Hochschule Neu-Ulm
University of Applied Sciences

Master Thesis
in the master program
Digital Transformation and Global Entrepreneurship
at University of Applied Sciences Neu-Ulm

Factors Influencing the Adoption Intention of Artificial Intelligence in German Supply Chain Management

1st examiner:	Prof. Dr. Christopher Williams
2nd examiner:	Prof. Dr. Daniel Schallmo

Author: Josefina Ciupke (Enrolment number: 362757)

Topic received: 01.01.2026
Date of submission: 06.03.2026

Abstract

This thesis examines the factors influencing artificial intelligence (AI) adoption intention among German supply chain management (SCM) organizations in a pre-adoption context. Although AI is increasingly perceived as strategically relevant, adoption in German SCM remains limited, with many organizations operating in early pre-adoption stages. Existing research on AI adoption in SCM has expanded in recent years and reflects diverse theoretical perspectives as well as the examination of several factors within the adoption process. However, empirical insights into adoption intention in the German SCM context and across pre-adoption stages remain limited. To address this gap, a systematic literature review was conducted to derive technological, organizational, and environmental factors related to AI adoption in SCM and to develop a conceptual framework for adoption intention. The framework was empirically tested using a cross-sectional survey of German SCM managers (n = 67) and multiple linear regression analysis.

The findings suggest that AI adoption intention is primarily shaped by managerial commitment and the perceived compatibility of AI with existing organizational structures and processes, while other examined factors do not exhibit independent explanatory power. Stage-specific analyses further suggest that determinant relevance may evolve across pre-adoption stages.

Keywords: artificial intelligence, adoption intention, supply chain management, pre-adoption, technology-organization-environment (TOE) framework

Table of Contents

List of Figures

List of Tables

List of Abbreviations

AI	Artificial Intelligence
AGI	Artificial General Intelligence
ANN	Artificial Neural Network
DOI	Diffusion of Innovations
DL	Deep Learning
EC	Exclusion Criteria
GAI	Generative Artificial Intelligence
IC	Inclusion Criteria
LLM	Large Language Model
ML	Machine Learning
NLP	Natural Language Processing
PEOU	Perceived Ease of Use
PU	Perceived Usefulness
RBV	Resource-Based View
RQ	Research Question
SC	Supply Chain
SCM	Supply Chain Management
SCOR	Supply Chain Operations Reference
SJR	SCImago Journal Rank
SLR	Systematic Literature Review
TAM	Technology Acceptance Model
TOE	Technology-Organization-Environment
TPB	Theory of Planned Behavior
TTF	Task-Technology-Fit
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance Inflation Factor
WoS	Web of Science

1 Introduction

The following chapter introduces the background and relevance of artificial intelligence (AI) adoption intention in German supply chain management (SCM) and derives the problem statement. Moreover, it defines the underlying research question (RQ), objectives, the methodological approach and structure of this thesis.

1.1 Background

AI is currently considered to be one of the most transformative technologies shaping organizational practices across industries and exhibiting characteristics of a general-purpose technology (Damioli et al., 2024). Initial skepticism, driven by concerns about data privacy, regulatory uncertainty, and high investment costs, has declined. Additionally, advances in AI capabilities, falling implementation costs, and growing institutional support have substantially increased organizational openness toward AI adoption worldwide (Maslej et al., 2025). Adoption rates reflect this development, as the share of firms applying AI in at least one business function increased globally from 55% in 2023 to 78% in 2024 (Maslej et al., 2025, p. 261). However, diffusion remains uneven across functions. While AI is comparatively established in information technology and human resources, adoption in SCM lags behind. Globally, SCM exhibits one of the lowest AI adoption rates, at approximately 17%, despite substantial cost and revenue potential (Maslej et al., 2025, p. 262).

Germany represents a particularly relevant context for examining this discrepancy. Studies indicate a strong increase in AI-related optimism, accompanied by high AI skill penetration and public investment (Maslej et al., 2025). Given Germany's industrial base, export orientation, and complex international supply chains (SC), SCM is strategically central, particularly in times of crisis (Ullrich, 2022). Despite these favorable conditions and increased awareness, adoption in SCM-related processes remains limited. Only a minority of firms apply AI in procurement (23%), SCM (15%), and production (9%) (ERA Group, 2024, p. 4) in the DACH region, and in logistics (22%) in Germany (Bitkom e.V., 2022). This adoption gap contrasts with the growing strategic relevance attributed to AI in SCs, including emerging applications such as AI agents (INFORM Software, 2025).

Following Rogers organizational adoption is defined as the "decision to make full use of an innovation" (Rogers, 1983, p. 172). More specifically, this thesis defines adoption as a strategic commitment involving resource allocation and, where necessary, organization-wide changes to processes and roles. It does not imply immediate implementation but extends beyond exploratory testing or feasibility assessment (Rogers, 1983).

1.2 Problem Statement

Recent evidence suggests that limited AI adoption in SCM cannot primarily be attributed to a lack of awareness or general interest. Instead, many SCM-related functions remain in pre-adoption stages, characterized by discussion, evaluation, and planning, while only a small share has progressed toward concrete deployment decisions (Bundesverband Materialwirtschaft, Einkauf und Logistik e.V. [BME], 2025; Handelsverband Deutschland e.V. [HDE] & Safaric Consulting GmbH, 2025; Statista, 2024; Bitkom Research, 2021). At the same time, the proportion of firms perceiving AI as irrelevant in Germany has declined, indicating substantial heterogeneity in organizations' intention to advance toward adoption (Bitkom, 2025).

Existing research provides only partial explanations for these differences. Practitioner-oriented studies identify numerous barriers and drivers influencing AI adoption in general (Falck et al., 2024; Statista, 2024), within SCM-related processes (Kempcke, 2021; BME, 2025), or affecting implementation (INFORM Software, 2025), yet largely remain descriptive and fragmented. Additionally, academic research offers similarly limited insights either focusing on factors associated with successful AI adoption processes, typically examining established adopters (Falayi et al., 2025; Usmani et al., 2022), or analyzing adoption determinants based on samples including non-adopters and early adopters (Pillai et al., 2022; Wang & Pan, 2022). In parallel, a descriptive body of literature identifies potential drivers, barriers (Dey et al., 2023; Singh et al., 2023; Pan et al., 2025; van Hoek, 2024; Nitsche et al., 2023; Mishra et al., 2023) and early implementation challenges across SCM contexts (Fosso Wamba et al., 2024; Nozari et al., 2022; Fries et al., 2025; Fries & Ludwig, 2024; Rad et al., 2025; Cannas et al., 2023). However, these studies predominantly examine isolated factors or mixed adoption samples and do not assess how enabling and inhibiting determinants jointly shape AI adoption intention across different pre-adoption stages, particularly in the German SCM context.

In summary, the concentration of German organizations in pre-adoption stages indicates substantial heterogeneity in organizational AI adoption intention. Accordingly, this thesis examines the determinants of AI adoption intention to explain why adoption in German SCM progresses only gradually despite increasing awareness and sustained evaluation efforts.

1.3 Research Objectives and Question

Building on the observed heterogeneity in organizational AI adoption intention in German SCM, this paper addresses the following central research question:

RQ1: “*Which factors influence AI adoption intention among German SCM organizations in the pre-adoption context?”*

In addition, the study pursues the following research objectives:

I. Identification and synthesis of influencing factors related to AI adoption in SCM through a systematic literature review (SLR)
II. Development of a conceptual model of AI adoption intention in SCM
III. Quantitative examination of the influence of the identified factors and organizations’ AI adoption intention in German SCM
IV. Descriptive assessment of the current status and application areas of AI across SCM-related functions in German SCM

From a theoretical perspective, the thesis contributes to the literature on AI adoption in SCM by synthesizing existing influencing factors and developing a conceptual model focused on AI adoption intention. By explicitly examining the pre-adoption context, the study advances the understanding of heterogeneity in organizational intentions to adopt AI, thereby addressing a context that remains underexplored in prior research (Frambach & Schillewaert, 2002). From a practical perspective, the thesis provides insights into current AI use cases and the key factors influencing its adoption across organizations, offering guidance for other firms and practitioners.

1.4 Research Design

This thesis follows a quantitative research design based on a deductive approach (Foster et al., 2021) (see Table 1). An SLR identifies and synthesizes relevant factors of AI adoption in SCM and provides the theoretical foundation for a context-specific conceptual model (Creswell, 2009). The relationships identified in this model are then empirically investigated. The empirical phase uses a cross-sectional survey design in the German SCM context. This quantitative approach is methodologically appropriate, as the study aims to examine the relationship between the identified factors and AI adoption intention through standardized measurement and statistical analysis, allowing for systematic comparison and analytical generalization within the defined context (Foster et al., 2021; Creswell, 2009). The proposed relationships are tested using multiple linear regression analysis.

Table 1: Phases, Procedures and Outcomes of Research Design

Phase	Procedure	Outcome
1. Literature review	SLR Bibliometric and thematic analysis	Influencing factors related to AI adoption in SCM
2. Development of conceptual model	Hypothesis building	Conceptual framework for AI adoption intention for SCM context
3. Quantitative data collection	Cross-sectional online survey	Dataset
4. Quantitative analysis	Descriptive statistics Multiple linear regression analysis	Hypothesis testing results

1.5 Structure of the Thesis

The thesis consists of eight chapters and is structured as follows:

Chapter 1 outlines the research topic, introduces the background and problem statement, and defines the research questions, objectives, and research design.

