas que as organizações podem adotar para utilizar efetivamente seu potencial. Conclui-se que a adoção da IA provavelmente evoluirá gradualmente, com o impacto transformador dependendo da superação de barreiras fundamentais e do alinhamento das capacidades tecnológicas aos objetivos organizacionais.

Palavras-chave: Gestão da Cadeia de Suprimentos, Inteligência Artificial, Adoção do Consumidor, Análise Preditiva, Transformação Digital

Título: Desbloqueando o Potencial da IA em Cadeias de Suprimentos: Impulsionadores, Barreiras e Caminhos Futuros

Autor: Daniel Nelles

Acknowledgements

This dissertation is the endpoint of my academic experience at Universidade Católica Portuguesa, a journey that has served to not only deepen my knowledge but also define my personal and professional goals. The experiences and lessons acquired during the time spent at Católica are sure to have a bearing on me beyond the program.

Special thanks to Peter V. Rajsingh, who not only read and provided comments on the earlier draft but also offered great constructive feedback to shape the final form of this thesis. His capacity to question my thinking and yet offer clarity and direction is one of the most valuable things that helped me refine my work, moving it much closer to what was needed to meet the MSc academic standard.

I am also very grateful to all the experts and professionals who participated in the interviews and shared their incredible insights into what AI could do for supply chain management. Also, I would like to thank and extend my appreciation to all other respondents for sparing their valuable time completing my survey and sharing very important data which added value to this research.

Finally, I express my heartfelt gratitude to my family and friends for being the biggest supporters during this whole journey. And specially to my parents for their motivation and providing the chance to study at Católica. Their trust in me was the continuous source of encouragement. And to my friends, for being there and providing moral support, as well as some happy moments that made this journey even more pleasant.

This thesis is not only about my own efforts but also a salute to the combined cooperation and effort of all those who have been with me in this academic pursuit. Thank you.

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List of Abbreviations

AI	Artificial Intelligence
DL	Deep Learning
e.g.	for example
GAI	Generative Artificial Intelligence
GAN’s	Generative Adversarial Networks
IoT	Internet of Things
ML	Machine Learning
SC	Supply Chain
SCM	Supply Chain Management
TAM	Technology Acceptance Model
VAEs	Variational Autoencoders
VAM	Value Adoption Model

1. Introduction

Artificial Intelligence (AI) has become a transformative force across industries and its use in Supply Chain Management (SCM) is a consequential application of AI (Ivanov & Dolgui, 2021; Pournader et al., 2021). Set to transform operations by boosting operational efficiency, enhancing the decision-making process, and augmenting organizational resilience, AI technologies incorporate Machine Learning (ML), predictive analytics, and process automation, new functionalities that provide the capacity to work in real-time with data and forecasting to solve some key problems within the Supply Chain. These include managing fluctuating demand, inventory optimization, and supplier coordination (Namdr et al., 2018). However, the actual implementation of AI is associated with several significant hurdles such as organizational resistance, fragmented data systems, and ethical concerns (Benzidia & Makoui, 2021). These make use and implementation a complex process; hence, understanding drivers is necessary for effective application of AI in the SCM domain (Holmström & Partanen, 2020).

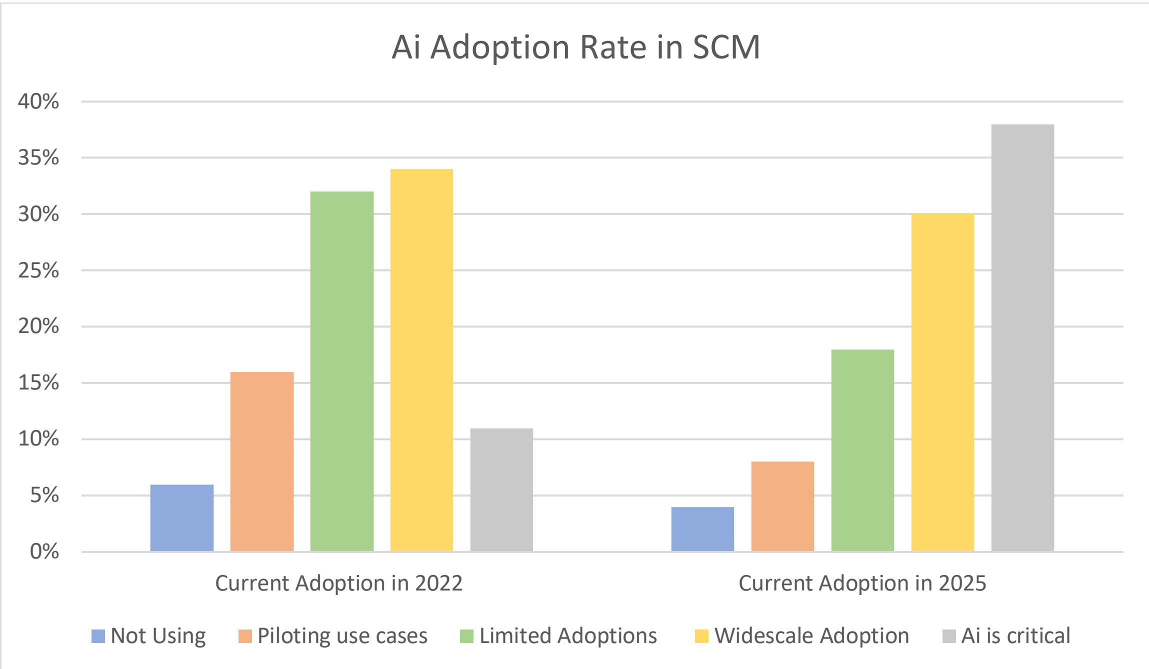

Figure 1 AI Adoption Rate in SCM (Adapted from Dolu Surabhi et.al, 2024)

Figure 1 spotlights the ongoing transformation of AI from a placeholder to a viable solution in SCM. Not using AI is expected to decrease from 6% in 2022 to 4% in 2025, which demonstrates significant diffusion. In 2022, 15% of companies were still piloting use cases, a figure that will hold steady at about 10% by 2025. Limited adoption was 32% in 2022 and is forecast to fall to 18% by 2025, as firms move closer to widespread adoption. Adoption that was 35% in 2022 is projected to remain high at 30% in 2025. Most striking is the number of businesses that say AI is critical. This will rise from 12% in 2022 to 38% in 2025, underlining further AI's increasing place as an important solution.

The Technology Acceptance Model (TAM) (Davis, 1989) and the Diffusion of Innovation model DOI (Rogers, 2003) discuss how innovators and early adopters are considered key dimensions for new technology gaining traction. But these models do not fully account for complexities of AI adoption in SCM with its highly volatile operational circumstances and complicated information ecosystems. AI holds immense potential to enhance decision-making under uncertainty (Shazadi et al., 2024). This is a neglected area of study, both theoretically and empirically, despite the importance of the topic (Waller & Fawcett, 2013). This thesis aims to fill this gap by elaborating determinants affecting the process of AI adoption in SCM. A mixed methods approach of qualitative and quantitative methodologies was used. Semi-structured interviews with AI and SC experts provided insights into industry-specific challenges and opportunities (Creswell et al., 2011). Further, a consumer survey captured perceptions and attitudes toward AI-enabled SC's. This was performed using Mayring and Fenzl's inductive categorization. Results were then triangulated with the existing literature. These methodologies aimed to answer the following Research Question:

RQ: What factors determine effective implementation of AI in Supply Chain Management?

Additionally, with scenario development for possible future trajectories of AI in SCM, management of organizations will be better prepared to deal with implementation and barriers to adoption (Sivarajah et al., 2017). Theoretical insight into the adoption of AI implicates scales such as TAM, DOI, and Value-Based Adoption Model (VAM). The structure of this thesis is as follows: Chapter 2 presents a review of the current literature on AI in SCM, Chapter 3 describes the research methodology with qualitative and quantitative approaches, Chapter 4 provides the findings that are mapped against theory in answer to the research objectives, and Chapter 5 teases out the implications of the findings through scenario development that might bring about different possible adoption trajectories. Finally, Chapter 6 begins to bring everything together with key findings, areas for future research, and where this research might be limited.

2. Literature Review

This literature review discusses AI, SCM and the logistics sector and the Adoption of Technological Innovation and Market Entry Strategies. Lastly, we examine the TAM and Adoption Dynamics Model.

2.1 Artificial Intelligence

AI has become a key asset for industry with the potential to bring substantial transformations in sectors like SCM. Utilizing algorithms and software enables machines to perform duties that typically demanded human involvement. Such responsibilities encompass functions such as analyzing information and making informed decisions (Kumar et al., 2019). There are generally two types of AI; Narrow AI that is tailored for tasks like recognition or search engines and General AI that seeks to mimic the wide range of human intellectual abilities. AI is changing how businesses work by learning and problem solving to enhance efficiency and tackle challenges in various ways (Vlacic et al., 2021).

The evolution of AI technology entails transitioning from simple task-oriented algorithmic applications to complex systems that learn and adapt to changing requirements over time. This development has been accelerated by recent advances by ML and deep learning (DL) operating with large datasets to improve functionality without being fed by inputs. ML algorithms make patterns and forecast-based decisions. On the other hand, DL uses neural networks for scanning multiple sorts of information of the same data types leading to a higher velocity and precision (Zhuhadar, 2023). SCM using AI has untapped potential to better tackle operational efficiencies in logistics, inventory management, and predictive analysis, improving SC's and reducing operational costs (Kanbach et al., 2023).

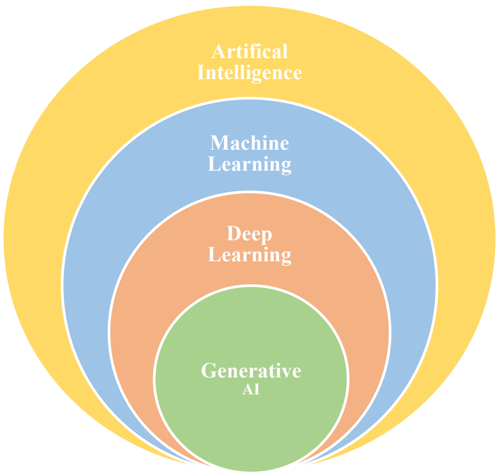

Figure 2 Overview of different stages of AI (Adapted from Kalota 2024)

Despite the immense benefits that AI brings, there are challenges associated with its adoption. There are ethical and privacy concerns pertaining to data protection as well as objections to surveillance. Then, costs related implementing AI technology may be prohibitive for firms becoming a major stumbling block for small players. The demand for professionals to manage and develop AI systems currently exceeds the supply. Lately, even legitimate pathways for safely introducing AI technologies are hard for many organizations to implement (Agrawal, 2023). The wave of AI is ushering in new business paradigms for operational excellence and strategic capability functions while setting new performance benchmarks (Chui et al., 2023).

2.1.1 Introduction to Generative AI

Generative AI(GAI) is not restricted just to interpreting and analyzing information and data but creates novel new material as well. This category of AI uses approaches like Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) to create outputs that closely resemble human content beings across domains including art and engineering (Zhuhadar, 2023). As opposed to traditional automation of tasks aimed at enhancing creativity, DALL-E, and ChatGPT blur the boundary between human and machine (Chui et al., 2023). Within the scope of product development, GAI can create several design prototypes and to shorten time to bring a product to market, reducing the cost of the innovation cycle (Cillo & Rubera, 2024).

2.1.2 Limitations and Risks

Risks and barriers exist for realizing the enormous transformational potential of GAI. Beyond just technical challenges there are economic, legal, and social concerns, as well. The principal problem with GAI is data privacy. GAI systems work with very large data sets, sometimes touching on very personal information. As a result, the possibility of a breach is high, which could cause significant economic loss and erode consumers trust (Chen et al., 2023). With uncertainty in copyright laws, conflicts might arise where original content creators might suffer from economic loss from unfair use of material not in the public domain to train models (Chui et al., 2023).

While deep generative models excel in producing lifelike and persuasive content, their power may be misused to produce misinformation that affects and sway’s public opinion, hence causing several social and economic impacts (Zhuo et al., 2023). GAI is further likely to disrupt labor markets disintermediating workers (Vlacic et al., 2021). Even though GAI may give rise to new employment opportunities, the overall effect could come out negative if substantial portions of the workforce become incapable of reorienting themselves towards new positions or if these positions are less lucrative than those relinquished (Chui et al., 2023).

2.2 Supply Chain and Logistics

SCM is an essential organizational function that concerns managing the flow and transformation of goods from the raw materials stage through to the final consumer. Thus, SCM is not only logistics but also with processes to achieve competitive advantages within the markets (Fitzgerald, 2024). SCM constitutes all the activities planned through active management of the SC to create value. It involves coordination among various actions that are performed by other firms such as suppliers, manufacturers, and retailers (Alfaro, 2024).

Better forecasting under AI enables companies to carry out more optimizations in routing plans and increase overall logistics efficiency. This changes the traditional SCM into a dynamic responsive interconnected system (Fosso Wamba et al., 2024). SCM has been greatly influenced by the latest developments in AI through ML and DL that underpin highly automated intelligent systems. Algorithms driven by AI have begun powering complex decision-making processes. As figure 3 shows, these functions help SCM solve the traditional challenge of effective management of big data, hence improving demand forecasting and inventory management (Li et al., 2020; Ren et al., 2017).