Chapter 2 provides the theoretical foundation of the thesis. It introduces key concepts related to AI and SCM and reviews relevant technology adoption models.

Chapter 3 presents the SLR, describing its methodological approach and the identification and synthesis of influencing factors related to AI adoption in SCM.

Chapter 4 develops the conceptual model derived from the literature and specifies the hypothesized relationships.

Chapter 5 refers to the applied empirical methodology, including the description of the selected survey design, data collection strategy, measurement, and statistical analysis. It further presents the empirical results and the testing of the hypothesized relationships.

Chapter 6 discusses the empirical findings, relating the results to existing literature.

Chapter 7 outlines the theoretical and practical contributions of the thesis, suggests directions for future research and discusses its limitations.

Chapter 8 summarizes the main findings of this thesis.

2 Theoretical Background

The following chapter outlines the theoretical foundations of the key concepts of SCM and AI, including current applications of AI in SCM. Furthermore, relevant technology adoption models are described to provide a theoretical basis for the conceptual model and research developed in this thesis.

2.1 Supply Chain Management

The field of SCM is a widely discussed concept in academic literature and practice (Lambert et al., 1998; Tan et al., 1998; Simchi-Levi et al., 2000; Mentzer et al., 2001; Bowersox et al., 2002; Christopher, 2016; Chopra & Meindl, 2016; Werner, 2020). However, a universally accepted definition of SCM has not yet been established, reflecting differing theoretical and practical perspectives, evolving technological and organizational contexts, and different objectives associated with SCM (Werner, 2020; Council of Supply Chain Management Professionals [CSCMP], n.d.). An overview of selected definitional approaches is provided in Appendix A.

In general, a SC refers to a network of interlinked organizations coordinating the flow of information, goods, and financial resources from initial suppliers to end customers (Chopra & Meindl, 2016; Mentzer et al., 2001; Christopher, 2016; Bowersox et al., 2002).

Although definitions differ in perspective, several common themes can be identified. Existing literature conceptualizes SCM as the integration of cross-functional and inter-organizational business processes along the SC, to improve efficiency and operational performance (Lambert et al., 1998; Simchi-Levi et al., 2000; Werner, 2020). Furthermore, SCM is conceptualized as a mechanism for joint value creation and the maximization of SC surplus for all participating actors (Christopher, 2016; Chopra & Meindl, 2016), as well as a strategic management philosophy that aligns relationships, structures, and processes to achieve long-term competitiveness (Mentzer et al., 2001; Tan et al., 1998; Bowersox et al., 2002). Within this broader conceptualization, the relationship between SCM and logistics remains subject to differing interpretations. While some authors treat logistics as a core component of SCM (Simchi-Levi et al., 2000; Werner, 2020; Tan et al., 1998), others distinguish SCM as a broader management concept that extends beyond traditional logistics functions (Lambert et al., 1998; Mentzer et al., 2001; Chopra & Meindl, 2016). Despite these differing perspectives, the literature converges on a shared understanding of SCM objectives centered on enhancing overall SC performance through network-level value creation and profitability (Chopra & Meindl, 2016; Lambert et al., 1998; Werner, 2020). This involves the coordinated management of interdependent processes to improve efficiency and effectiveness while balancing cost, time, quality, and flexibility across organizational boundaries (Mentzer et al., 2001).

In line with this understanding, the thesis conceptualizes SCM as an integrative management approach implemented within and across organizations to coordinate interdependent processes aimed at enhancing overall SC performance.

Building on these shared objectives, SCM activities are commonly structured using process-oriented reference frameworks that illustrate how coordinated value is operationalized. A widely recognized model is the Supply Chain Operations Reference (SCOR) model, which is used as a standardized framework for describing, analyzing and improving SC processes and organizes activities into five top-level processes: plan, source, make, deliver and return (Werner, 2020; APICS, 2017). These processes include strategic and operational planning, procurement and supplier coordination, production, distribution and logistics activities, as well as reverse flows (see Appendix B).

SCs operate as interconnected systems characterized by bidirectional exchanges of goods, information, services, financial resources, and knowledge (Harland, 2024; Bowersox et al., 2002). This interconnectedness has become particularly evident during global crises such as Covid-19 or ongoing wars, where localized shortages spread across interconnected networks, and previously 'nexus suppliers' became critical (Harland, 2024). This shifted the competition between individual firms to competition between SCs, requiring enhanced end-to-end coordination across organizational boundaries (Lambert et al., 1998; Becker, 2024; Christopher, 2016; Bowersox et al., 2002). These challenges are intensified by increasing globalization, longer lead times, and rising geopolitical and economic volatility, which strain the predictability of supply and demand within SCs (Christopher, 2016; Harland, 2024). Shortened product life cycles and volatile customer demand further increase the need for agility across procurement, production, and distribution processes (Christopher, 2016; Becker, 2024; Chopra & Meindl, 2016). Such dynamics contribute to phenomena such as the bullwhip effect, where minor demand fluctuations amplify upstream variability across multiple tiers (Werner, 2020; Christopher, 2016). Under these conditions, forecasting remains inherently uncertain, often resulting in supply-demand mismatches and operational inefficiencies (Christopher, 2016; Chopra & Meindl, 2016). In addition, fragmented data structures and incompatible information systems limit transparency and coordination across SC partners, thereby reinforcing systemic variability (Somapa et al., 2018; Mahmud et al., 2021). Simultaneously, regulatory requirements related to sustainability and due diligence increase complexity and create tensions between efficiency and compliance objectives (European Union, 2022; European Union, 2024b; Federal Republic of Germany, 2021; Chopra & Meindl, 2016; Werner, 2020).

Overall, SCM is characterized by increasing complexity, uncertainty, and interdependence, requiring adaptive and integrative management approaches. In this context, emerging technologies such as AI may play an essential role in addressing these challenges by enhancing visibility, coordination, and decision-making across SC networks. The following chapter therefore introduces the concept of AI and its potential in addressing these SC challenges.

2.2 Artificial Intelligence

Several future-oriented reports and discussions underscore the fact that we are at the beginning of a so-called 'technology supercycle' (Webb & Jordan, 2024; Magyar, 2025), in which AI forms the foundation for far more profound developments (Yee et al., 2025; Webb & Jordan, 2024). While the Future Today Institute in 2023 still referred to a 'text-to-everything' era (Future Today Institute, 2023), Webb forecasted that based on sensor data, AI will make the transition from 'words to actions' and independently perform complex tasks (Webb & Jordan, 2024). Furthermore, the importance of so called 'agentic AIs', which will cooperate within network structures to make autonomous complex decisions and accomplish tasks more efficiently without human intervention, is growing (Yee et al., 2025; Webb & Jordan, 2024). These projections illustrate not only the speed of technological progress but also the long-term relevance of AI as a groundbreaking key technology. This is further confirmed by the annually published Hype Cycle for emerging technologies from Gartner, in which AI-related technologies continuously appear as central trends, thereby underlining their sustainable development and long-term significance (Gartner, 2022; Gartner, 2023; Gartner, 2024).

Despite its current prominence, the term AI was already introduced in 1955 by John McCarthy. He was convinced that machines could be enabled, through the precise description of learning and intelligence, to simulate these processes and by using language, solve problems, form concepts, learn and adapt themselves (McCarthy et al., 1955). Numerous definitions of AI coexist, reflecting differing conceptions of intelligence and rapid technological development (Russell & Norvig, 2022; Buxmann & Schmidt, 2021). A widely used understanding describes AI as "computer systems designed to perform tasks that typically require human intelligence. These systems leverage algorithms, data, and computational power to recognize patterns, make decisions, and learn from experiences"

(Yee et al., 2025, p. 18; European Parliament, 2023). However, such broad definitions have been criticized for potentially attributing intelligence to systems that merely reproduce learned patterns (Ertel, 2025). Earlier definition attempts emphasize different aspects. McCarthy (2007), who introduced the term, defined AI as “the science and engineering of making intelligence machines” (McCarthy, 2007, p. 2). In contrast, Rich offers a more universal definition by stating that AI “is the study of how to make computers do things at which, at the moment, people are better” (Rich, 1983, as cited in Ertel, 2025, p. 2), thus framing AI in relative and capability-based terms. Against this background, the European Union’s AI Act provides a legally binding and operationally applicable definition: “’AI system’ means a machine-based system that is designed to operate with varying levels of autonomy and that may exhibit adaptiveness after deployment, and that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments” (European Union, 2024a, Art. 3(1)).

2.2.1 Distinctions and Attributes of Artificial Intelligence

A widely recognized distinction in AI research differentiates between weak and strong AI. Weak AI is designed to perform specific, clearly defined tasks using computational and statistical methods (Buxmann & Schmidt, 2021; Hanne & Dornberger, 2017; Gursoy & Cai, 2024). Such systems can replicate selected cognitive functions, including perception, navigation, translation, text and speech recognition, yet remain dependent on human guidance and control (Mockenhaupt & Schlagenhauf, 2024).