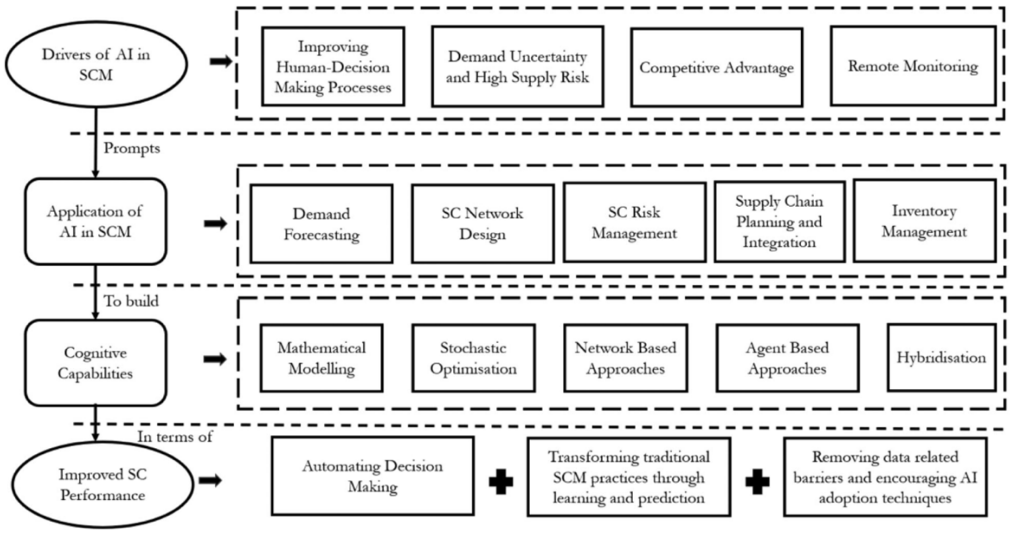

Figure 3 Synthesis Framework (R.Sahrma et al. 2022)

Applications of AI in SCM include different dimensions, from automated warehousing to intelligent transportation management and from advanced predictive analytics to demand planning. AI-driven systems help optimize logistics operations and make inventory management more efficient by giving predictive views on patterns in consumer demand, thus improving operational efficiency, customer service and satisfaction in a big way (Industry Week, 2024). AI has the potential to completely remodel SC's across the globe in ways that they will become agile and capable of meeting market needs (Fosso Wamba et al., 2024). The future of SCM lies in strategy use of AI technologies that promises to fundamentally transform global SC's towards greater efficiency, sustainability, and responsiveness as well as sensitivity to market dynamics across the globe (Maersk, 2024).

2.3 Management Frameworks

The following management frameworks were used.

2.3.1 Adoption of Technological Innovations

There are various factors that explain innovation diffusion: relative advantage, compatibility, complexity, trialability, and observability of results. The rate of diffusion is significantly contingent on these attributes (Rogers, 2003; Tornatzky & Klein, 1982). An innovation's relative advantage, meaning to what degree it is perceived to be better than the idea it supplants, is important for adoption. Innovations with higher perceived relative advantages have demonstrable performance benefits or user convenience and are likely to diffuse more rapidly (Rogers, 2003; Moore & Benbasat, 1991). Innovations that are compatible with the values of individuals in decision-making units, past work, and needs are also adopted with relative ease while those that require a lot of value or behavioral change create resistance (Rogers, 2003; Kautz & Jensen, 2012).

Trialability is the final influential factor where a result is discernible to the individual using the innovation. Innovation effects should be visible through benefits and ease of use. For perceived benefits, outputs that are more tangible are more likely to be adopted (Rogers, 2003; Wejnert, 2002). Features of social systems also bear upon the rate of diffusion. This is the system of norms and the interpersonal network within which the members of a social system are embedded and the readiness of opinion leaders to change. More interconnected systems in which opinion leaders tend to be early adopters will diffuse innovations more rapidly and more widely (Rogers, 2003; Wejnert, 2002).

The adoption decision may be viewed as an individual or collective choice within a social system and depends on change agents in conveying relative advantage, especially through media. Hence, there is need for effective mass media for information dissemination about the innovation. Interpersonal channels also play a role where face-to-face interactions influence individual interests and concerns (Coleman, Katz, & Menzel, 1966). Understanding these forces, strategists can design ways to increase the pace at which new technologies are adopted (Ledger & Bakhai, 2021).

2.3.2 Market Entry Strategies

The stage in the market cycle when an organization introduces products or services is a fundamental strategic choice for any company. Moving or entering first can be highly advantageous in terms of competitiveness. Alternatively, late market entry can also sometimes prove to be fruitful under certain conditions. First movers are firms which initiate the introduction of a product or service into the market (Suarez & Lanzolla, 2007). Often these are the firms possess technological leadership and benefit from the effects related to the learning curve. By moving first with new technologies, first movers may be able to attain cost reductions due to efficiency and new process methods of production. (Lieberman & Montgomery, 1988; Kerin, Varadarajan & Peterson, 1992). First movers also have the privilege of shaping consumer perceptions and setting industry standards that may culminate in high barriers for possible later entrants. These barriers may require greater resource investments for laggards.

First movers hence forward move with scale and experience advantages that improve their operating efficiencies and strengthen their market power (Rao and Rutgenberg, 1979; Smiley and Ravid, 1983). The pre-emption of valuable assets is another strategic advantage for first movers in markets. New market entrants can claim all the necessary resources and factors of production, such as the key supply sources, top-notch locations, and other amenities. These may prove highly expensive for later entrants making it impossible to compete in some cases (Lieberman & Montgomery, 1988).

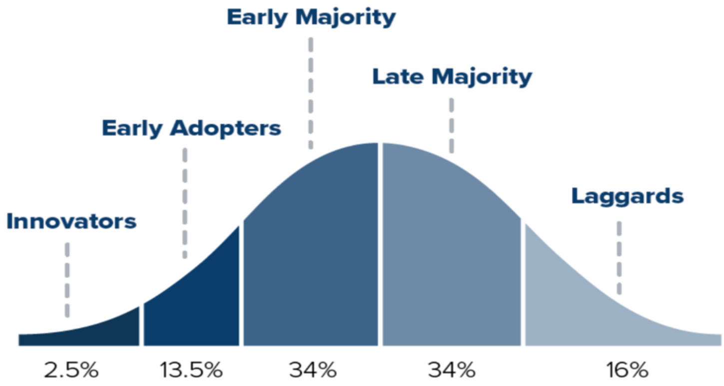

Figure 4 Innovation Adopters (Bass, F. M., 1969)

Second-mover advantages can arise for strategic reasons. Second movers free ride upon the market research and consumer education of the first movers. This shaves away some of the costs and risks of market development and uncertainties (Lieberman & Montgomery, 1988; Kerin et al., 1992). In addition, late entrants can free themselves from mistakes made by the first movers. They can imitate up-to-date technologies and methods, thus leapfrogging over leaders. Second movers can also introduce innovations that better fit changing customer needs (Markides & Lourdes, 2013).

Market entry timing is a choice that depends on several factors, such as assessing resources, risks, and competitor responses. First moving allows firms to build strong market positions with the usage of AI and erect barriers in front of second movers (Markides & Geroski, 2004). However, they may have to live with the tremendously high risks that are attendant in untested markets. For instance, second movers stand to benefit from first movers by leveraging the already-created infrastructure and customer consciousness, although they should bear the burden of clearly differentiating their product to wrest market share from established competitors (Goldner & Tellis, 1993). Market entry timing is a strategic choice that sets a company's degree of competitiveness and success. Each early and late market entry presents different strengths and limitations; thus, the timing of market entry is vital for gaining competitivity in the market.

2.3.3 Technology Acceptance and Adoption Dynamics

The Technology Acceptance Model (TAM) developed in 1985 by Davis proposes that user adoption is driven primarily by two aspects: perceived usefulness and perceived ease of use from the technology. (Davis, 1985; Chau, 1996). According to TAM, perceived usefulness forms the primary determinant of the intention to use any technology. This is defined as the extent to which an individual feels that using a certain piece of technology would improve his or her work performance or quality of results in comparison with no use. Moreover, perceived ease of use is another factor that enters this decision but to a slightly lesser degree than perceived usefulness (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989). Initially, TAM was developed for explaining computer usage behavior; however, it has been applied to a wide range of technological implementations in fields as diverse as e-commerce, mobile banking, and online education (King & He, 2006; Marangunic & Granic, 2015). The model's extension is indicative of its applicability to new technologies and changing user environments.

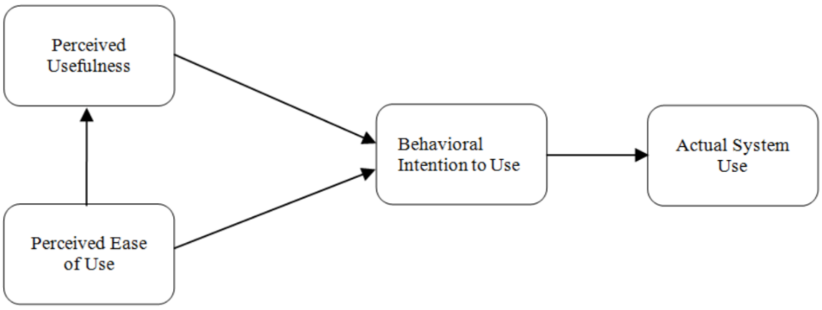

Figure 5 Technology Acceptance Model (Adapted from Davis, 1985)

Sohn and Kwon (2020) state that the Value-Based Adoption Model (VAM) advances TAM by introducing a wider array of factors. Users perceive both practical benefits and personal pleasure from use of the technology. Thus, VAM integrates both functional benefits such as usefulness with emotional benefits like enjoyment to propel adoption behavior. But several inherent challenges remain in technology adoption. New innovations may be complex and perceived as too technical by the users, which negates usefulness and ease of use. Moreover, perceived net value may also be negatively affected by high costs associated with new technologies (Kim et al., 2007).

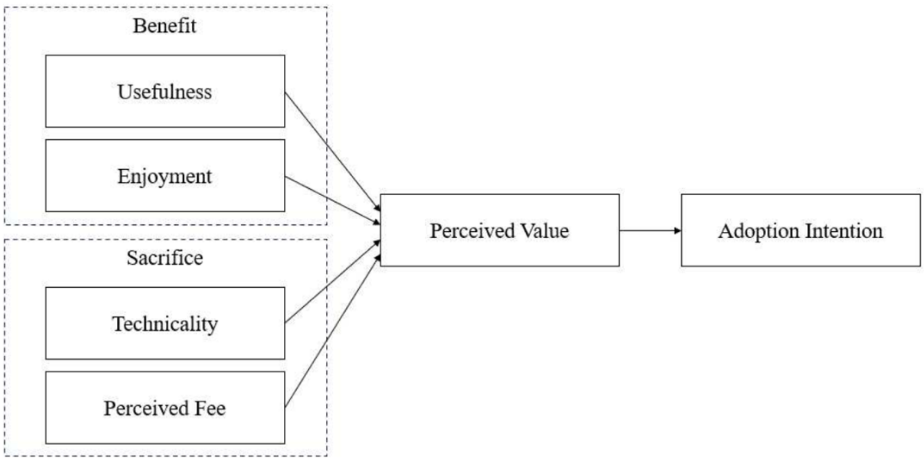

Figure 6 Value-based Adoption Model of Technology (Adopted from Kim et al., 2007)

Nevertheless, the TAM and VAM frameworks provide insight into the dynamics of technology acceptance and adoption (Bargozzi, 2007). Technology is a fast-moving target, and these models can be utilized to anticipate user responses and help channels enhance user reception and use.

2.3.4 Adoption of Frameworks to answer the Research Question

The theoretical frameworks above will enable us to examine of how AI can transform SCM and set dimensions for testing our various hypotheses.

Adoption of Technological Innovation (Rogers, 2003)	
Hypothesis:	Adopted from:
H1: Relative advantage positively influences the eagerness to adopt.	Moore and Benbasat, 1991; Rogers, 2003
H2: Compatibility positively influences the eagerness to adopt.	Moore and Benbasat, 1991; Rogers, 2003
H3: Complexity positively influences the eagerness to adopt.	Tornatzky, and Klein, 1982; Moore and Benbasat, 1991
H4: Observability positively influences the eagerness to adopt.	Rogers, 2003; Meuter et al., 2005
H5: Trialability positively impacts the eagerness to adopt.	Meuter et al., 2005
Value-based Adoption Model (Kim et. al., 2007)	
H6: Perceived value has a positive correlation with the intention to adopt.	Kim et al., 2007
H7: Usefulness has a positive correlation with perceived value.	Venkatesh and Davis, 2000; Davis, Bagozzi and Warshaw, 1989; Kim et al., 2007
H8: Enjoyment has a positive correlation to perceived value.	Zhou, 2011; Agarwal and Karahanna, 2000
H9: Technical ease positively correlates with perceived value.	Thong et al., 2002; Kim et al., 2007; Davis, 1989
H10: Perceived cost is inversely correlated with perceived value.	Shin, 2009; Voss et al., 1998

Table 1 Hypothesis Overview

3. Methodology

This study gathered data in a mixed-methods design. Qualitative data were collected through semi-structured interviews with experts in AI and professionals from the SCM industry. Quantitative data were collected through a consumer survey. Triangulation with the findings of the literature review was performed for an in-depth analysis.

3.1 Qualitative Data

Semi-structured interview questions were developed following standard qualitative research principles to understand of drivers, barriers, and the scope of opportunity regarding AI adoption. Six major themes were in examined concerning constraints in Data Quality and Standardization, AI Complexity and Usability, Privacy and Ethical Concerns, Adoption Rates and ROI Focus, Resistance to Change, and Real-Time Insights and Decision-Making. Purposive sampling was guided by the established qualitative strategies that require diverse industry representation and role inclusion (Patton, 2002). Consistent with the tenets of qualitative research, data collection process was undertaken through open-ended questions that would elicit rich and exploratory responses (Bryman, 2015).