Strong AI, in contrast, aims to replicate the full spectrum of human cognitive abilities (Buxmann & Schmidt, 2021) and potentially even exceed them (Mockenhaupt & Schlagenhauf, 2024; Gursoy & Cai, 2024; Hanne & Dornberger, 2017). Although often associated with the concept of Artificial General Intelligence (AGI), no fully developed strong AI currently exists, but is often regarded as a long-term aim of research (Buxmann & Schmidt, 2021; Mockenhaupt & Schlagenhauf, 2024; Gursoy & Cai, 2024; Hanne & Dornberger, 2017). There is still considerable debate about whether current models, such as ChatGPT, already show elements of AGI. Looking further ahead, if systems were to surpass human intelligence, this stage is usually described as super AI (Mockenhaupt & Schlagenhauf, 2024; Gursoy & Cai, 2024). Current applications therefore fall within the domain of weak AI.

Therefore, AI can be characterized by core functional capabilities. At a general level, AI systems interpret data, learn from experience, and apply acquired knowledge to achieve defined objectives in dynamic environments (Mockenhaupt & Schlagenhauf, 2024). Central components commonly highlighted in the literature include machine learning (ML), automated reasoning, natural language processing (NLP), knowledge representation, and perceptual capabilities (Russell & Norvig, 2022; Nilsson, 1998).

2.2.2 Subareas of Artificial Intelligence

AI comprises several subareas, including ML, Deep Learning (DL), and NLP. ML constitutes a central subfield of AI and allows systems to derive patterns and learn from data without explicit rule-based programming (Mitchell, 1997; Goodfellow et al., 2016; Russell & Norvig, 2022; Géron, 2022; Buxmann & Schmidt, 2021; Murphy, 2012). Typical applications include classification, regression, and clustering tasks (Jo, 2021). ML can be further distinguished in different categories that are using labeled data for training (supervised learning), extracting patterns from unlabeled data (unsupervised learning) and reward-based feedback mechanisms to optimize actions (reinforcement learning) (Russell & Norvig, 2022; Marsland, 2015; Mockenhaupt & Schlagenhauf, 2024; Buxmann & Schmidt, 2021).

DL represents a subfield of ML that is built on deep artificial neural networks (ANN). By applying nonlinear transformations across multiple interconnected layers, such networks can model complex and high-dimensional relationships in datasets (Goodfellow et al., 2016; Hanne & Dornberger, 2017; Krizhevsky et al., 2017). However, increasing model complexity reduces transparency regarding how outputs are generated, giving rise to the so-called ‘black box’ problem (Buxmann & Schmidt, 2021). Explainable AI approaches therefore seek to provide insights into model behavior and decision processes (Mockenhaupt & Schlagenhauf, 2024), although interpretability remains conceptually ambiguous and only partially specified in current regulation such as the European AI Act (European Union, 2024a).

Additionally, NLP enables the analysis and generation of human language by computers. Recent advances have been driven by Large Language Models (LLM), which are trained extensively on massive volumes of text data to predict and generate coherent language outputs (Jurafsky & Martin, 2026). Modern LLMs are primarily based on transformer architectures, whose self-attention mechanisms allow the simultaneous processing of contextual relationships within text sequences (Vaswani et al., 2017; Jurafsky & Martin, 2026; Russell & Norvig, 2022). LLMs are typically pretrained on large-scale datasets using self-supervised objectives and subsequently fine-tuned to improve task performance and alignment with human instructions, including reinforcement learning from human input (Ouyang et al., 2022; Jurafsky & Martin, 2026). In the context of this study, it should be noted that the field of AI consists of a wide range of additional methods and approaches beyond the concepts of ANN, ML, and DL discussed. To maintain the scope of this thesis, the focus has therefore been limited to fundamental aspects of AI to establish a general understanding of its basic principles.

2.3 Artificial Intelligence in Supply Chain Management

AI, with its broad range of functions and capabilities, offers promising applications in SCs, which are characterized by complex and dynamic challenges as outlined in Chapter 2.1. Reviews consistently demonstrate that applications span the entire SC (Teixeira et al., 2025; Culot et al., 2024; Daios et al., 2025; Richey et al., 2023; Sharma et al., 2022; Pournader et al., 2021; Atwani et al., 2022) and can be mapped to the processes of the SCOR model.

Within the plan process, demand forecasting and inventory-related AI applications are particularly prominent (Teixeira et al., 2025; Culot et al., 2024; Daios et al., 2025; Richey et al., 2023; Sharma et al., 2022; Pournader et al., 2021; Atwani et al., 2022). Accurate forecasting is critical, as underestimation leads to stockouts while overestimation results in excess inventory and tied-up capital (Chopra & Meindl, 2016). While earlier reviews emphasize forecasting and planning, more recent studies highlight advanced DL and LLM-based approaches, enabling improved decision-making, automation and irregular demand handling (Teixeira et al., 2025; Daios et al., 2025; Mediavilla et al., 2022; Saha et al., 2024).

In the source process, AI is frequently applied to supplier selection and evaluation (Atwani et al., 2022; Pournader et al., 2021; Sharma et al., 2022; Culot et al., 2024; Teixeira et al., 2025). Given the multi-criteria and strategic nature of supplier decisions (Kahraman et al., 2003; Abdulla et al., 2023), AI-based approaches enable data-driven assessments, dynamic weighting of criteria, and enhanced transparency compared to traditional methods (Abdulla et al., 2023).

Within the make process, AI supports production planning, scheduling, resource optimization, quality control and predictive maintenance (Atwani et al., 2022; Sharma et al., 2022; Richey et al., 2023; Teixeira et al., 2025; Culot et al., 2024). Predictive maintenance enables failure detection based on sensor data and reduces downtime and operational costs (Ucar et al., 2024) and automation-oriented applications including AI-driven robotics in warehouse operations, are also highlighted (Daios et al., 2025).

The deliver process is predominantly associated with logistics and route optimization, warehouse management, and network analysis (Atwani et al., 2022; Richey et al., 2023; Teixeira et al., 2025; Daios et al., 2025; Culot et al., 2024). Conversely, applications in the return process focus on reverse logistics optimization and waste reduction (Teixeira et al., 2025; Daios et al., 2025).

Beyond SCOR-related processes, AI also acts as an overarching enabler in risk management and SC simulation. AI-driven analytics support threat detection, scenario modeling, and decision support, thereby strengthening transparency, foresight, and resilience (Sharma et al., 2022; Pournader et al., 2021; Baryannis et al., 2019). Additional applications include customer-facing tools such as chatbots (Richey et al., 2023; Daios et al., 2025), compliance monitoring (Richey et al., 2023), warranty forecasting (Culot et al., 2024) and sustainability performance tracking (Teixeira et al., 2025). The identified AI application areas are summarized in Appendix C in detail according to the SCOR framework.

2.4 Organizational Adoption

This chapter establishes the theoretical foundation for investigating the factors influencing AI adoption intention in German SCM. It first introduces key concepts of innovation adoption and discusses select models that explain how adoption intentions and decisions are formed at the organizational level.

The adoption of new technologies or innovations is not only a technical, but above all an organizational and social challenge, as innovation adoption takes place within social systems and is influenced by structural conditions and collective norms (Rogers, 1983; Venkatesh et al., 2003). The theoretical basis for understanding innovation adoption is provided by Rogers' diffusion of innovations (DOI) theory. Rogers conceptualizes diffusion as "the process through which individuals (or other decision-making unit) passes from first knowledge of an innovation, to forming an attitude toward the innovation, to a decision to adopt or reject, to implementation of the new idea, and to confirmation of this decision" (Rogers, 1983, p. 165). Accordingly, the diffusion process can be described through the five stages knowledge, persuasion, decision, implementation and confirmation. Moreover, Rogers emphasizes that in this process, attitudes toward an innovation primarily emerge from perceptions of its attributes (relative advantage, compatibility, complexity, trialability, observability) and their alignment with the decision maker's context (Rogers, 1983).

While this five-stage model provides a general framework applicable to different decision-making units, Rogers (1983) emphasizes that innovation adoption within organizations follows a more complex and distinct process. Organizational innovation typically progresses through the stages of agenda-setting and matching, followed by redefining, clarifying and routinizing (implementation). These stages capture how organizations identify problems and opportunities, evaluate the fit of an innovation, modify structures or processes to support it, and subsequently integrate it into routine operations (Rogers, 1983).

Building on Rogers' diffusion process, Frambach & Schillewaert (2002) conceptualize organizational adoption as a process consisting of the initiation and implementation stage, separated by a formal adoption decision. During the initiation phase, organizations develop awareness of an innovation and gain initial information. This is followed by a consideration phase, in which more detailed information is gathered, and key innovation characteristics are assessed to reduce uncertainty and form a more concrete attitude toward the innovation. These evaluative activities lead to an intention phase, in which assessments of the innovation are consolidated into a clear behavioral intention. This intention reflects the organization's overall evaluation of the innovation and its perceived suitability as a response to organizational needs. Intention is therefore considered as a central construct and the nearest predictor of actual adoption behavior (Ajzen, 1991; Rogers, 1983). This logic is primarily provided by the Theory of Planned Behavior (TPB). According to TPB behavioral intention is jointly shaped by attitudes, subjective norms, and perceived behavioral control (Ajzen, 1991). Although the TPB was originally developed to explain individual behavior, prior research has extended its logic to organizational decision-making by conceptualizing intention as a collective construct that reflects an organization's strategic commitment toward adoption (Maduku et al., 2016; Ahn & Ahn, 2020). While concerns regarding an intention-behavior gap have been raised (Jeyaraj et al., 2023), adoption intention remains a widely used construct to capture an organization's willingness to adopt an innovation. In contrast, intention to use typically refers to continued usage following adoption. It should be noted that existing literature often does not clearly distinguish between these concepts and frequently applies them interchangeably when examining factors influencing adoption across both adopters and non-adopters (Jeyaraj et al., 2023). The initiation phase then culminates in an adoption or rejection decision, which corresponds to Rogers' original decision stage. The adoption decision initiates the subsequent implementation phase, which is strongly influenced by employees' individual acceptance and actual use of the innovation (Davis et al., 1989; Gallivan, 2001; Venkatesh et al., 2003). Organizational adoption can therefore only be considered complete when the innovation is assimilated into organizational routines and supported by individual-level acceptance and usage. This highlights the interdependence between organizational decisions and individual behavior in the successful adoption of innovations.