The responses were analyzed thematically through inductive coding: this involves the identification of patterns and themes that emerge in the data (Braun and Clarke's 2006). The American Psychological Association (APA, 2017) ethical guidelines were met by keeping the participants anonymous and obtaining informed consent in accordance with principles of transparency and confidentiality. This helps in bringing the credibility, dependability, and ethical honesty of the results of the study.

3.2 Quantitative Data

The quantitative approach adopted was a survey developed in accordance with guidelines proposed by earlier researchers who introduced and validated new models, including the VAM (Kim et al. 2007) and the DOI Theory by Rogers (2003). Likert-scale questions allowed respondents to indicate their level of agreement or disagreement with a given statement on a scale of one to five.

The survey was conducted online with a diverse sample of respondents from a variety of industries and professional backgrounds, specifically those working in logistics and SCM. Following the cleaning and preparation of the data, a total of n=178 valid entries were obtained. These were then subjected to analysis. Descriptive statistics were calculated in R, a statistical programming language, to summarize the distributions and central tendencies of the responses (Field, 2013). A multiple linear regression analysis was conducted to examine the relationship between several independent variables, including dimensions such as usefulness and enjoyment, and the dependent variable, namely adoption intention. At this stage, each hypothesis was evaluated based on its statistical significance, as determined by the p-values and confidence intervals (Cohen, 1988). Montgomery (2012) further suggested that diagnostic checks, such as tests of residuals and variance inflation factor (VIF), can be employed to validate model assumptions and ensure the reliability of results.

4. Results

The following findings were based on insights gathered from the interviews and the customer survey.

4.1 Qualitative Results

Interviews with AI and SC experts were analyzed using a structured approach to identify the key factors influencing AI adoption. Participants were aged between 38 and 48, held leadership roles such as Chief Technology Officer and Senior Consultant. Six main themes emerged: Data Quality and Standardization, AI Complexity and Usability, Privacy and Ethical Concerns, Adoption Rates and ROI Focus, Resistance to Change, and Real-Time Insights and Decision-Making.

The most frequently mentioned theme was Adoption Rates and ROI Focus (38 mentions), followed by Resistance to Change (34 mentions). Subcategories such as Unstructured Data, Ease of Use, and Predictive Analytics provide further depth. These findings aligned with prior research emphasizing the importance of user engagement and ethical considerations in AI adoption (Brynjolfsson & McAfee, 2017). The following sections explore each theme in detail, focusing on the subcategories to provide a comprehensive understanding of the challenges and opportunities in integrating AI into SCM.

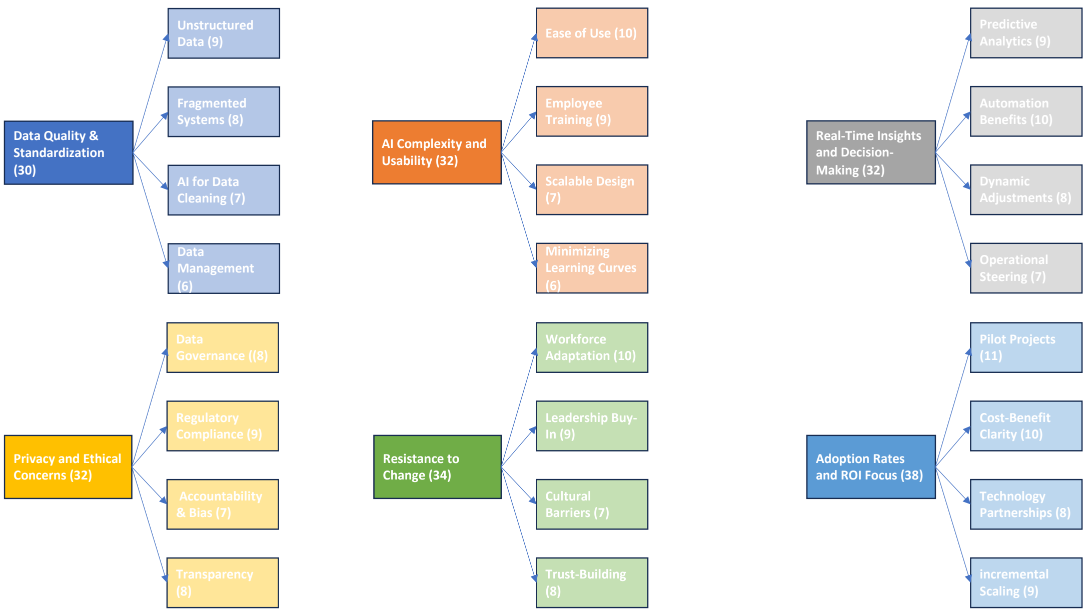

Figure 7 Overview of Survey Results

4.1.1 Data Quality and Standardization

Data quality and standardization were critical themes that all the twelve interviewees raised for effective AI integration into SCM. The most important challenges were unstructured data, fragmented systems, cleaning of data, and centralized data management. This theme speaks to the fundamental nature of good data if the promises of AI tools are to be informational and actionable insights. One frequently highlighted issue was unstructured data E.g., supplier contracts, invoices, and inventory records. As expressed by Interviewee B,

“The biggest obstacle is not in collecting the data but making it usable. While Optical Character Recognition (OCR) tools can extract information, AI must convert it into actionable insights.”

Nine Interviewees agreed within the context that the handling of unstructured data often derails the speed of AI implementation.

Another common problem eight of the interviewees described was the issue of data fragmentation across departments as a key barrier to standardization. "Cross-departmental coordination virtually does not exist due to data fragmentation," noted Interviewee D. In the view of many respondents, this needed to be solved through strong integration tools that could gather data into central platforms. Interviewee H stressed that "instituting cloud-based solutions is a prerequisite for getting the needed visibility for AI-driven decisions." Seven interviewees highlighted the importance of AI for data cleaning, especially because AI can manage a large volume of inconsistent data and make this very accurate. As Interviewee G noted, "AI tools are very good at identifying anomalies and filling gaps in the data set, which saves a lot of time compared with manual work." It thus allows organizations to concentrate on deriving value from insights rather than expending an inordinate number of resources on data preparation.

Finally, six of the participants viewed centralized data management as a prerequisite for the adoption of AI. As put by Interviewee A, “Inadequate centralization of data is like teaching AI mostly to work in a vacuum. Consolidation breeds uniformity and paves a way to launch AI on a broader front along the SC.”

The participants believed unified data architecture would automatically lead to more seamless integration and enhance trust in AI recommendations. Overall, the topic of data quality and standardization brings out how foundational data practices can support AI’s potential to drive operational excellence.

4.1.2 AI Complexity and Usability

Complexity and usability of AI systems were pivotal factors held to influence successful adoption and integration of AI into SCM. Eleven of the interviewees explicitly noted that one of the biggest challenges is making AI systems user-friendly and adaptable while addressing the inherent technical demands of these solutions. One major issue raised was the mention of ten interviewees regarding the ease of use of AI tools. As in the words of Interviewee G, “Most of the AI platforms today are so complicated that they cast a cloud of frustration and underutilization.” Such complexities impede, especially employees who do not have advanced technical knowledge. Interviewee H supplemented,

"We cannot assume that the users are going to understand every little detail about the AI model. The interface has to make up the difference in bringing together complexity and usability."

Less-frequent solutions included simple and intuitive user interfaces, which would allow adoption across a broader range of workers. Another very common subtheme was the need for employee training, noted by nine interviewees. As one respondent noted, "Just deploying AI tools is not where the story ends; it is equally important to train employees to use them effectively." Extensive training programs increase confidence as well as user adoption. One such Interviewee B, noted, “Workers are more likely to adopt AI tools when they understand how they can complement their roles, rather than replace them.”

Another critical factor that was raised by seven of the interviewees is scalability with AI solutions. As expressed by Interviewee A, “Scaling organizations need their AI systems to keep pace with the organization by working with new data, new workflows, and market shifts.” It provides room for AI relevance throughout time and business value delivery acceleration fueled by changing operational needs. Still, it was warned by Interviewee F that scalability comes with its own set of added intricacies in execution, needing proper planning and strong infrastructure. Finally, six interviewees brought up the challenge of minimizing learning curves. Complex dashboards and very technical outputs often do not encourage engagement, especially with most of the less tech-savvy employees. As mentioned by Interviewee C, "AI tools should be designed like consumer technology intuitive, and with minimal learning required E.g., smartphones." An orientation towards accessibility can significantly enhance user engagement and satisfaction. In general, the interviews disclosed clear consent. The necessary condition for the effectiveness of AI systems is the fusion of sophistication with usability. The trade-off is ensuring that ease of use, robust training, scalable designs, and intuition in interface reduce resistance and maximize the potential of the organizations in using their AI investments. From these, it stands underlined that AI designers need to build their solutions for end-users, ensuring accessibility with functionality.

4.1.3 Privacy and Ethical Concerns

Privacy and ethical issues were frequently mentioned, highlighted through the interviews, by ten out of the twelve respondents, to be applied as the key influencers before adopting AI in SCM. The issues were around data governance, regulatory compliance, bias in AI systems, and the need for transparency. These challenges identified the role of ethical considerations to be met for the proper, resourceful, radical use of AI technologies. The data governance topic was the most central concern that was mentioned by eight interviewees. According to Interviewee B, “Without proper governance frameworks, data risks becoming a liability rather than an asset.” Clear policies concerning who can access, use, and store data were considered an essential first step toward building trust and meeting regulations. Interviewee E went on to stress the same thing again, stating, “Enterprises have to ensure that data is secure and traceable throughout, more so when it involves AI-based systems.”

Another minor theme that was widely highlighted by nine interviewees was regulatory compliance and its impact on AI adoption. As Interviewee D pointed out, "Acts like GDPR have very stringent rules on data handling, which can anyway make the AI projects complicated or delayed." Although undoubtedly designed as vital safeguards, they largely serve up further holds for companies that operate within high-regulated industry sectors. Interviewee H also identified compliance as an opportunity: "Companies can differentiate themselves and build trust with their stakeholders by engineering AI systems for privacy, but not only that."

Seven participants raised the issue of bias and accountability in AI systems. As noted by Interviewee A, "AI models are no better than the data on which they are trained. Biases in the data may result in unfair or inaccurate outcomes." This view was supported by views expressed by Interviewee F that "Frameworks of accountability are required so that AI decisions can be audited, and biases be rectified if found." It was considered that establishing the mechanisms for monitoring and mitigating biases is very important from the point of view of preserving the ethics."

Eight participants highlighted that transparency in AI systems can redress privacy and ethical worries. As Interviewee G stated, "Most times, AI systems are treated as black boxes, which might eventually erode trust among users and other stakeholders." Describing how decisions are arrived at by tracing them back to inputs, or how algorithms work, were a couple of must-do activities. As Interviewee C mentioned, "Transparency is not only for ethics but also for increased user confidence and adoption." In brief, the obstacles that lie before the adoption of AI are privacy and ethical concerns. At the same time, they are opportunities for companies to create trust and leadership in responsible AI use. Companies can deal with these challenges by managing effective data governance, regulatory compliance, biases, and transparency towards building ethical and impactful AI systems.

4.1.4 Adoption Rates and ROI Focus

Adoption rates and the focus on ROI were two major dynamics critical of AI implementation in SCM. This theme was noted by all twelve interviewees, throwing into relief the challenges and the opportunities of demonstrating tangible value from AI projects. The discussion revolved around pilot projects, cost-benefit clarity, technology partnerships, and incremental scaling. Pilot projects were identified as one of the strategies that would help accelerate the adoption of AI, by eleven interviewees. As outlined by interviewee C,

"Organizations can only achieve an AI-first approach by first minimizing risk through small scale pilots. Only then can they understand what the pilots did."

Such initiatives allow organizations to test AI solutions in an environment that is within their control and thereafter scale up with their stakeholders on board. Interviewee G stressed their value: “We use pilot projects to define quick wins and improve the process if we decide to go for a full implementation.”

Cost-benefit clarity was another theme that dovetailed with many of the other common themes; ten Interviewees noted the need to prove ROI. As one interviewee mentioned, “Organizations are hesitant to invest in AI without clear evidence of its financial and operational benefits.” It is very important to provide detailed projections on tangible outcomes in terms of cost saved, efficiency gained, and other tangible outcomes that would help make the case to decision-makers. To this, another interviewer added, “Success stories from early adopters can help paint the picture of what value AI investments could bring and reduce skepticism.”

Technology partnerships were viewed as one of the key enablers to successful adoption, with nine interviewees pleading that they partner with experienced vendors and consultants of AI. “Many organizations lack the in-house expertise to implement AI effectively and hence the importance of partnerships,” noted Interviewee A. The use of external expertise can help organizations learn from the common pitfalls and, in turn, quicken the process of learning.

"We are entering into strategic partnerships which help us get hold of the latest technology at the same time minimizing costs since we are not expected to build everything from zero," Interviewee D added.

Finally, incremental scaling is a low-risk way and guarantees sustainable adoption. This was mentioned by eight interviewees who said that it could be achieved practically to manage risk. Respondent F said, “Incremental scaling of AI implementation will help address issues and help optimize processes as we upscale.” This will reduce the probability of expensive failures and ensure resource efficiency. Respondent E remarked how important it was to align scaling efforts with organizational goals: "AI should grow in tandem with business priorities to assure its relevance and impact." To sum up, the two biggest drivers of AI integration in SCM are adoption rates and ROI focus. Pilot projects, cost-benefit clarity, strategic partnerships, incremental scaling these are the kinds of levers that organizations feel comfortable using to gain confidence, show value, and effectively scale AI solutions. The insights bring out the need for phased, value-centric ways of adopting AI.

4.1.5 Resistance to Change

Nine of the twelve interviewees stressed the major impediment to successful adoption of AI in SCM is resistance to change. This theme reflects labor issues that organizations have related to technology adoption, leadership support, cultural barriers, and building trust. It was the most frequently noted subtheme, mentioned by ten interviewees. Many employees are worried that AI will replace them, and their work will be disrupted. As one interviewee mentioned, "Workers are skeptical about applying AI in practice they perceive it as a threat, not a support in increasing efficiency." This view was shared by another respondent who commented that early engagement of workers in adoption, and demonstration on how AI will enhance their tasks works reject the device is of importance.

Strong leadership buy-in was the next most frequently discussed theme, with nine interviewees emphasizing its importance. AI projects often stall for lack of energy unless a very strong leadership level is supportive. One interviewee noted, "Not only should the leaders approve the funds, but they should also champion the cause for aligning the AI initiatives with organizational goals." Also, as pointed out by another interviewee, "Leadership hesitancy is many times due to lack of knowledge of the possible aspects of AI, which again underlines the need for education at the Executive level." Cultural barriers were another key frequently noted challenge, by eight interviewees. Most organizations find it very difficult to nurture an innovation culture, this being a critical success factor for AI. As put by Interviewee C, “Old-school mindset and less acceptance toward experiments widely curb the space for AI.” Overcoming the impediments like these by embarking on a culture of learning and constant betterment might be worthwhile. Interviewee H added, "Companies that are open to failure as part of the learning process will be more successful in integrating AI into their businesses."

Seven interviewees called for building trust, especially regarding AI’s ability to make decisions e.g., Interviewee B noted, “AI would be trusted by workforce and stakeholders when its processes and results are explainable and transparent.” Early wins and open communication regarding what AI can do and not do are required to get the ball of trust rolling. This is covered in the statement of Interviewee G: "Trust should increase as employees realize concrete benefits resulting from AI, such as reducing their work burden or enhancing decision-making." In sum, such a high level of resistance makes the challenge of adopting AI more difficult, but not hopeless. More specifically, through the provision of workers' skills, obtaining the top management support, addressing the cultural issues, and infusing trust, organizations will manage to create an ecosystem that not only becomes home for initiation but also nourishes the positive application of AI. This was in response to interview insights as well, which showed that attention should be paid to human factors along with the technical implementation.

4.1.6 Real-Time Insights and Decision-Making

Eight of the twelve interviewees stressed this point as very impactful. Evident was the fact that being able to make dynamic changes and automating processes with predictive analytics would transform responsiveness to operational effectiveness. Predictive analytics is one of the major subthemes that nine of the interviewees mentioned. "It allows us to predict demand and potential disruptions," as stated by Interviewee B. AI makes predictive decisions based on ascertaining trends from historical data. Interviewee F said, "It helps match inventory better with market trends, lowering costs as it raises customer satisfaction."

Ten interviewees pointed out the advantages of automation in real-time decision-making. According to Interviewee A, "AI automates routine tasks of inventory restocking and order routing, whereas human resources can focus more on strategic activities." This not only increases the level of work done per unit time but also lowers the attendant human-error risks. Interviewee D illustrated: "In logistics, for instance, AI-based automation has dramatically improved delivery timelines by allowing dynamic changes in routes based on traffic conditions to ensure the shortest path at the current time." Another commonly cited benefit, noted by eight interviewees, was the capacity to make dynamic adjustments. With AI systems, SC's can really move with the required speed to accommodate changed circumstances and increased demand or supply disruption. As Interviewee G noted, "AI allows us to change our operations in real-time, which is a critical need in the volatile market today."

Seven interviewees noted it as a big improvement for AI operational steering capabilities e.g., Interviewee H described it as: "From passive planning to active decision-making, AI allows us to steer our SC in real-time." This would mean an overall level of visibility increased by orders that organizations can continuously optimize their SC operations with. To sum up, real-time visibility and the ability to act define one of the closest far-reaching benefits resulting from the application of AI to SCM. Enabling predictive analytics alongside features such as automation, dynamic adjustments, and operational steering will empower enterprises to be agile, efficient, and competitive players in the marketplace pace of change. The degree to which this theme resonated across the interview's underscores how key an enabler it is in capitalizing upon AI technologies.

4.2 Quantitative Results

This chapter presents the findings and statistical analysis of questionnaire data. Results are presented using descriptive statistics and regression models to derive insights into the drivers and barriers of AI adoption.

4.2.1 Demographic Overview

The following subsection discusses three major dimensions: gender composition, income distribution, and propensity to adopt AI technologies.

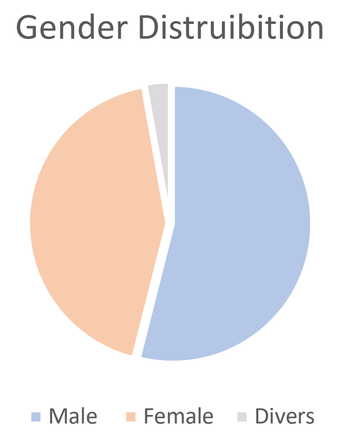

Figure 8 Gender Distribution Overview

The respondents appeared balanced in terms of gender, with the males constituting about 55% and the females 43% of the sample, the total respondents for the entire survey are 178. A small minority chose diverse or preferred not to disclose. Such balance in representation allowed the study to bring out varied lenses that would paint a clear picture of whether and how gender relates to attitudes toward AI-enhanced technologies. People from different gender identities were included in the sample; hence, the results could be generalized. Figure 8 shows the gender balance.

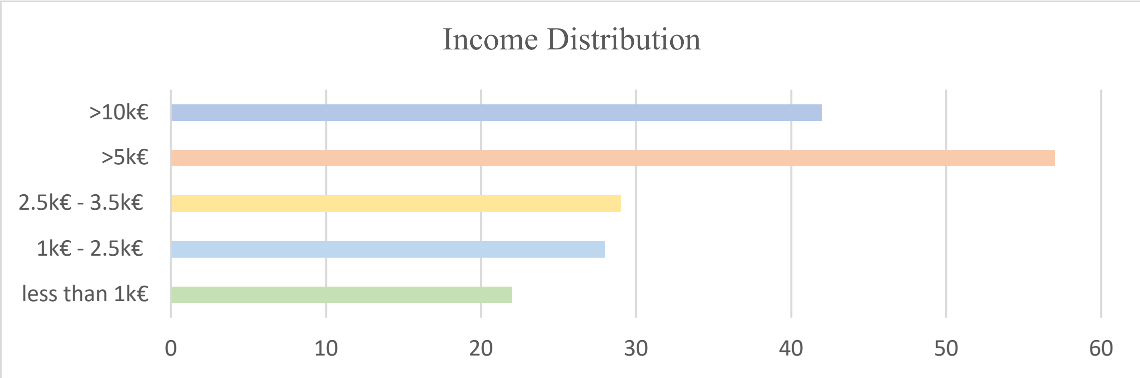

Figure 9 Income Distribuition Overview

The incomes of the respondents reflected a wide spectrum of participant backgrounds, dominated by higher income brackets. As depicted in Figure 9, around 56% of respondents stated they earned more than €5,000 per month, with a further 20% indicating earnings between €2,500 and €3,500 a month. Smaller proportions indicated earnings in yet lower brackets, less than €1,000 a month or between €1,000 and €2,500 per month. This income distribution helped reveal possible variations based on affordability and financial security. High representation from the upper brackets may suggest an inherent bias, as financial capacity is likely to influence perceptions.

As shown in Figure 10, most respondents were positive about adoption. Close to 60% said they would probably adopt AI systems, and an additional 30% said yes, reflecting large overall enthusiasm for AI technologies. Only a minor share of participants expressed some negative feelings, as there were few who selected "probably not" or "definitely not."

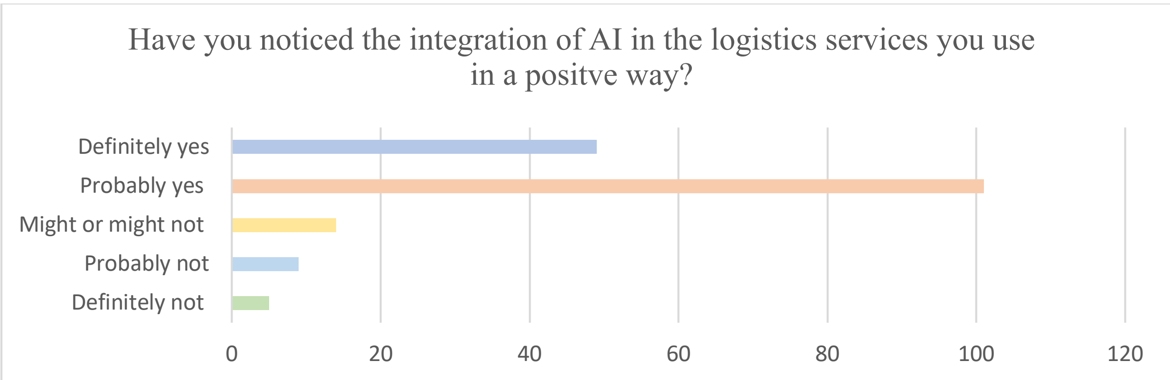

Figure 10 Awareness of AI Integration in SCM

These results show a positive attitude towards the adoption of AI for the entire sample. The high levels of readiness to adopt are prognostic since the subjects believed that such systems with AI would bring added value and relevance to their needs. In addition, the data showed at least some wave of optimism from the respondents, which revealed minimal resistance. Supporting these trends are findings from other large-scale technology adoption studies where being exposed to benefits of technology and information generally facilitate positive attitudes.

4.2.2 Descriptive Statistics – Eagerness to adopt

Descriptive Statistics

	Variable	Mean	SD
1	Relative_advantage	8.19	1.66
2	Compatibility	11.87	2.54
3	Complexity	8.26	1.91
4	Observability	9.06	1.86
5	Trialability	8.87	2.37
6	Eagerness_to_Adopt	9.84	1.58

Figure 11 Descriptive Statistics DOI Model

Descriptive statistics of the data and variables were computed to provide mean tendencies, variations, and distributions of responses at each level as a prerequisite for hypothesis testing and analysis. Each variable is a composite measure of opinions and attitudes toward AI-enabled platforms in Supply Chain Management and was developed from several questions in the survey. The dependent variable, Eagerness to Adopt AI-enabled platforms, seeks to express the perceptions of respondents through some of its main dimensions such as Relative Advantage, Compatibility, Complexity, Observability, and Trialability (see Figure 11). These dimensions highlighted the different factors based on which adoption likelihood can be explained and, respectively, respondents' attitudes toward AI technologies. The dimension of Relative Advantage, having a mean score of 8.19 and a standard deviation of 1.66, assessed the perceived advantages of using AI-based systems over existing methods. In general, respondents perceived AI systems to be advantageous. Though the variation was moderate, it indicated that indeed views on the benefits somewhat differed across participants.

Compatibility measured how much the values, skills, and experience of the respondent matched the AI-based tools. It had a mean of 11.87 and a standard deviation of 2.54. This high mean signified that more than half of the respondents perceived AI tools to be compatible with their workflow or context. However, a relatively high variability implied that for some respondents, these tools were not as much in alignment with their skills and experience. Complexity scored a mean of 8.26, with a standard deviation of 1.91, which reflects the perceived difficulty in using AI systems. Numerous respondents said it was easy to use the systems; however, some others mentioned the challenges in managing technical aspects of the systems, meaning ease of use was not something that could be achieved universally. Observability, which captured the proportion to which the advantages of AI systems are visible, achieved a mean of 9.06 with a standard deviation of 1.86. This implies that not all respondents were already seeing clear benefits of AI implementation, but rather a fraction that requires more evidence to associate clear advantages or effectiveness in practice.

Trialability had a mean of 8.87 and standard deviation 2.37, underlining the significance of being able to experiment with AI systems. High variability in responses, which is evidenced by large standard deviation values, speaks to the fact that indeed expectations regarding the opportunity to trial these systems varied significantly across participants. Finally, Eagerness to Adopt is the dependent variable representing the tendency of the respondents to adopt AI platforms. With a mean of 9.84 with a standard deviation of 1.58. It showed that the respondents generally have a positive attitude toward adoption, with opinions that are rather stable.

4.2.3 Eagerness to Adopt Regression Model

The Quantitative analysis also investigated factors influencing Eagerness to Adopt AI-enabled platforms with the help of the DOI framework (Rogers, 2003). A multiple linear regression model was used to test the five hypotheses concerning the relationships between Relative Advantage, Compatibility, Observability, Trialability, and Complexity with Eagerness to adopt. The model presented significant statistical results and explained 46.0% of the variance in adoption intentions (Adjusted R^2 = 0.460), with an F-Statistic of 152.010($p < 0.001$), which further proved the strength, and reliability of the model.

Regression Results (Models 6-10)

	Dependent variable:				
	Eagerness_to_Adopt				
	(1)	(2)	(3)	(4)	(5)
Relative_advantage	0.485***				
	(0.062)				
Compatibility		0.424***			
		(0.034)			
Observability			0.282***		
			(0.061)		
Trialability				0.348***	
				(0.043)	
Complexity					0.098**
					(0.046)
Constant	5.871***	4.815***	7.293***	6.754***	9.139***
	(0.516)	(0.417)	(0.561)	(0.393)	(0.351)
Observations	178	178	178	178	178
R^2	0.259	0.463	0.109	0.273	0.025
Adjusted R^2	0.255	0.460	0.104	0.269	0.019
Residual Std. Error (df = 176)	1.366	1.163	1.499	1.354	1.568
F Statistic (df = 1; 176)	61.652***	152.010***	21.506***	65.982***	4.519**
Note:			*p<0.1; **p<0.05; ***p<0.01		

Figure 12 Eagerness to adopt Regression Model

The Relative Advantage was found to be the highest predictor of Eagerness to Adopt (β = 0.485, $p < 0.01$), hence supporting Hypothesis 1 (H1). This finding accords with Rogers' (2003) argument that innovations perceived to be much better than the existing solutions have higher chances of being accepted. Respondents who perceived AI platforms to bring concrete benefits in decision-making, efficiency, and accuracy showed significantly higher eagerness to adopt. This calls for the clear communication of strategic and operational benefits of the AI solutions by the organizations to these prospective adopters.