In line with the two-stage perspective on organizational adoption introduced above (Rogers, 1983; Frambach & Schillewaert, 2002), this thesis defines adoption in a narrow sense as the "decision to make full use of an innovation as the best course of action available" (Rogers, 1983, p. 172). Accordingly, the organizational adoption decision entails a strategic commitment involving the allocation of resources and potentially encompassing changes to organizational structures, routines, and roles, thereby clearly extending beyond exploratory activities such as experimentation or feasibility testing (Rogers, 1983; Damanpour & Schneider, 2006). Moreover, this thesis defines adoption intention (also referred to as intention to adopt) as the organizational-level willingness to adopt an innovation prior to the formal adoption decision (Jeyaraj et al., 2023). Therefore, the organizational adoption process consists of a pre-adoption phase (initiation), followed by the adoption decision, which leads into the post-adoption phase (implementation) as illustrated in the following figure (Damanpour & Schneider, 2006):

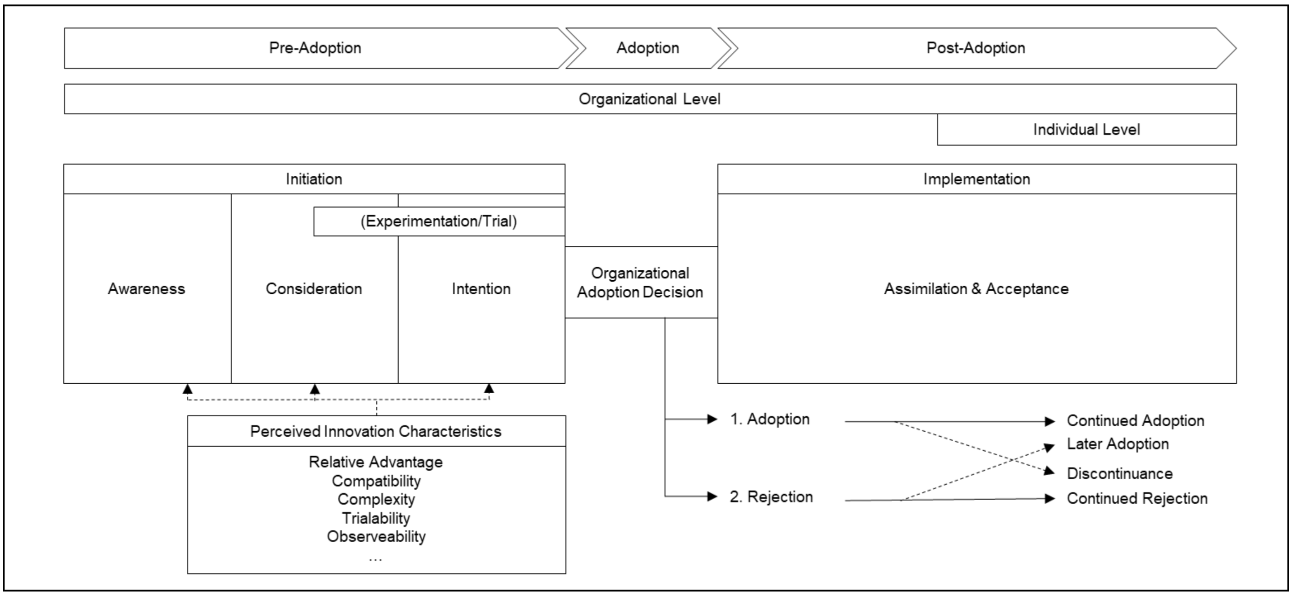


Figure 1: Organizational Adoption Process

Note: Author's own illustration adapted from Rogers (1983) and Frambach & Schillewaert (2002)

Building on this organizational perspective, subsequent research has developed specific technology adoption models:

The Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990) attempts to explain how organizations adopt or implement innovations and is widely used in different areas and applications (Oliveira & Martins, 2011). It distinguishes three contextual dimensions influencing organizational innovation adoption.

The technological context refers to both emerging technologies and existing IT infrastructure, which may enable or constrain adoption. The organizational context captures internal characteristics such available resources, organizational structure, management support or firm size. The environmental context includes external influences such as industry characteristics, competitive dynamics, and regulatory requirements. By integrating both internal and external drivers, the TOE model provides a comprehensive account of factors relevant to technology adoption at the organizational level. Importantly, TOE provides a flexible conceptual structure that can be adapted to specific innovations and contexts (Baker, 2011).

Furthermore, individual-level technology acceptance is explained by the Technology Acceptance Model (TAM) model, through Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU reflects the extent to which a technology enhances job performance, while PEOU refers to the degree to which it can be used without significant effort (Davis et al., 1989). Both constructs influence behavioral intention, which in turn predicts actual usage behavior. Although TAM focuses on individual acceptance, it highlights the importance of performance-related evaluations and usability perceptions for successful organizational adoption.

In contrast, Venkatesh et al. (2003) developed the Unified Theory of Acceptance and Use (UTAUT) to integrate multiple prior acceptance models. According to UTAUT, the determinants performance expectancy, effort expectancy, social influence and facilitating conditions explain individual intention to adopt an innovation. As it integrates social norms and enabling conditions alongside performance perceptions, UTAUT provides a more comprehensive explanation of innovation acceptance within organizational contexts (Venkatesh et al., 2003).

While additional theoretical perspectives on innovation adoption exist, the selected models provide the most relevant conceptual foundation for examining organizational AI adoption in the SCM context.

3 Literature Review

This chapter presents an SLR to identify the influencing factors related to AI adoption in SCM. It first outlines the research objectives, methodological design, and then presents the findings through a descriptive analysis, followed by a thematic synthesis. The SLR provides the conceptual foundation for the subsequent empirical analysis of this thesis.

3.1 Research Design

The SLR in this thesis follows the systematic review guidelines proposed by Tranfield et al. (2003), which provide a standardized and transparent approach for developing evidence-based synthesis in management research. The review process consists of the stages planning, conducting, and reporting (Tranfield et al., 2003). The planning stage defines the underlying research questions, the applied search strategy and inclusion and exclusion criteria for this research (see Chapters 3.2 and 3.3). The conducting stage involves a systematic search, screening and evaluation of studies, and documentation according to PRISMA guidelines (Page et al., 2021). In the reporting stage, findings are synthesized to identify influencing factors related to AI adoption in SCM (see Chapter 3.5). The review integrates findings from both quantitative and qualitative empirical studies, enabling the synthesis of empirically validated factors and context-specific insights.

To ensure methodological transparency, an internal review protocol was developed, which is described in detail in the following chapters.

3.2 Research Objectives and Questions

The main objective of the following SLR is to provide a comprehensive understanding of factors influencing AI adoption in SCM. It enables the identification of recurring factors, inconsistencies, and contextual variations across studies, thereby establishing a knowledge base for the subsequent empirical analysis in the German context. The SLR aims to answer the following research questions:

RQ2: *"Which influencing factors related to AI adoption in SCM are identified in existing scientific literature?"*

RQ3: *"How can the identified factors be organized and synthesized to provide a structured overview of AI adoption in SCM?"*

3.3 Review Methodology

Following Tranfield et al. (2003), transparency and reproducibility were ensured through explicit documentation of data sources, applied search strategies, inclusion and exclusion criteria.

3.3.1 Data Sources

The literature review was performed using the Web of Science (WoS) Core Collection. This database was selected because of its established reputation for indexing peer-reviewed and high-quality journals and covers a wide range of information systems, SCM, and operations management related research. Moreover, the database supports the transparent citation tracking and reproducibility of the search process.

3.3.2 Search Strategy

Defining an appropriate search strategy is a critical step in a SLR, as it determines the comprehensiveness and validity of the evidence base. According to Petticrew & Roberts (2006), an effective search strategy must achieve the balance between sensitivity and specificity. Therefore, this review adopted an iterative, concept-based approach guided by the PICOC framework (population, intervention, comparison, outcome, context) as proposed by Booth et al. (2016). Search terms were grouped into conceptual blocks using Boolean operator OR and subsequently combined using AND. Initial search configurations, which combined population-related terms with detailed AI, adoption, and SCM subprocess keywords, yielded more than 100.000 records. This result reflected the conceptual range of AI research in SCM. Through iterative refinement and sensitivity testing, the search string was narrowed to four thematic blocks aligned with adapted PICOC dimensions.