Compatibility showed a significant and positive relationship with Eagerness to Adopt (β = 0.424, $p < 0.01$), supporting H2. This underlined the need for AI platforms to easily work with existing processes. In a volatile business environment such as SC's, technologies and their perceived value to the business need to mesh well with ongoing processes for intentions to be actualized (Moore & Benbasat, 1991; Rogers, 2003). Thus, compatibility pointed to AI less being more of a supportive than disruptive system.

Trialability (ß = 0.348, $p < 0.01$) and Observability (ß = 0.282, $p < 0.01$) were found to be significant predictors of acceptance. This result supported H5 and H4, respectively. Trialability through experimentation aids the intent to adopt. When the opportunity is given to test whether AI can pay dividends, such as through trials among users which lowers perceived risk, clients who gain direct experience of benefits are more likely to adopt (Meuter et al., 2005). Observability relates to the need for noticeable success stories and clear proof of the benefits of AI. Obvious gains, for instance, in cost reduction, better performance, or eased workloads boost faith in the technology and promote acceptance.

It is interesting that Complexity did not come out as a significant predictor ($\beta = 0.098$, $p = 0.046$), thus slightly contesting Hypothesis 3 (H3). Whereas previous research (Tornatzky & Klein, 1982; Moore & Benbasat, 1991) pointed out that Complexity stands in the way of adoption, the weak influence found in this research would seem to indicate that would-be adopters gave greater weight to Compatibility, and Trialability than Observability. This implied that users could accept some level of complexity provided that the benefits and real-life results of adopting AI are clearly communicated.

4.2.4 Descriptive Statistic – VAM

Descriptive Statistics

	Variable	Mean	SD
7	Perceived_value	13.39	2.18
8	Usefulness	6.01	2.51
9	Enjoyment	11.94	2.48
10	Technical_ease	7.2	2.56
11	Perceived_fee	6.21	0.96
12	Adoption_intention	12.08	2.5

Figure 12 Descriptive Statistic VAM Model

For the second model centers on Adoption Intention. The variable Perceived Value had a mean score of 13.39 and standard deviation 2.18: respondents generally valued AI platforms, somewhat variably between participants. This captured the usefulness benefits that come with using these platforms. It had a mean score of 6.01, standard deviating more at 2.51, expressing wider variability in perceiving respondent utility for AI.

Enjoyment had a mean of 11.94 with a standard deviation of 2.48. Responses captured general positive feelings about using AI systems, for either deriving pleasure or fulfillment. Technical ease had a mean score of 7.2 and a standard deviation of 2.56 depicting the simplicity and friendliness of use of these platforms. Several of the respondents thought these platforms were relatively easy to use, though several other responses about difficulties or mixed experiences were also expressed.

Perceived Fee, which was the composite variable measuring the Questions of cost-related concerns on adopting AI platforms, displayed a mean of 6.21 with a standard deviation of 0.96. The standard deviation for this construct being low, opinions on costs were somewhat stable across the board of respondents. Adoption Intention, finally, the dependent variable representing the likelihood of the respondents to adopt AI-enabled platforms, with the mean score of 12.08 with a standard deviation of 2.5, which implied that the majority somewhat tended towards adoption with different levels of enthusiasm.

4.2.5 VAM Regression Model

Regression Results

	Dependent variable:				
	Perceived_value			Adoption_intention	
	(1)	(2)	(3)	(4)	(5)
Usefulness	-0.184***				
	(0.064)				
Enjoyment		0.648***			
		(0.045)			
Technical_ease			0.052		
			(0.064)		
Perceived_fee				1.239***	
				(0.172)	
Perceived_value					0.923***
					(0.051)
Constant	14.496***	5.661***	13.020***	4.382***	-0.284
	(0.418)	(0.551)	(0.490)	(1.081)	(0.691)
Observations	178	178	178	178	178
R^2	0.044	0.539	0.004	0.228	0.651
Adjusted R^2	0.039	0.536	-0.002	0.223	0.649
Residual Std. Error (df = 176)	2.141	1.488	2.186	2.202	1.480
F Statistic (df = 1; 176)	8.187***	205.518***	0.654	51.861***	328.596***
Note:			*p<0.1; **p<0.05; ***p<0.01		

Figure 14 Regression Analysis VAM

The quantitative analysis of VAM factors was accomplished regarding the Adoption Intention of AI-enabled platforms in SCM. Multiple linear regression analysis tested five hypotheses created to measure the relationship between Usefulness, Enjoyment, Technical Ease, Perceived Fee, and Perceived Value with their subsequent impact on adoption intention. The model was statistically significant with 65.1% variance in Adoption Intention explained (Adjusted R^2 = 0.649), having an F-statistic of 328.596, ($p < 0.01$), denoting overall robustness and fit of the data.

Perceived Value, however, turned out to be the strongest predictor of adoption intention (ß = 0.923, $p < 0.01$), thus confirming Hypothesis 6 (H6) on its central role in the adoption of technology. This result would seem to further underline that users needed to perceive a clear balance between benefits and costs for AI adoption (Kim et.al 2017). High perceived value was an indication of a belief by users that AI-enabled platforms contribute something that is useful (E.g., operational efficiency, better decisions) thus justifying their adoption. This advocated the relationship, which was significant and positive, between Enjoyment and Perceived Value (ß = 0.648, $p < 0.001$), thereby backing Hypothesis 8 (H8). As an intrinsic motivator, enjoyment played an important role in driving perceived value by users. The perceived enjoyment experienced by users when interacting with an AI-based platform shaped their appraisal of it as high in usefulness, underlining the primacy of satisfaction and adoption behavior (Zhou, 2011; Agarwal and Karahanna, 2000).

On the other hand, Usefulness showed an unexpected negative relationship with Perceived Value (ß = -0.184, $p < 0.01$), contrary to H7. While, in general, the literature (Davis et al., 1989; Venkatesh and Davis, 2000) has primed usefulness positively into adoption, this result pointed to the fact that perceived utility might not be a key determinant of value for AI-enabled SC's. Thus, while users can consider AI tools to be functionally adequate, these same tools may be judged to be somewhat deficient in providing more than what has been pre-set in terms of added value. Likewise, Technical Ease of use also did not have a significant effect on Perceived Value (ß = 0.052, $p = 0.413$), rejecting H9. This finding implied that ease, although an asset in the acceptance of technology by users, would be less important when it faces other drivers e.g., pleasure. Respondents seemed to be ready to pay the price for some technical complexity provided they saw enough benefit accruing to them as a result.

Perceived Fee surprisingly revealed a very strong positive impact on Perceived Value (ß = 1.239, $p < 0.001$), contrary to Hypothesis 10 (H10). An inverse relationship was expected. The justification for this unexpected finding was that high costs may signal superior quality or add benefits for users, in line with the findings in price-quality literature (Shin, 2009; Voss et al., 1998). Such users might find the high fees associated with AI-enabled platforms justified as an investment providing valuable returns in terms of improved operations and strategies.

The results underscored two very important observations; first, Perceived Value and Enjoyment were the most dominant factors for the formation of adoption intention, indicating the importance of intrinsic user satisfaction and perceived benefits. Therefore, making the user experience better and communicating clear value propositions is essential for increasing adoption. Second, traditionally, central to technology adoption has been Usefulness and Technical Ease (e.g., TAM); in this study, their relatively diminished importance suggested that users have re-prioritized criteria that favor more experiential-driven factors. These results provided empirical evidence that AI adoption in SCM is influenced less by functional utility and ease of use, but more by perceived benefits and user engagement with the platform. From a practitioner's point of view, companies looking to increase AI adoption should put more emphasis on strategies that work toward maximizing perceived value and enjoyment by the user. This would also mean developing attractive interfaces and assuring seamlessness in articulating benefits of platforms enabled by AI to make adoption happen. Moreover, though costs may at first seem to be barriers, they can be redefined as investments in quality and long-term efficiency for enhancing perceived value. Addressing these can help a company surmount resistance to adoption and usher in wider implementation of AI technologies in SCM.

5. Discussion

This discussion is split into two parts. The first triangulates insights from the literature review, qualitative data from expert interviews and quantitative data from the consumer survey. It discusses how drivers and barriers affect the adoption of AI in SCM. The second part takes the scenario development approach outlining possible future paths for adoption of AI. It provides strategic insights for the industry.

5.1 General Discussion

The results from qualitative analysis revealed several core drivers and inhibitors of AI adoption in SCM. The literature frames AI as a powerful factor enabling efficiency, predictive capabilities, and real-time decision-making. Major drivers were found to be in automation, predictive analytics, and the capability to improve operational responsiveness. The TAM (Davis, 1989) treats perceived usefulness and ease of use as cornerstones for the acceptance of any technology. AI can take over routine tasks and offer actionable insights, their direct impact on perceived usefulness enhances acceptance (Queiroz, 2019).

The notion that predictive analytics may promote better SCM was among the drivers mentioned most often. With AI-based forecasting, the level of uncertainty in demand and supply can be drastically reduced, as emphasized by Waller and Fawcett (2013) in their discussion of big data. For instance, the use of AI to predict patterns of demand or disruptions enables firms to align their operations proactively, which increases the agility of the SC. This also aligns with current studies on the use of AI to reduce risks and increase accuracy (Rai et al., 2019). Another key driver was personalization, which contributes to adapting the SC to the special needs of an organization. According to Huang and Rust (2021), constantly increasing AI's contribution relates to improving customer and stakeholder experiences through tailor-made solutions. Integration of AI into SC's enables firms to better focus operations on the characteristics of the market they serve, thus making them more responsive while improving customer satisfaction. Nevertheless, high levels of personalization are contingent on the quality of data and, above all, implementation.

Automation was also one of the most reported drivers of adoption. By automating mundane tasks as inventory management and route optimization, operational complexity and costs are reduced. This fits with the viewpoint of Brynjolfsson and McAfee (2017), who saw AI more as a tool in scaling efficiency across organizations. Automation is a potential tool, its efficacy is bound to employee goodwill and trust, emphasizing the need to overcome such barriers as resistance to change. The high potential of AI is still fraught with significant barriers such as the quality of data, resistance to change, and ethical issues. These results correspond to the literature on complicated processes of implementing new technologies within the SC (Holmström & Partanen, 2020). The most significant barrier that emerged was the quality and standardization of data. Barriers to effective AI implementation consistently highlight disjointed data systems and the unstructured nature of data. This challenge is in line with the argument of Waller and Fawcett (2013) that inconsistencies in data impede the scaling of predictive analytics and AI systems. Low data quality acts as a fishbone to accuracy and comes along with incremental costs and protracted implementation.

The other common theme was resistance amongst the workforce and leadership to embrace AI. Cotter's (1996) work on organizational change speaks to the critical need for buy-in of leadership and organizational readiness for any successful change. Building trust through training programs were identified as ways to beat employee resistance (Holmström and Partanen, 2020). Ethical and privacy concerns also complicate AI adoption. With regulations like the GDPR laying out strict rules about use of data, organizations need to ensure compliance which can be challenging (Jobin et al., 2019). AI algorithms and decision-making call for transparent frameworks for governance and accountability (Raisch and Krakowski, 2021).

Most interviewees noted almost the same thing, that AI is great when it is used as an auxiliary tool but not as a standalone solution. This resembles Raisch and Krakowski's (2021) "automation-augmentation paradox" which states that even when tasks can be automated using AI, in complex decision-making it is the human who must take control. Furthermore, with the rapid evolution of AI technologies, there is some amount of risk exposure investing in infrastructure that is moving at a fast pace (Agrawal et al., 2018). The process of early adoption may provide advantages of being the first to enter the market. However, it also enhances the vulnerability (Bai & Sarkis, 2020).

In conclusion, AI application in SCM has great potential to transform processes, but adoption must be well-managed (Fosso Wamba et al., 2018). Proper data quality, cultural readiness, and ethical compliance are key and will help unlock the role that AI could play in the future (Lee et al., 2004).

5.2 Scenario Development

This section develops four alternative future scenarios building on levels of adoption (high or low) and quality of implementation (high or low) identified through the qualitative study. These dimensions reflect key themes from the interviews and literature surrounding data quality, readiness of the organization, and trust in AI systems. The scenarios paint an outlook on how AI may change SC operations and offer insights for companies managing transformation during this technological wave.

Widespread Adoption with High Impact – High Adoption/High Implementation (1)

The first scenario imagines a future in which AI attains wide adoption, well supported with good quality implementation across industries. Firms would be able to surmount challenges such as highly fragmented data systems and resistance to change and will realize seamless integration of AI tools that provide significant operational and strategic benefits. Predictive analytics, automation, and real-time insights would be mainstream from that point forward in SC processes. They would drive efficiency, agility, and customer satisfaction to new levels. The transformative potential of this scenario was considered important by several interviewees. For example, Interviewee E noted, "AI can optimize SC's to reduce inefficiencies and enable real-time insights, but this will happen if and only if companies invest in robust systems and training." The comment by Interviewee B was also similar: "If data issues are dealt with at an early stage, AI tools give results with meaning, thus building trust in the organization." Such findings are relevant for Brynjolfsson and McAfee (2017), who argue that those companies that properly implement AI in the early stages will lead in establishing new industry benchmarks. This is a future to hope for where high-quality implementation unlocks AI's full potential in SCM, with an overall estimated probability of 30%. This, however, would require sustained investments, strong governance frameworks and some cultural adaptation that fosters employee and stakeholder engagement.

AI as a Driver of Niche Market Growth – Low Adoption/High Implementation (2)

The second scenario is that AI implementation is of very high quality, but its adoption remains only within a few industries or high-niche applications. While these AI tools result in excellent logistics optimization, demand forecasting, and sustainability initiatives, wider adoption is impeded by regulatory constraints, high costs, and resistance to change. Organizations in fast-moving sectors, like retail and e-commerce, might still accomplish strong implementation by focusing on very particular applications with a measurable return.

A constant underlying theme from the interviewees was that narrow AI applications were the precursor for more general AI e.g., interviewee C noted, “AI is most effective in the first place in narrowed problems, like inventory management or logistics, where outcomes are more concrete and immediate.” This was seconded by interviewee H, who observed, “AI’s scoped apps, for instance in predictive maintenance, can add value without having to apply it on a wide front.” It is in line with Roger’s (2003) Diffusion of Innovation theory, suggesting that a few visionaries would appreciate piecemeal innovation, while the rest remained hesitant. This happens to be the closest likely medium-term outcome for the bulk of organizations. Companies may well be able to reach targeted efficiencies in certain areas with effective deployment, but there can be other transformative effects left on the table. The likelihood for such an event should be estimated at 40%, given the rate at which AI is currently assimilated, which is far from being ubiquitous across different sectors.

High Adoption, Limited Sustained Value – High Adoption/Low Implementation (3)

This third scenario posits risks from the fast uptake of AI without adequate readiness. Adoption is high, but implementation quality is poor. This results in heterogeneous outcomes and trust deflation, plus operational inefficiencies in organizations. A firm that gives precedence to swiftness over quality might make short-term gains, but at the same time, might find it difficult to manage AI-enabled improvements in the long run. Several respondents raised red flags about the risks of fast adoption. For instance, Respondent G warned, “Organizations that hurriedly implement AI without addressing data and training challenges risk forfeiting trust in these systems.” Likewise, Respondent F pointed out, “Ethical issues, e.g., biased algorithms and breaches of privacy. These come to the front when implementation is quick and lacks control.” These statements echo the results obtained by Raisch and Krakowski (2021) who underline that if deployed improperly, AI can also increase inefficiencies rather than help solve them. It emphasizes the necessity for organizations to balance feeling with readiness. Although the initial excitement about AI would push an organization to be an adopter, inadequacies in planning and governance could bring about reputational damage and increased costs. The estimated likelihood of this happening is 20%, reflecting the risk for organizations in not overcoming foundational barriers before AI adoption.

Low Adoption and Suboptimal Integration – Low Adoption/Low Implementation (4)

The fourth and final scenario represents a worst-case outcome where both adoption levels and implementation quality remain low with an estimated probability of 10%. Fragmented data systems along with employee skepticism and a lack of trust do not allow AI to gain traction. Hence, it has minimal impact on the operations of the SC. This would result in a widespread rejection of AI to a large extent. Ethical lapses from biased decision-making and breaches of privacy further erode confidence, making AI truly difficult to embrace.

As interviewee A mentioned, "Both data quality and resistance to change will drag. Therefore, AI projects will not pick up speed." This has also been agreed with by the reactions from Interviewee D, who remarked, "Especially if there have been breaches of privacy, ethical issues can haunt trust and adoption in the long term." This basically reiterates problems identified by Jobin et al. (2019) coupled with the imperative to instill confidence in AI systems regarding governance frameworks and ethical accountability. This circumstance forms a cautionary tale for organizations that may be taking the complexity of AI integration lightly. Companies caught up in this spiral are seriously at risk of losing competitive leverage and even becoming extinct with the continuously accelerating acceptance of AI across the business landscape.

The four scenarios depict varied pathways that AI adoption in SCM could take. The first scenario is the best possible outcome, whereby wide transformation and competitive advantages would be realized. But this vision would require significant investments in change, strong governance, and organizational readiness. The second scenario is what realistically could be expected over the short term, with successful high-quality implementation bringing success in specific industries or applications. The third and fourth scenarios highlight the risks of poor planning and resistance, which means that strategic preparation and strong governance would be needed. These potential futures frame the future of AI as a transformative phenomenon for SC operations.

6. Conclusion and Limitations

6.1 Conclusion

This thesis covered adoption and implementation of AI in SCM with its capacity to improve efficiency and foster innovation. The study used expert interviews and analyses of the literature to understand the key drivers, barriers, and the future path of AI implementation. AI has transformative potential in the sense that it can perfect processes via predictive analytics, automation, and personalization. Adoption is impeded by several barriers, including data quality, resistance, and ethics worries. Fragmented data coupled with employee skepticism underscore firm level changes needed, while increased attention to privacy and biases frames required governance guardrails. The scenarios developed evidenced outcomes along a spectrum, from transformational adoption to niche-focused success. The results stress the need for strategic planning, organizational readiness, and ethical implementation. In sum, foundational challenges must be addressed along with trust building must if AI is to successfully revolutionize SCM.

6.2 Limitations

The generalizability of the findings may, however, be open to questions for several reasons, which warrant careful consideration. First, the semi-structured interviews were conducted with a relatively small and focused sample of AI and Supply Chain Management (SCM) experts. While their expertise provided valuable insights, it also introduces potential biases stemming from the professional backgrounds and experiences of these individuals. These experts are likely to have pre-existing familiarity with AI technologies and may hold positive views toward their adoption, which could have influenced the results.

Second, the technological context in which the study was situated, namely AI applications in SCM further limits the broader applicability of the findings. The challenges, opportunities, and dynamics associated with implementing AI in supply chain processes are unique and may differ significantly from those in other industries, such as healthcare, finance, or education. For instance, industries with varying levels of technological integration, regulatory environments, or stakeholder expectations may experience different adoption barriers and facilitators. This industry-specific focus narrows the ability to generalize the conclusions to contexts beyond SCM.

6.3 Theoretical Contribution

The Thesis contributes to theoretical debates on AI adoption in SCM by pulling together key drivers and barriers and their implications, building on frameworks such as TAM, DOI, and VAM, while bringing into context predictive analytics, automation, and personalization as potential enablers of adoption. It also addresses, as barriers, problems with data quality, and resistance to change, in addition to ethical considerations by emphasizing the role of data governance and trust-building actions. The scenarios developed further enhance theoretical discourse by providing a means of understanding potential trajectories for AI, hence filling the void between theory and adoption.

6.4 Practical Contribution

Insights can guide decision-makers within organizations who wishes to embed some element of AI into their SC operations. The results could further give companies ways to plan for implementing AI to streamline work processes, reduce costs, and increase customer satisfaction. Furthermore, the study brought out that there is a need to overcome the barriers relating to quality, fear of losing jobs, and ethics. However, high investments in data quality management, training, and ethical practices of AI could win back the trust and guarantee acceptance.

6.5 Further Research

Future research is needed to understand both front and back-end applications of AI in relation to procurement optimization and risk management and how these processes affect broader organizational resilience and efficiency. Research on how AI affects employee interaction dynamics and ways to mitigate friction and promote trust might offer significant implications for change management. Further research could offer validation of developed scenarios in further industries and regions.

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8. Appendices

8.1 Appendix A: Interview Questions

Nr.	Question
1.	Please state your age, the specific industry you are currently engaged in, and describe your role concerning technology adoption, particularly in supply chain management.
2.	What specific barriers do you frequently encounter when integrating AI technologies into supply chain management systems? What strategies do you recommend to overcome these barriers effectively?
3.	Can you evaluate the rate at which AI technologies are being accepted and implemented within supply chain management? What key factors significantly accelerate or hinder this adoption rate?
4.	How do data privacy concerns and potential ethical dilemmas influence organizational decisions toward AI adoption in supply chain management? Could you provide examples where these concerns affected adoption choices?
5.	In your experience, do AI implementations typically success in niche markets or are they scaling to widespread market penetration? What market dynamics or industry characteristics influence this trend?
6.	In what specific ways has the implementation of AI technologies enhanced the operational efficiency and user satisfaction of SCM systems?
7.	Discuss the effects of AI integration on the technical performance and ease of use of SCM platforms. Are there instances where AI has introduced complexities?
8.	What additional value do users perceive in SCM platforms that incorporate AI features compared to those that do not? What features or functionalities contribute to this perceived value?
9.	Do you perceive that the integration of new AI features into SCM platforms could change user engagement or utilization patterns? How do these features align with user expectations and requirements?
10.	Do you concur with the view that early adoption of generative AI provides a substantial competitive advantage in the supply chain sector? What are the observable benefits or drawbacks of being an early adopter?

11.	From your perspective, can late adopters of generative AI in the supply chain domain achieve success and possibly surpass early adopters in certain areas? What strategies might enable these late adopters to excel?

Table 2 Summary Interview Question

8.2 Appendix B: Interview A

Nr.	Question
Response Q1:	I am 42 years old and work for a provider of AI solutions for supply chain management. Our platform helps companies digitize and automate decision-making, building on my extensive experience in this field.
Response Q2:	• The challenges of today are not mainly technological but pertain to the design of AI solutions that are actionable and data-driven, with added business logic integrated, to enable the provision of precise recommendations at an operational level, and hence toward more autonomous decision-making. • Another key challenge is managing transformation and change, as moving from dashboards to systems that make autonomous decisions is a significant shift for many employees, requiring trust-building and gradual adaptation to new ways of working.
Response Q3:	• Achieving high levels of automation in decision-making is a gradual process; while some applications reach up to 92% autonomy, many start lower and improve over time by addressing data quality and refining algorithms based on user feedback and evolving insights. • Complete automation is unlikely due to the dynamic nature of enterprise environments, with ever-changing products, systems, and market needs. Continuous integration of diverse data sources is essential to maintain high accuracy and adaptability.
Response Q4:	• Data privacy and ethics are essential in Germany, where regulations limit performance tracking of individuals, requiring compliant, privacy-respecting design for recommendation systems. • The U.S. adopts new technologies faster with a flexible, trial-oriented approach, while Germany emphasizes strict compliance and privacy, often slowing innovation.

Response Q5:	• AI adoption has shifted from niche proofs of concept to scalable, value-driven projects, with companies now demanding measurable outcomes like productivity gains and working capital reduction. • A recent global implementation at a major multinational successfully optimized inventory levels across all sites, demonstrating significant results even at the CFO level, with impacts visible in the company's balance sheet.
Response Q6:	• AI implementations have significantly increased productivity, with metrics such as the number of products managed per planner rising dramatically; companies like Amazon went from managing 3,000 to over 10,000 products per planner due to automation. • Traditional industries need similar gains, aiming for a setup where most products are autonomously managed, allowing planners to focus only on exception-based interventions.
Response Q7:	• Technical challenges in AI implementation, such as model training or scalability, are largely addressed through cloud solutions and pre-trained models, making them manageable for most companies adopting AI. • Complexity for employees remains a key issue; while expert understanding is needed for AI system design and performance, expecting all users to grasp every detail is unrealistic. Instead, AI tools should be designed for intuitive, productive use, similar to consumer tech like smartphones.
Response Q8:	• Traditional SCM platforms have long supported planning processes, but new AI applications add value by enhancing short-term execution, automating tasks, and improving decision-making in real-time. • AI enables a shift from simply planning to actively steering supply chain operations, reducing the need for external tools like Excel and BI software, and significantly boosting productivity in the execution horizon.
Response Q9:	• Younger, tech-savvy employees tend to adopt AI more easily, and their rise into decision-making roles will likely accelerate company-wide tech adoption.

	• New graduates often feel frustrated with outdated systems; there's growing demand for intuitive, consumer-grade tools that reduce repetitive tasks and boost engagement.
Response Q10:	• Early adoption of AI tools in supply chain management offers a competitive edge, especially in areas like fulfillment, service reliability, speed, and cost efficiency. • Companies that achieve reliable, timely deliveries, similar to Amazon, gain customer trust and improve key metrics like delivery accuracy, capital efficiency, and cost-to-serve, which are crucial indicators of successful transformation.
Response Q11:	• Fast followers benefit by learning from early adopters' mistakes, leveraging mature technology without the high initial costs faced by pioneers. • Sectors like consumer goods lead in AI adoption, while industries like pharma and chemicals often lag, with late adopters relying more on outsourcing than new tech.

Table 3 Summary Interview A

8.3 Appendix C: Interview B

Nr.	Question
Response Q1:	I am 48 years old, working as a Managing Director for a leading procurement consulting firm, focusing on the Data and AI enhancement of Supply Chain Management.
Response Q2:	• Barriers include challenges with data integration, quality, and interpretation, especially in unstructured data. Examples include OCR for supplier lists, contracts, and invoices, and generating executive summaries or automated recommendations. • Suggested strategies involve leveraging AI for data enrichment, automating document analysis, and enhancing spend analysis for efficiency gains .
Response Q3:	• Adoption rates for even basic AI tools like ChatGPT are moderate, with only 20–30% of users working intensively with such tools. • Awareness and practical demonstrations by experts are crucial to overcoming user resistance and fostering engagement.