The AI block (intervention) included overarching AI-related terms, as more specific technical keywords primarily returned algorithm-focused studies unrelated to adoption. The SCM block (context) incorporated the top-level SCOR subprocesses to capture the diversity of AI applications across SCM activities. The adoption block (outcome one) combined general adoption-related terms with constructs derived from TAM, UTAUT, TOE, and DOI to capture both individual and organizational perspectives. Terms such as adoption, implementation, and usage, were intentionally included, as these concepts are frequently used interchangeably in the literature. In addition, anticipated implementation challenges may be conceptualized as perceived aspects of the innovation, influencing adoption decisions (Rogers, 1983). The factor block (outcome two) comprised classical terms for positive and negative determinants to identify research explicitly discussing influencing factors. To enhance thematic precision, adoption- and SCM-related terms were restricted to the title field, while AI and factors terms were searched within the topic field (title, abstract, keywords). This configuration ensured that retrieved studies explicitly addressed AI adoption in SCM while maintaining conceptual breadth through SCOR-related subprocesses. A detailed overview of the applied search keywords is provided in Appendix D.

3.3.3 Inclusion and Exclusion Criteria

This thesis applied predefined inclusion and exclusion criteria during the screening and selection process, to ensure reproducibility and transparency. Included studies examined factors influencing AI adoption, acceptance, implementation, or integration within SCM at the organizational, individual, or managerial level and explicitly referred to SCOR-related subprocesses. Eligible publications were restricted to peer-reviewed journal articles indexed in the WoS Core Collection, written in English, and published between 2015 and 2025. The temporal restriction reflects the marked increase in Big Data research since 2015, followed by AI adoption (Khanfar et al., 2024; Hakami et al., 2025). SLRs and meta-analyses were excluded to avoid duplication of synthesized evidence. Studies focusing exclusively on technical model or algorithm development without addressing adoption aspects were also excluded. Furthermore, studies lacking methodological transparency or full-text availability were excluded. The inclusion and exclusion criteria, as summarized in Table 2, guided the systematic filtering of studies retrieved from the WoS database.

Table 2: Inclusion and Exclusion Criteria of Screening and Selection Process

Inclusion Criteria	**Exclusion Criteria**
IC1: The study addresses factors, drivers, barriers, or determinants influencing AI adoption, acceptance, implementation, or integration in the SCM context on organizational, individual, or managerial adoption level.	EC1: The study does not refer to the SCM context or a sub-process according to the SCOR framework.
IC2: The study is classified as a peer-reviewed journal article.	EC2: The study is a SLR or meta-analysis.
IC3: The study is written in English.	EC3: The study focuses solely on technical model or algorithm development without addressing adoption- or acceptance-related aspects.
IC4: The study was published between 2015-2025.	EC4: The study lacks methodological transparency or sources.
	EC5: The study is not available in full text through open or institutional access.

3.4 Study Identification and Selection

The identification and selection process followed PRISMA guidelines (Page et al., 2021), where relevant studies are identified, screened, and assessed for eligibility to conclude with a final inclusion.

3.4.1 Identification of Studies

The database search was conducted in October 2025 using the finalized search string described in Chapter 3.3.3. The search was pre-restricted to articles and review articles published in English between 2015 and 2025. The final search returned a total of n = 1,638 records from WoS.

3.4.2 Screening and Eligibility

After removal of one duplicate, all records were imported into Excel for screening. First, the titles were reviewed to exclude studies clearly unrelated to AI or SCM. In the second stage, abstracts were assessed for relevance to AI adoption in SCM. In the third stage, full texts were evaluated against all predefined inclusion and exclusion criteria. Additionally, forward and backward snowballing were conducted following Wohlin (2014) to identify further relevant studies. All newly identified papers were subsequently assessed using the same inclusion and exclusion criteria.

3.4.3 Inclusion of Final Studies

The overall procedure of the conducted SLR is outlined in the following figure:

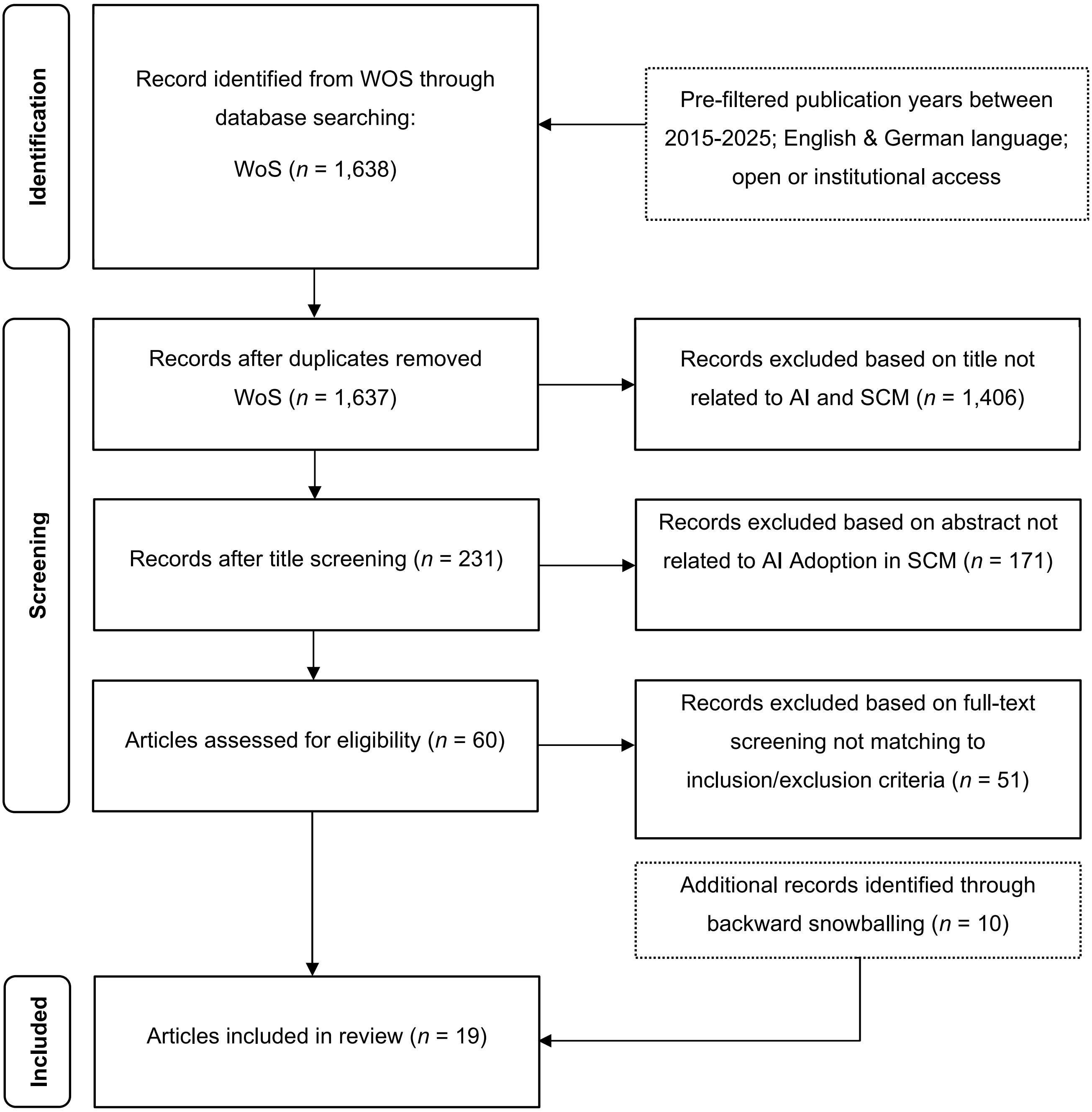


Figure 2: PRISMA Flow Chart of the Study Selection Process

Note: Author’s own illustration adapted from Page et al. (2021)

3.5 Data Synthesis

In the following chapter, the studies identified as relevant through the SLR screening process are first analyzed based on their descriptive characteristics and subsequently examine regarding their findings on the identified AI adoption factors in the SCM context.

Table 3: List of Reviewed Studies with Assigned Item Numbers

Item	Study	Item	Study
[1]	Pan et al. (2025)	[11]	van Hoek (2024)
[2]	Chatterjee et al. (2021)	[12]	Nitsche et al. (2023)
[3]	Alnipak & Toraman (2025)	[13]	Singh et al. (2023)
[4]	Pillai et al. (2022)	[14]	Nozari et al. (2022)
[5]	Usmani et al. (2023)	[15]	Fries et al. (2025)
[6]	Falayi et al. (2025)	[16]	Mishra et al. (2023)
[7]	Fosso Wamba et al. (2024)	[17]	Fries & Ludwig (2024)
[8]	Chen et al. (2025)	[18]	Rad et al. (2025)
[9]	Wang & Pan (2022)	[19]	Cannas et al. (2023)
[10]	Dey et al. (2023)		

3.5.1 Descriptive Analysis

Following Tranfield et al. (2003), key characteristics of the selected studies, such as geographical distribution, authorship patterns, and methodological approaches are analyzed to provide an overview of the current literature and to identify general research trends.

3.5.1.1 Countries and Publication Years

All reviewed studies were published between 2021 and 2025, indicating a recent and rapidly growing academic interest in AI adoption related to SCM. While earlier research on AI in SCM has largely concentrated on technological aspects such as algorithm and system development, the studies identified in this review increasingly emphasize the organizational and individual factors influencing the adoption and implementation of these technologies. This trend may reflect a broader digital transformation momentum that has accelerated in recent years, further driving academic interest in understanding how AI technologies are adopted within SCs.

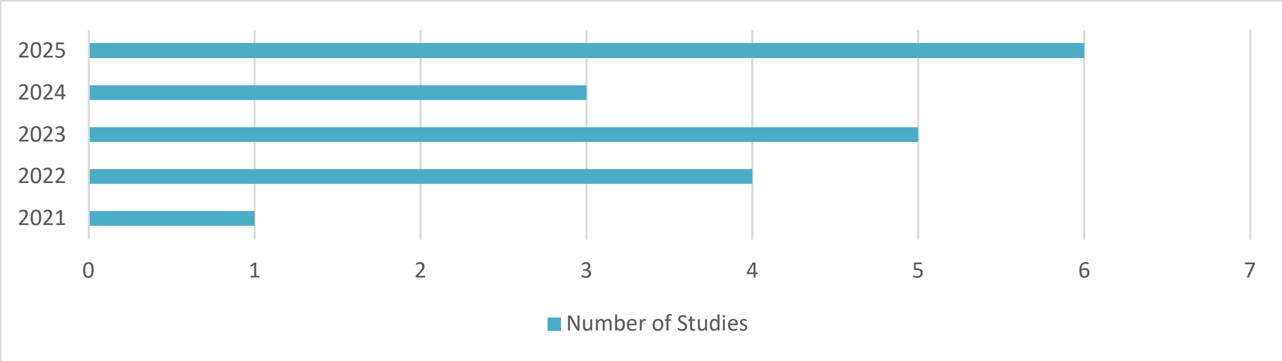


Figure 3: Distribution of the Reviewed Studies by Publication Year (2021–2025)

Most studies were conducted in India and China, followed by Germany and Türkiye. Single studies were carried out in the USA and UK, France, Spain, Iran, Nigeria, Vietnam, Italy, and within an international context. Overall, Figure 4 shows a regional concentration of empirical research in Asia.

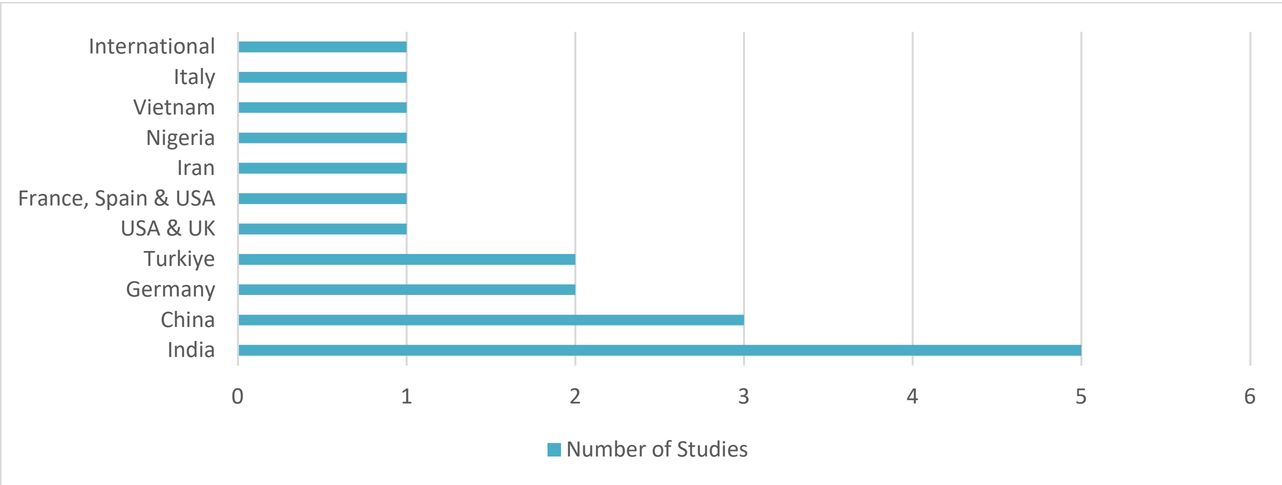


Figure 4: Distribution of Studies by Country

3.5.1.2 Journals

The reviewed studies were published across a diverse set of journals. The *International Journal of Production Research* (*n* = 3) accounts for the largest share, followed *by Computer Supported Cooperative Work – The Journal of Collaborative Computing and Work Practices* (*n* = 2), *Sustainability* (*n* = 2), and *Supply Chain Management: An International Journal* (*n* = 2). The remaining studies were published in a variety of other journals, such as the *International Journal of Computer Applications*. Overall, the distribution of journals indicates a strong anchoring of the topic in the field of SCM, while also covering different academic disciplines, such as sustainability and information management. In addition, the variation in SCImago Journal Rank (SJR) values (ranging from .309 to 3.472) demonstrates that the reviewed studies were published in both highly ranked and more specialized journals, reflecting a balanced mix of top-tier and niche research journals.

Table 4: Distribution of the Reviewed Studies by Journal

Journal Title	Count	SJR
Technological Forecasting and Social Change	1	3.472
Review of Managerial Science	1	2.316
International Journal of Production Research	3	2.242
Production Planning & Control	1	2.198
Supply Chain Management: An International Journal	2	2.117
International Journal of Logistics Research and Applications	1	1.452
Operations Management Research	1	1.424
Sensors	1	.764
Sustainability	2	.688
Systems	1	.579
Computer Supported Cooperative Work - The Journal of Collaborative Computing and Work Practices	2	.549
Logforum	1	.309
Migration Letters	1	-
International Journal of Computer Applications	1	-

3.5.1.3 Co-Authorships

To determine the co-authorships of the reviewed studies, VosViewer was used to illustrate relationships between the authors. Of the total 61 identified authors, only eight were connected through joint publications. Figure 5 illustrates the co-authorship network of the analyzed studies. This illustration indicates a low level of collaboration among the analyzed studies and within the research field of AI adoption in SCM. The few existing connections are concentrated around two small author clusters.

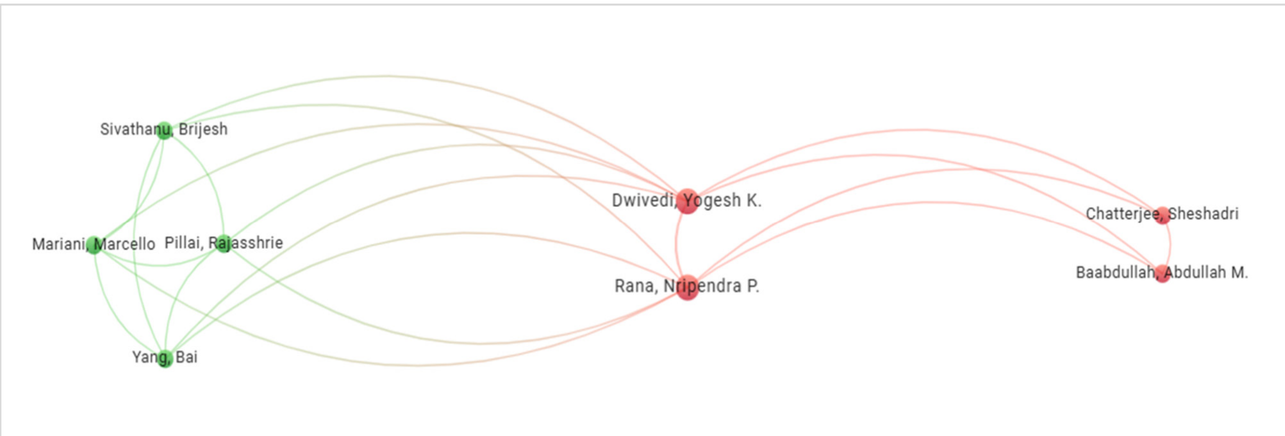


Figure 5: Co-Authorship Network of the Reviewed Studies

3.5.1.4 Data Collection Methods

Most studies employed quantitative survey designs using structured questionnaires with Likert scales (*n* = 13). Other approaches include qualitative interviews combined with observations [15;17], simulations [18], expert assessments [12;13], and direct interviews with companies [19]. In general, several mixed-method approaches were applied in the reviewed studies (*n* = 2). For instance, [18] combined quantitative data from simulations with qualitative interviews, while [17] also linked qualitative insights from interviews with quantitative sales figures to evaluate the performance of an ML forecast. Overall, the methodological landscape is dominated by quantitative survey-based research, suggesting that the field is still in an early stage of empirical maturity with limited qualitative or longitudinal insights into adoption dynamics.

Table 5: Data Collection Methods Used in the Reviewed Studies

Data Collection method	Count	Item
Survey	13	[1];[2];[3];[4];[5];[6];[7];[8];[9];[10];[11];[14];[16]
Qualitative interviews and observations	2	[15];[17]
Delphi study	1	[12]
Qualitative interviews and simulations	1	[18]
Expert evaluation	1	[13]
Semi-structured interviews	1	[19]

3.5.1.5 Research Designs

For factor extraction, studies were categorized according to the methodological section from which adoption factors were derived. In mixed-method studies, the respective research design of the section containing the extracted factors was used for categorization. This approach ensured that the classification accurately reflects the methodological origin of the identified factors rather than the overall research design of the study.

Table 6: Research Design Used for Factor Extraction of the Reviewed Studies

Research design	Count	Item
Quantitative	14	[1];[2];[3];[4];[5];[6];[7];[8];[9];[10];[11];[13];[14];[16]
Qualitative	5	[12];[15];[17];[18];[19]

3.5.1.6 Research Areas

Most studies are anchored in the field of Business & Economics (*n* = 7) and in Engineering (*n* = 4), followed by Operations Research & Management Science (*n* = 3), Computer Science (*n* = 3) as well as Science & Technology - Other Topics and Environmental Sciences & Ecology (each *n* = 2). Only a few studies originate from the social sciences, public administration, or interdisciplinary research areas such as Industry 4.0 Supply Chain. This distribution indicates that the research focus in the examined studies lies primarily within economically and technically oriented disciplines (see Table 7).