Response Q4:	• The main challenge is creating secure environments that comply with regulations, such as ensuring data doesn't leave controlled cloud systems. • There is hesitance among users due to privacy concerns, particularly in regions with stricter regulations like Europe.
Response Q5:	• AI adoption is expanding from niche areas to scalable, global implementations. • An example is optimizing inventory management globally in multinational companies, leading to measurable impacts, such as reduced working capital.
Response Q6:	• AI has enabled productivity gains, such as significantly increasing the number of contracts or supplier reviews completed. • Other improvements include automation of planning processes and better forecasting, reducing manual tasks and improving response times
Response Q7:	• Technical scalability issues are less common due to advancements in cloud technology and pre-trained models. • Complexity arises for employees, requiring intuitive interfaces that don't demand a deep understanding of AI mechanics.
Response Q8:	• AI features add value by enabling predictive planning and operational efficiencies. • Enhanced decision-making capabilities, such as supplier recommendations and spend analysis, are key drivers of perceived value .
Response Q9:	• Younger, tech-savvy users tend to adapt faster, but awareness and practical support remain critical for broader adoption. • Demonstrating the ease and functionality of tools is essential to increase engagement.
Response Q10:	• Early adopters gain speed and experience benefits but bear higher costs and risks. • Over time, as tools become more user-friendly, the advantage of being an early adopter may diminish.

Response Q11:	• Late adopters benefit from mature, simplified tools and avoid initial pitfalls. • Industries vary, with fast-moving consumer goods leading adoption while others, like pharma, lag.

Table 4 Summary Interview B

8.4 Appendix D: Interview C

Nr.	**Question**
Response Q1:	I am 45 years old and work as the Chief Technology Officer in the logistics industry. My primary responsibility is to implement and integrate innovative technologies, especially AI, into our supply chain processes.
Response Q2:	• One of the main obstacles to AI integration is the lack of sufficient data quality needed for accurate analysis. • Additionally, there is often resistance within the workforce toward automation. By conducting training sessions and starting with pilot projects, we build trust and demonstrate early successes.
Response Q3:	• The acceptance of AI in supply chain management is growing, although more slowly than anticipated. • High implementation costs and uncertainty regarding return on investment (ROI) often slow down progress. Success stories and increasing market competition, however, are helping to accelerate adoption.
Response Q4:	• Data privacy and ethical considerations significantly impact the decision to adopt AI, especially in Europe under GDPR regulations. For instance, concerns around data security have led us to modify or abandon planned AI monitoring systems. • Transparent communication and clear ethical guidelines are crucial to gaining stakeholder trust.
Response Q5:	• AI technologies have so far proven most effective in specific niche applications where they address targeted problems. • Broad scaling is more challenging and requires a higher maturity level of the technology and increased user-friendliness.

Response Q6:	• AI has significantly boosted efficiency in inventory management and enhanced demand forecasting accuracy, which leads to better planning. • This relieves employees from repetitive tasks, allowing them to focus on more strategic decisions.
Response Q7:	• AI integration greatly improves data analysis and response times; however, it can initially make user interfaces more complex, which may overwhelm some users. • Achieving a balance between functionality and ease of use is essential.
Response Q8:	• Users particularly value the automation and precise predictions provided by AI-enabled SCM platforms. • Predictive analytics and automated decision-making increase confidence in the platform and foster data-driven supply chain management.
Response Q9:	• New AI features can change user behavior by providing deeper insights and personalized recommendations, which offer users greater control and understanding. • This enhances engagement, provided that the features are intuitive and aligned with user expectations.
Response Q10:	• Early adopters of generative AI can gain a clear competitive edge through innovation and faster decision-making. • However, high costs and early-stage errors in these technologies pose a significant risk.
Response Q11:	• Late adopters can benefit from the experiences of early adopters by implementing more mature and optimized AI solutions. • By focusing on proven technologies and adopting best practices, late adopters may even surpass early adopters in certain areas by avoiding initial mistakes.

Table 5 Summary Interview C

8.4 Appendix E: Interview D

Nr.	**Question**

Response Q1:	I am a Senior Consultant with over 15 years of experience in supply chain management, specializing in the integration of AI and emerging technologies. My focus is on driving efficiency, transparency, and innovation within global logistics networks while addressing operational and organizational challenges.
Response Q2:	• A significant challenge is the lack of data standardization and transparency across the supply chain, as many organizations have fragmented or siloed data. This often leads to inefficiencies and limited visibility into operations. • AI-powered tools can address these gaps by centralizing and standardizing data, enabling real-time tracking and better-informed decisions throughout the supply chain.
Response Q3:	• AI adoption in supply chain management is progressing slowly because companies are focused on foundational tasks like data cleansing, restructuring, and infrastructure upgrades before they can scale AI solutions. • Adoption rates can be accelerated by demonstrating clear, measurable ROI through small, targeted pilot projects that showcase the practical benefits of AI integration.
Response Q4:	• Privacy regulations, such as those in Europe, are essential for safeguarding data but often delay the adoption of AI by adding layers of complexity to compliance. This creates a competitive gap with less-regulated markets. • To overcome these concerns, organizations need to adopt advanced data anonymization techniques and ensure transparency in how AI algorithms operate to gain stakeholder trust and ensure regulatory alignment.
Response Q5:	• AI has the potential for widespread application across supply chains, from logistics and procurement to sustainability and risk mitigation. A holistic approach can maximize its impact. • Companies that limit AI to niche areas risk losing out on transformative efficiencies that come from integrating AI into the broader supply chain network, enabling better decision-making across all functions.

Response Q6:	• AI reduces the need for manual intervention in routine processes, such as demand forecasting, inventory management, and procurement, leading to significant efficiency gains. • Predictive analytics and real-time insights provided by AI improve operational responsiveness, minimizing disruptions and enabling proactive supply chain management.
Response Q7:	• The integration of AI often overwhelms organizations due to its technical complexity and the lack of alignment with strategic goals. Many struggle to understand where AI fits within their supply chain. • Simplifying the implementation process with modular AI solutions and investing in team training can reduce complexity and improve technical performance and adoption rates.
Response Q8:	• Users value AI for its ability to handle repetitive tasks with speed and accuracy, such as automating forecasts and generating insights, but they often underestimate its broader potential. • Many users remain skeptical, fearing the technology is too complex or that it might replace jobs. Addressing these concerns with clear demonstrations of AI's complementary role can build trust and encourage adoption.
Response Q9:	• Early adopters of AI gain a competitive edge by streamlining operations and establishing themselves as industry leaders in innovation. • They face challenges such as higher initial costs and the need to refine processes due to the use of untested technologies
Response Q10:	• Late adopters benefit from mature, proven AI technologies and lower implementation costs. • By focusing on specific areas for improvement, they can integrate AI efficiently and achieve measurable results quickly.
Response Q11:	• Late adopters should implement scalable, targeted AI solutions to address precise gaps in their supply chain. • Partnering with experienced AI providers allows them to fast-track implementation and compete effectively.

Table 6 Summary Interview D

8.5 Appendix F: Interview E

Nr.	Question
Response Q1:	I am 38 years old and currently serve as the Head of Innovation and Technology at a large manufacturing company. My role involves overseeing AI and automation projects to streamline and modernize our supply chain operations.
Response Q2:	• Common barriers include legacy systems that are difficult to integrate with new AI tools and a general lack of AI expertise among employees. • To overcome these, we've invested in upskilling programs and selective technology upgrades that make gradual integration possible without overwhelming the existing systems.
Response Q3:	• AI adoption in supply chain management is picking up momentum, especially as more companies see successful case studies from industry leaders. • However, skepticism remains, particularly around the costs and potential disruption. Clear evidence of ROI and incremental adoption help build confidence among stakeholders.
Response Q4:	• Data privacy is a significant concern, especially with AI systems that handle sensitive customer and supplier data. Ethical concerns also arise when discussing automated decision-making in labor management. • To address these, we implement strict data governance policies and ethical AI frameworks to ensure transparency and responsible use.
Response Q5:	• AI is particularly successful in niche applications, such as predictive maintenance in manufacturing, where it can deliver measurable benefits. • Broad scaling is more challenging due to varying needs across departments and regions, but as technology matures, broader applications are becoming feasible.
Response Q6:	• AI has streamlined several aspects of our operations, from inventory management to quality control. • In particular, predictive analytics have reduced stockouts and excess inventory, leading to cost savings and increased customer satisfaction.

Response Q7:	• AI has improved the overall performance of our systems, especially in data processing and predictive capabilities. • However, certain AI features, like complex dashboards, have created a steeper learning curve for some users, which we address through targeted training sessions.
Response Q8:	• AI-enabled platforms offer a real-time view of the supply chain and provide actionable insights, which traditional systems cannot. • Features like anomaly detection and automated alerts add value by helping teams proactively manage potential issues before they escalate.
Response Q9:	• New AI features tend to increase user engagement, especially those that offer personalization and real-time updates. • However, there's often an adjustment period as users adapt to the new capabilities, so we ensure continuous feedback loops to align features with user needs.
Response Q10:	• Early adoption of generative AI provides an edge by enabling faster product innovation and optimizing design processes. • However, it requires a willingness to navigate early-stage issues and a clear plan for integrating these tools without disrupting existing workflows.
Response Q11:	• Late adopters can still succeed by leveraging established tools and focusing on tailored applications that address specific business needs. • By learning from early adopters' experiences, they can avoid pitfalls and implement generative AI more efficiently, potentially achieving a quicker return on investment.

Table 7 Summary Interview E

8.6 Appendix G: Interview F

Nr.	Question
Response Q1:	I am a Technology Advisor with over 10 years of experience specializing in AI-driven transformation for supply chain and logistics. My expertise lies in helping businesses strategically leverage AI to improve decision-making, streamline operations, and enhance competitive positioning in rapidly evolving markets.

Response Q2:	• A major obstacle is resistance to change, particularly from leadership teams who are unsure how AI fits into their existing strategies. • Educating stakeholders on the long-term benefits of AI and providing clear ROI projections can help overcome this resistance.
Response Q3:	• Adoption is accelerating in industries where agility is a priority, such as retail and e-commerce, but heavily regulated sectors are slower to adapt. • Clear government policies and industry standards can serve as enablers to boost adoption across diverse sectors.
Response Q4:	• Ethical concerns, such as the potential misuse of predictive algorithms for workforce management, create significant hesitation. • Establishing AI governance frameworks and transparent auditing systems builds trust and mitigates ethical risks.
Response Q5:	• AI adoption is increasingly widespread, particularly in industries with complex supply chains where the value of real-time data analytics is clear. • The ability to customize AI solutions for unique supply chain challenges determines the success of broader penetration.
Response Q6:	• AI enhances efficiency by enabling predictive maintenance, demand forecasting, and real-time tracking, reducing downtime and waste. • Success depends on user adoption, which can be improved with intuitive interfaces and integration with existing platforms.
Response Q7:	• AI improves technical performance by reducing decision-making latency and increasing system responsiveness, though it requires robust data pipelines. • Investing in scalable infrastructure is crucial to ensure the long-term viability of AI solutions in supply chains.
Response Q8:	• Users value AI most for its ability to provide actionable insights, such as dynamic pricing models or disruption alerts. • Tailored AI features, like inventory optimization or sustainability analytics, drive higher perceived utility among stakeholders.
Response Q9:	• Engagement improves when AI tools are intuitive and solve day-to-day challenges, such as optimizing procurement processes.

	• Building confidence through training and demonstrating immediate, measurable benefits fosters deeper user engagement.
Response Q10:	• Early adopters gain a competitive edge by setting new standards in efficiency and innovation, but they must accept the risk of unproven technologies. • Continuous monitoring and refinement of AI implementations are key to maximizing these advantages.
Response Q11:	• Late adopters can achieve success by focusing on high-impact areas where AI solutions are already refined, such as last-mile logistics. • Leveraging partnerships with proven AI vendors ensures a smooth implementation process and reduced risk.

Table 8 Summary Interview F

8.7 Appendix H: Interview G

Nr.	**Question**
Response Q1:	I am 42 years old and currently work as the Senior Manager of Supply Chain Solutions at a leading logistics firm. My responsibilities include driving the integration of AI technologies and innovative processes to enhance efficiency, transparency, and resilience across our global supply chain network.
Response Q2:	• Lack of data availability and transparency in the supply chain. • Implement systems for end-to-end visibility and use AI for tracking and optimization.
Response Q3:	• Adoption of AI is slow due to foundational research and data structuring. • Preparatory tasks and clear use cases will accelerate adoption.
Response Q4:	• AI impacts the entire supply chain, not just niche markets. • Companies should aim for holistic, end-to-end solutions.
Response Q5:	• AI reduces manual processes, saving time and resources. • Automating repetitive tasks enhances productivity.
Response Q6:	• Many companies find AI integration complex and confusing. • Clear guidelines and education on AI usage are essential.

Response Q7:	• Users value AI for targeted tasks but remain skeptical of broader applications. • Better education on effective AI usage is needed.
Response Q8:	• Users value AI for targeted tasks but remain skeptical of broader applications. • Better education on effective AI usage is needed.
Response Q9:	• Early movers gain market leadership and address current challenges. • Higher costs and lack of established practices pose risks.
Response Q10:	• Late adopters benefit from cost-effective, mature technologies and proven strategies. • Targeting unaddressed niches and learning from early adopters' mistakes can lead to success.
Response Q11:	• Focus on adopting optimized solutions and avoiding early adopters' pitfalls. • Leverage advanced technologies to address specific gaps or market needs.

Table 9 Summary Interview G

8.8 Appendix I: Interview H

Nr.	**Question**
Response Q1:	I am 36 and a Supply Chain Technology Analyst with a specialization in evaluating the practicality and impact of emerging technologies like AI. My role focuses on critically assessing the alignment of technological solutions with business objectives, uncovering overlooked risks, and identifying opportunities for meaningful innovation.
Response Q2:	• Cultural resistance and fear of job displacement are bigger barriers than technical challenges. • Companies should focus on human-centric processes before AI integration.
Response Q3:	• Adoption often driven by market pressure, not readiness or need. • Waiting for refinement and structural preparation yields better outcomes.