Table 7: Distribution of Research Areas among the Reviewed Studies

Research Area	Count
Business & Economics	7
Engineering	4
Operations Research & Management Science	3
Computer Science	3
Science & Technology - Other Topics	2
Environmental Sciences & Ecology	2
Social Sciences - Other Topics	1
Public Administration	1
Industry 4.0 Supply Chain: From Connectivity Provisioning, Data Management to Cyber Resilience	1

3.5.1.7 Citation Analysis

The citation analysis was conducted with the help of WoS database statistics, referring to the total number of citations across all databases. As shown in Table 8, the reviewed studies show considerable variation in citation counts, ranging from zero to 439 citations. Only a few studies have already achieved notable academic visibility, whereas most papers have received relatively few citations so far. This pattern reflects the novelty of the research domain, as the papers were published between 2021 and 2025 and therefore not yet had sufficient time to accumulate citations.

Table 8: Citation Analysis of the Reviewed Studies

Item	Citation frequency	Item	Citation frequency
[2]	439	[9]	16
[4]	140	[12]	13
[10]	115	[11]	10
[1]	105	[5]	4
[7]	102	[17]	3
[19]	88	[8]	3
[14]	68	[18]	2
[15]	66	[3]	1
[13]	30	[6]	0
[16]	18		

3.5.2 Thematic Analysis

The selected studies were analyzed thematically with regard to research focus, theoretical models, SCOR processes, contextual differences, emerging themes, research gaps, and influencing AI adoption factors related to the SCM context. A structured overview is provided in the Appendix E.

3.5.2.1 Research Focus

Beyond methodological differences, the identified studies primarily differ in their research focus. A central stream focuses on explaining AI adoption in SCM related contexts, primarily aiming to identify the factors that drive or hinder adoption at the organizational and individual level. These studies predominantly apply quantitative models to examine adoption decisions and usage intentions across firms and users (Chatterjee et al., 2021; Pillai et al., 2022; Usmani et al., 2023; Falayi et al., 2025; Alnipak & Toraman, 2025; Chen et al., 2025).

A second stream addresses drivers and barriers for AI adoption implementation, mainly analyzing why adoption remains limited or problematic in practice. Using expert-based, analytical, and qualitative approaches, these studies investigate technological, organizational, regulatory, and human-related impediments that support or complicate successful AI deployment and therefore serve as insightful factors that also may influence the adoption decision (Singh et al., 2023; Nozari et al., 2022; Mishra et al., 2023; Rad et al., 2025; Fries & Ludwig, 2024; Cannas et al., 2023). Beyond adoption-oriented research several studies examine the outcomes of AI adoption, focusing not only on the adoption decision but also on the effects of AI on SC performance, resilience and agility (Pan et al., 2025; Wang & Pan, 2022; Dey et al., 2023).

Finally, a smaller body of literature adopts an exploratory perspective, focusing on early-stage adoption, maturity levels, and initial application experiences of AI in SC contexts. These studies aim to provide an overview of emerging use cases, adoption patterns, and unresolved challenges in practice (Fosso Wamba et al., 2024; van Hoek, 2024; Nitsche et al., 2023; Fries et al., 2025).

3.5.2.2 SCOR processes

Overall, it can be stated that considerable variation in terms of the SCOR processes are addressed. Many studies explicitly examine end-to-end SCM and therefore all SCOR processes are addressed, particularly research on AI-driven resilience, performance, or broader assessments of adoption across industries (Pan et al., 2025; Usmani et al., 2023;

Falayi et al., 2025; Dey et al., 2023; Nitsche et al., 2023; Wang & Pan, 2022). A substantial share, however, focuses on the make processes of SCOR, including work conducted in the manufacturing sector (Chatterjee et al., 2021; Pillai et al., 2022; Cannas et al., 2023) and in production planning environments (Fries et al., 2025). Other studies primarily analyzed plan processes, particularly in the context of forecasting and production planning (Chen et al., 2025; Fries & Ludwig, 2024). The deliver processes, specifically warehouse order picking, is also addressed by Rad et al. (2025). Logistics processes spanning source, deliver, and return are examined by Alnipak & Toraman (2025), where studies such as from van Hoek (2024) concentrated exclusively on the source processes.

Overall, the literature demonstrates a substantial thematic and process-related diversity ranging from broad quantitative studies in the manufacturing sector to explanatory single-case analyses in food retailing and explorative investigations on generative AI (GAI). This results in a heterogeneous picture of AI adoption in the SCM context, including both established, industry-driven SCs and innovative, data-intensive or highly domain-specific environments.

3.5.2.3 Research models

Moreover, the reviewed studies can be grouped into four main research streams. A subset of the reviewed studies explicitly applies established adoption models, with a clear dominance of TOE-based frameworks.

Four studies build on TOE either as a standalone model or in combination with complementary theories. Pillai et al. (2022) and Usmani et al. (2023) employ integrated TOE-DOI frameworks, embedding diffusion-related characteristics within the technological, organizational, and environmental contexts. Falayi et al. (2025) rely on a pure TOE framework. Chatterjee et al. (2021) extend TOE by integrating TAM, linking organizational conditions with individual-level technology perceptions. Beyond TOE, several studies apply alternative or non-TOE theoretical lenses to explain AI adoption or its effects. Alnipak & Toraman (2025) combine TPB and TAM (including trust) to analyze GAI acceptance at the individual level, while Chen et al. (2025) integrated TPB and Task-Technology-Fit (TTF) to examine how task-technology fit shapes adoption intention on the individual level. Wang & Pan (2022) merge TOE and Resource-Based-View (RBV) to conceptualize AI-related capabilities as strategic resources.

The reviewed model driven adoption studies can be systematically grouped according to their focus along the AI adoption process. First, several studies focus exclusively on non-adopters and examine factors shaping the intention or initial decision to adopt AI, thereby capturing pre-adoption evaluations and perceived drivers or barriers of organizational (Chatterjee et al., 2021) and individual adoption (Alnipak & Toraman, 2025; Chen et al., 2025). Second, a smaller stream targets adopters only, aiming to emphasize drivers or barriers for the organizational adoption based on concrete adoption experience (Usmani et al., 2023; Falayi et al., 2025). Third, a distinct mixed-grouped perspective combines organizational non-adopters, planned adopters, and early adopters and simultaneously addresses initial adoption intentions as well as continued willingness to adopt AI, thereby conceptualizing adoption as an ongoing process in organizations (Pillai et al., 2022; Wang & Pan, 2022).

Overall, the reviewed model driven studies reflect a comprehensive understanding of influencing factors for the organizational adoption in the SCM context, by integrating anticipatory evaluations by non-adopters and experience-based assessments from early-adopters.

Table 9: Adoption Models, Level, Dependent Variable, Adoption Stage and Research Design of the Reviewed Studies

Item	Adoption Model	Research Level	Dependent variable	Research design
[6]	TOE	Organizational	AI-driven SCM	Quantitative
[4]	TOE & DOI	Organizational	Adoption intention & potential use	Quantitative
[5]	TOE & DOI	Organizational	[Decision for] AI implementation	Quantitative
[2]	TOE & TAM	Organizational/Individual	Intention to adopt	Quantitative
[9]	TOE & RBV	Organizational	Willingness to adopt AI	Quantitative
[3]	TAM & TPB	Individual	Intention to use	Quantitative
[8]	TTF & TPB	Individual	Intention to adopt GAI technology	Quantitative

In contrast, the remaining studies do not apply established adoption models but follow exploratory, empirical, or socio-technical approaches, focusing on early-stage adoption, maturity, and implementation experiences. Such experiences are not merely post-adoption outcomes, as they generate learning effects that shape subsequent adoption decisions (Saghafian et al., 2021). For non-adopters, anticipated implementation challenges may function as perceived barriers influencing initial adoption decisions and expectations regarding feasibility, risk, and organizational readiness (Rogers, 1983). Accordingly, implementation-related findings were included in the analysis, as they inform perceived and anticipated barriers relevant to the adoption decision. The following table summarizes the research level, adoption focus, and applied research design of the studies:

Table 10: Levels, Focus, Adoption Stage and Research Design of the Reviewed Studies

Item	Research Level	Adoption Focus	Research design
[10]	Organizational	AI usage	Quantitative
[7]	Organizational	Early-stage AI adoption maturity; benefits & challenges	Quantitative
[13]	Organizational	Barriers to AI adoption	Quantitative
[14]	Organizational	Challenges of AI implementation	Quantitative
[15]	Organizational/Individual	Socio-technical AI implementation & use experiences	Qualitative
[17]	Organizational/Individual	Socio-technical implementation & use experiences	Qualitative
[18]	Organizational/Individual	Benefits, challenges and success factors of AI implementation	Qualitative
[19]	Organizational	Benefits & challenges of AI implementation	Qualitative
[1]	Organizational	AI usage	Quantitative
[11]	Organizational	Readiness, benefits & barriers to AI adoption	Quantitative
[12]	Organizational	Use-case evaluation & barriers to AI adoption	Qualitative
[16]	Organizational/Individual	Barriers to AI adoption	Quantitative

3.5.3 Quantitative Insights on Influencing Factors related to AI Adoption

To systematically extract the factors influencing AI adoption in SCM, the reviewed studies were first categorized into quantitative and qualitative research designs (see Chapter 3.5.1.5). This separation ensured methodological consistency and prevented the overlap of empirically validated factors with exploratory insights.