Response Q4:	• Privacy issues are solvable; accountability for AI errors is a bigger challenge. • Clear processes for addressing AI mistakes are crucial.
Response Q5:	• AI adoption remains limited to isolated use cases with minimal overall impact. • Focus on targeted, realistic applications instead of broad adoption.
Response Q6:	• Benefits often exaggerated, poor data leads to flawed decisions. • Hybrid human-AI models outperform full automation.
Response Q7:	• AI increases complexity without proper data and system integration. • Simplify the tech stack before implementing AI.
Response Q8:	• Overpromised features often fail to deliver practical value. • Focus on incremental gains that address user needs.
Response Q9:	• Top-down designs ignore actual user needs, reducing engagement. • Involve users in development to improve relevance and adoption
Response Q10:	• Early adopters face high costs and risks with unproven tech. • Late adoption often delivers better ROI with mature solutions.
Response Q11:	• Late adopters benefit from refined tools and lower risks. • Must stay agile to avoid falling behind market demands.

Table 10 Summary Interview H

8.9 Appendix J: Interview I

Nr.	**Question**
Response Q1:	I am a Digital Transformation Leader with over 15 years of experience in integrating AI and emerging technologies into supply chain ecosystems. My focus is on enabling businesses to embrace innovation and realize the transformative potential of AI to drive efficiency, resilience, and sustainability.
Response Q2:	• The primary challenge is fragmented data systems, which slow down integration and limit the insights AI can provide. • Investing in centralized data management and cloud-based solutions creates a strong foundation for AI success.

Response Q3:	• Adoption is gaining momentum as businesses recognize the competitive edge AI provides. • Collaboration with technology partners and leveraging proven frameworks accelerates implementation.
Response Q4:	• Privacy concerns are real but manageable with robust anonymization and encryption techniques. • Ethical AI frameworks ensure fairness and transparency, fostering trust among stakeholders.
Response Q5:	• AI is transitioning from niche applications to broader adoption, spanning logistics, procurement, and sustainability. • Industries that embrace scalable and customizable AI solutions see the highest impact.
Response Q6:	• AI has drastically improved demand forecasting, inventory management, and operational responsiveness. • Enhanced decision-making capabilities lead to faster and more reliable outcomes.
Response Q7:	• AI strengthens technical performance by streamlining workflows and reducing latency in decision-making. • Cloud-based AI solutions simplify scalability and integration across supply chain platforms.
Response Q8:	• Users value AI for its predictive analytics, which enable proactive risk management and optimization. • Seamless integration with existing tools enhances user confidence and satisfaction.
Response Q9:	• Engagement increases as AI tools become more intuitive and aligned with user needs. • Providing ongoing training and support ensures adoption across all user groups.
Response Q10:	• Early adopters gain an edge by leading innovation and setting industry benchmarks. • The ability to iterate and refine AI systems solidifies long-term leadership.

Response Q11:	• Late adopters can succeed by focusing on proven technologies and avoiding experimental pitfalls. • Strategic partnerships and targeted applications allow them to catch up effectively.

Table 11 Summary Interview I

8.10 Appendix K: Interview J

Nr.	**Question**
Response Q1:	I am a Supply Chain Strategist with 20 years of experience in operational efficiency and risk management. My focus has been on challenging the over-reliance on emerging technologies like AI, advocating instead for practical solutions that balance innovation with proven methodologies.
Response Q2:	• A major challenge is the overestimation of AI's applicability, leading to costly missteps and wasted resources in unprepared organizations. • A phased approach, starting with small-scale projects to learn and adapt, is more effective before scaling AI implementation.
Response Q3:	• AI adoption is slow as companies prioritize foundational work like data structuring over rapid implementation. • Demonstrating ROI through pilot projects and partnering with experienced vendors accelerates adoption.
Response Q4:	• Privacy laws often delay AI adoption, but internal uncertainty about data use amplifies these delays. • Proactively implementing anonymization techniques and clear data policies can mitigate concerns.
Response Q5:	• AI primarily succeeds in niche applications like logistics optimization, with broad adoption hindered by complexity. • Clear standards and scalable tools are needed for AI to penetrate entire supply chains effectively.
Response Q6:	• AI's impact on operational efficiency is often overstated, especially with incomplete or poor data inputs. • Simplifying AI tools for ease of use can increase user satisfaction and practical efficiency gains.

Response Q7:	• AI often adds complexity to systems, requiring significant resources for integration and troubleshooting. • Modular AI solutions and alignment with existing workflows are critical for minimizing disruptions.
Response Q8:	• Users value AI for automating specific tasks like forecasting but remain skeptical of broader capabilities. • Tailored, industry-specific solutions improve perceived value and foster trust in AI tools.
Response Q9:	• Engagement varies widely, with resistance stemming from unclear benefits or fear of job displacement. • Clear training and intuitive tools aligned with user needs are essential for increasing adoption.
Response Q10:	• Early adopters can set industry standards but face high costs and untested technologies, which carry risks. • Late-stage entry with mature AI systems often delivers greater long-term stability and ROI.
Response Q11:	• Late adopters benefit from refined, cost-effective technologies and proven strategies from early movers. • Focusing on targeted, scalable applications ensures a competitive position without excessive risks.

Table 12 Summary Interview J

8.11 Appendix L: Interview K

Nr.	**Question**
Response Q1:	I am a Technology Advisor with over 10 years of experience specializing in AI-driven transformation for supply chain and logistics. My expertise lies in helping businesses strategically leverage AI to improve decision-making, streamline operations, and enhance competitive positioning in rapidly evolving markets.
Response Q2:	• A major obstacle is resistance to change, particularly from leadership teams who are unsure how AI fits into their existing strategies. • Educating stakeholders on the long-term benefits of AI and providing clear ROI projections can help overcome this resistance.

Response Q3:	• Adoption is accelerating in industries where agility is a priority, but heavily regulated sectors are slower to adapt. • Clear government policies and industry standards can serve as enablers to boost adoption across diverse sectors.
Response Q4:	• Ethical concerns, such as the potential misuse of predictive algorithms for workforce management, create significant hesitation. • Establishing AI governance frameworks and transparent auditing systems builds trust and mitigates ethical risks.
Response Q5:	• AI adoption is increasingly widespread, particularly in industries with complex supply chains where the value of real-time data analytics is clear. • The ability to customize AI solutions for unique supply chain challenges determines the success of broader penetration.
Response Q6:	• AI enhances efficiency by enabling predictive maintenance, demand forecasting, and real-time tracking, reducing downtime and waste. • Success depends on user adoption, which can be improved with intuitive interfaces and integration with existing platforms.
Response Q7:	• AI improves technical performance by reducing decision-making latency and increasing system responsiveness, though it requires robust data pipelines. • Investing in scalable infrastructure is crucial to ensure the long-term viability of AI solutions in supply chains.
Response Q8:	• Users value AI most for its ability to provide actionable insights, such as dynamic pricing models or disruption alerts. • Tailored AI features, like inventory optimization or sustainability analytics, drive higher perceived utility among stakeholders.
Response Q9:	• Engagement improves when AI tools are intuitive and solve day-to-day challenges, such as optimizing procurement processes. • Building confidence through training and demonstrating immediate, measurable benefits fosters deeper user engagement.
Response Q10:	• Early adopters gain a competitive edge by setting new standards in efficiency and innovation, but they must accept the risk of unproven technologies.

	• Continuous monitoring and refinement of AI implementations are key to maximizing these advantages.
Response Q11:	• Late adopters can achieve success by focusing on high-impact areas where AI solutions are already refined, such as last-mile logistics. • Leveraging partnerships with proven AI vendors ensures a smooth implementation process and reduced risk.

Table 13 Summary Interview K

8.12 Appendix M: Interview L

Nr.	**Question**
Response Q1:	I am a 54 years old Supply Chain Innovator with a focus on leveraging cutting-edge technologies like AI to transform operations and create value. My experience spans implementing scalable AI systems that enhance efficiency, drive agility, and deliver measurable business outcomes.
Response Q2:	• The biggest hurdle is the lack of actionable insights due to unstructured data and poor data quality. • Leveraging AI to clean, standardize, and integrate data ensures better outcomes.
Response Q3:	• Adoption rates are accelerating, especially in fast-moving industries like retail and e-commerce. • Clear ROI and tangible results from pilot programs drive quicker acceptance.
Response Q4:	• Privacy concerns are manageable with proactive data protection policies and secure AI frameworks. • Transparency in AI decision-making builds confidence among stakeholders.
Response Q5:	• AI adoption is moving beyond logistics to areas like sustainability and risk management. • Industries that prioritize flexibility and customization see the most success.
Response Q6:	• AI reduces inefficiencies by automating routine processes and providing real-time insights.

	• Enhanced collaboration and decision-making boost overall performance.
Response Q7:	• AI increases technical efficiency by automating repetitive tasks and optimizing system performance. • Scalable infrastructure ensures seamless integration with existing platforms.
Response Q8:	• Users appreciate AI's ability to deliver real-time disruption alerts and improve forecasting accuracy. • Tailored AI tools that solve specific pain points are highly valued.
Response Q9:	• Engagement improves when AI systems are intuitive and solve everyday challenges effectively. • Regular updates and feedback loops help align tools with user expectations.
Response Q10:	• Early adoption provides a first-mover advantage by enabling companies to set industry standards. • Continuous learning and system refinement ensure long-term benefits.
Response Q11:	• Late adopters thrive by focusing on areas where AI is already proven and effective. • Partnering with established AI vendors minimizes risk and accelerates results.

Table 14 Summary Interview L

8.2 Appendix N: Survey Questions

VAM

Question	Variable	Hypothesis	Adopted from:
In what ways have you noticed AI being used in Logistics? (Q7&8)	**Perceived Value**	H1: Perceived value has a positive correlation with the intention to adopt.	Kim et al., 2007
Do you agree with the following statement: AI in logistics improves the speed of service delivery. (Q9)			
How likely are you to recommend AI-enhanced logistics services based on your experiences? (Q19)			
How would you rate the following statement: AI makes the logistics services more reliable. (Q10)	**Usefulness**	H2: Usefulness has a positive correlation with perceived value.	Venkatesh and Davis, 2000; Davis, Bagozzi and Warshaw, 1989; Kim et al., 2007
How would you rate the following statement: It is easy to interact with AI-enabled services. (Q11)			
What aspects of AI implementation most influenced your decision? (Q18)			

How likely are you to use logistics services that heavily incorporate AI in the future? (Q13)	**Enjoyment**	H3: Enjoyment has a positive correlation to perceived value.	Zhou, 2011; Agarwal and Karahanna, 2000
How often do you interact with AI-driven customer service tools in logistics? (Q14)			
How satisfied are you with these AI-driven interactions? (Q15)			
Which factors would make you more likely to use AI-enhanced logistics services? (Q12)	**Technical Ease**	H4: Technical ease positively correlates with perceived value.	Thong et al., 2002; Kim et al., 2007; Davis, 1989
Have you faced any issues or challenges with AI-driven logistics services? (Q16)			
How often do you encounter AI technology in logistics and what is your preference for its usage? (Q22)			
Do AI-driven logistics services offer a better price-to-service ratio compared to traditional methods? (Q26)	**Perceived Fee**	H5: Perceived cost is inversely correlated with perceived value.	Shin, 2009; Voss et al., 1998
Has the introduction of AI in logistics services affected your budget allocation for logistics expenses? (Q27)			

How likely are you to use logistics services that heavily incorporate AI in the future? (13)	**Adoption Intention**		
How satisfied are you with these AI-driven interactions? (Q15)			
How likely are you to recommend AI-enhanced logistics services based on your experiences? (Q19)			

Table 15 VAM Survey Question

Adoption of Technological Innovations

Question	**Variable**	**Hypothesis**	**Adopted from:**
How much do you agree with this statement: "AI integration in logistics leads to more personalized service." (Q25)	**Relative Advantage**	H6: Relative advantage positively influences the eagerness to adopt.	Moore and Benbasat, 1991; Rogers, 2003
How has AI affected the quality of logistics services based on your experience? (Q24)			
Which factors would make you more likely to use AI-enhanced logistics services? (Q12)			
How likely are you to recommend AI-enhanced logistics services based on your experiences? (Q19)	**Combability**	H7: Compatibility positively influences the eagerness to adopt.	Moore and Benbasat, 1991; Rogers, 2003
How often do you interact with AI-driven customer service tools in logistics? (Q14)			

How likely are you to use logistics services that heavily incorporate AI in the future? (Q13)			
How concerned are you about data privacy and security when using AI-driven logistics services? (Q20)	**Complexity**	H8: Complexity positively influences the eagerness to adopt.	Tornatzky, and Klein, 1982; Moore and Benbasat, 1991
What measures could increase your trust in using these AI services? (Q21)			
How would you rate the following statement: It is easy to interact with AI-enabled services. (Q11)			
How often do you encounter AI technology in logistics and what is your preference for its usage? (Q22)	**Observability**	H9: Observability positively influences the eagerness to adopt.	Rogers, 2003; Meuter et al., 2005
What specific AI technologies are you aware of in logistics services? (Q23)			
Have you noticed the integration of AI in the logistics services you use? (Q7)			
What aspects of AI implementation most influenced your decision? (Q18)	**Trialability**	H10: Trialability positively impacts the eagerness to adopt.	Meuter et al., 2005
Have you faced any issues or challenges with AI-driven logistics services? (Q16)			
How satisfied are you with these AI-driven interactions? (Q15)			

How would you rate the following statement: It is easy to interact with AI-enabled services. (Q11)	**Eagerness to adopt**		
How often do you encounter AI technology in logistics and what is your preference for its usage? (Q22)			
How likely are you to recommend AI-enhanced logistics services based on your experiences? (Q19)			

Table 16 Adoption of Technological Innovation Survey Questions