The extraction of factors followed a two-step deductive-inductive approach (Mayring, 2014). First, factors were deductively structured according to their adoption level. Organizational-level factors were assigned to the dimensions of the TOE framework, while individual-level factors were documented separately. In a second step, an inductive consolidation was applied within these levels by identifying conceptual commonalities and synthesizing related factors into higher-order categories. These categories were labeled based on shared meaning rather than predefined theoretical terminology.

For quantitative studies involving hypothesis testing, factor extraction was based on the exact constructs and their operationalization as reflected in the measurement items. This required cross-study comparison to assess if authors used conceptually similar terms and whether they referred to equivalent underlying constructs. In studies employing causal-analytic approaches such as Fuzzy DEMATEL only the causal driving factors were extracted. Factors tested but found to be non-significant were retained, as their relevance may vary across geographical and organizational contexts. In contrast, factors mentioned only narratively in quantitative studies were not extracted, as they lacked empirical validation.

This approach ensured that the resulting synthesis accurately reflects validated constructs and maintains the conceptual clarity and explanatory strength of the original studies. The labels of the higher-order categories were derived from conceptual similarities among the extracted factors and subsequently aligned with terminology commonly used in the adoption literature.

Table 11 presents the resulting concept matrix, following Webster & Watson (2002), which synthesizes the identified organizational factors influencing AI adoption within the SCM context:

Table 11: Influencing Factors Related to Organizational AI Adoption

Dimension	Factor	[1]	[2]	[4]	[5]	[6]	[7]	[9]	[10]	[11]	[13]	[14]	[16]	Count
Technological	Technological Readiness	✓	✓	✓	✓	✓				✓	✓	✓		8
	AI-Complexity		✓		✓		✓				✓	✓	✓	6
	Benefits		✓	✓	✓		✓	✓						5
	Compatibility		✓	✓	✓		✓			✓				5
	Costs			✓	✓		✓			✓	✓			5
	Cybersecurity Concerns									✓	✓	✓		3
Organizational	Employee Capability					✓	✓		✓	✓		✓		5
	Management Support		✓		✓	✓			✓	✓				5
	Organizational Resources		✓				✓		✓	✓				4
Environmental	Market Complexity				✓	✓		✓			✓	✓		5
	External Support		✓	✓	✓			✓		✓				5
	Competitive Pressure		✓	✓	✓	✓								4
	Government Support			✓	✓		✓				✓			4

Across the reviewed studies, technological readiness is conceptualized as the fundamental technological backbone required for deploying and operating AI systems, typically encompassing IT systems, data integration, connectivity, and existing digital systems (Usmani et al., 2023; Chatterjee et al., 2021; Falayi et al., 2025; van Hoek, 2024), as well as the availability of IT-related human expertise (Pillai et al., 2022; van Hoek, 2024). Moreover, broader digital IT capabilities, including the ability to integrate third-party digital solutions, access digital services, ensure digital data storage and provide high-speed internet connectivity are emphasized, thereby capturing both system integration and digital maturity (Pan et al., 2025; van Hoek, 2024). When sufficiently developed, these capabilities support and amplify AI adoption and its performance by reducing implementation constraints (Pan et al., 2025; Chatterjee et al., 2021; Usmani et al., 2023; Falayi et al., 2025), whereas deficiencies in infrastructure, connectivity, or technical capability constitute obstacles to adoption and implementation (van Hoek, 2024; Singh et al., 2023; Nozari et al., 2022).

While technological readiness determines whether organizations are technically able to deploy AI technologies, the literature further highlights AI benefits as a central motivational driver of AI adoption. These benefits reflect an overarching expectation of operational and strategic value creation, encompassing efficiency and productivity gains, quality improvements, cost reductions, competitive positioning, and new value opportunities within SCM processes (Chatterjee et al., 2021; Pillai et al., 2022; Usmani et al., 2023; Wang & Pan, 2022). Beyond these economic and performance-related effects, the literature emphasizes AI's intrinsic functional capabilities, such as enhanced decision support, improved risk control, and increased process automation, which enable SCM organizations to manage the complexity and uncertainty of their business more effectively (Wang & Pan, 2022; Fosso Wamba et al., 2024). Consequently, benefits arise from the interaction of technological-economic improvements and AI-specific functional capabilities, jointly strengthening organizations' motivation to adopt AI in SCM.

Beyond expected benefits, compatibility emerges as a enabler of AI adoption and describes the degree to which AI technologies fit with an organization's existing systems, processes, and SCM workflows (Chatterjee et al., 2021; Pillai et al., 2022; Usmani et al., 2023). Compatibility thus captures whether AI can be integrated into established organizational and SCM structures without requiring extensive technological or cultural change. In contrast, a lack of compatibility manifests through integration difficulties, particularly when AI technologies must face rigid legacy systems or highly standardized processes, thereby hindering adoption (van Hoek, 2024; Fosso Wamba et al., 2024). Overall, the literature indicates that compatibility functions as an enabler for adoption when AI aligns smoothly with existing digital and operational environments but becomes a barrier when substantial system adaptations or interoperability efforts are required.

In addition to compatibility, financial and economic considerations influence AI adoption. Costs are broadly conceptualized as financial burdens associated with AI adoption (Fosso Wamba et al., 2024), encompassing investment, implementation, operational, and maintenance expenses that increase the perceived risk and difficulty of adopting AI solutions (Pillai et al., 2022; Usmani et al., 2023; van Hoek, 2024). This cost consideration ranges from immediate financial outlays related to acquisition and implementation to more economic aspects, such as uncertainty regarding returns on investment and ongoing maintenance obligations (Singh et al., 2023) that can influence AI adoption.

Beyond cost-related constraints, AI-complexity represents a barrier to AI adoption (Chatterjee et al., 2021; Usmani et al., 2023) and is associated with increased uncertainty through insufficient data quality and availability, accuracy concerns, biases and errors (Fosso Wamba et al., 2024), uncertain processing and functions of AI algorithms (Singh et al., 2023), lack of contextual awareness (Mishra et al., 2023; Nozari et al., 2022) and ethical concerns (Fosso Wamba et al., 2024). As a result, difficulties in understanding, trusting, and translating AI outputs into actionable insights may limit organizations' willingness to rely on AI in operational and strategic SCM processes.

Furthermore, cybersecurity concerns constitute an additional barrier to AI adoption. Risks related to data breaches, privacy violations, and system vulnerabilities undermine organizational trust in AI systems and may reduce organizations' intention to rely on AI technologies (van Hoek, 2024; Singh et al., 2023; Nozari et al., 2022).

From the organizational related perspective of TOE, management support consistently emerges as a key organizational enabler of AI adoption in the SCM contexts. Active top management commitment, reflected in resource allocation, strategic guidance, and the creation of supportive conditions such as skills development and cultural readiness are widely discussed as strengthening both organizations' willingness and capability to adopt AI (Usmani et al., 2023; Falayi et al., 2025; Dey et al., 2023). Managerial support is further associated with more positive beliefs regarding the usefulness and value of AI, thereby facilitating individual adoption decisions (Chatterjee et al., 2021). Conversely, limited leadership support impedes AI adoption (van Hoek, 2024). Overall, Management Support functions as a critical enabling condition at both the organizational and individual level.

Building on this foundational role of management support, employee capabilities constitute a key enabler of AI adoption in SCM by determining organizations' ability to understand, apply and operate AI technologies. Relevant capabilities range from general digital skills (Falayi et al., 2025) to advanced AI-related competencies such as cross-functional expertise and AI-supported decision-making abilities (Dey et al., 2023). Conversely, limited AI familiarity, resistance to technological change, and shortages of qualified professionals are reported to undermine organizational sensemaking and readiness, which may constrain AI adoption (van Hoek, 2024; Fosso Wamba et al., 2024; Nozari et al., 2022).

Complementing employee capabilities, organizational resources further influence the circumstances under which AI can be successfully adopted, as an employee-focused organizational culture can foster learning and individual acceptance of AI (Dey et al., 2023; Falayi et al., 2025). Moreover, a general digital engagement supports successful adoption (van Hoek, 2024). In addition, the availability of training resources supports the development of internal AI capabilities and facilitates adoption (Chatterjee et al., 2021; Wang & Pan, 2022) while insufficient training structures constitute a structural barrier (Fosso Wamba et al., 2024).

As outlined in Chapter 2.1, the SCM context is characterized by high dynamism and environmental uncertainty. Accordingly, in the environmental context, market complexity constitutes a relevant factor influencing AI adoption in SCM, reflecting volatile demand, shifting market conditions, and increasing complexity of SCM environments. In dynamic and uncertainty settings, AI adoption is facilitated when organizations perceive AI to enhance responsiveness, resilience, and information processing capabilities (Wang & Pan, 2022; Falayi et al., 2025). At the same time, environmental uncertainty can also constrain AI adoption when unstable market conditions, fragmented stakeholders, or project-based structures increase data integration challenges, perceived risks, and investment uncertainty, thereby reducing organizations' willingness to adopt AI (Singh et al., 2023; Usmani et al., 2023). Overall, the findings indicate that environmental uncertainty exerts a dual influence on AI adoption, acting as either a driver or barrier depending on organizational context and implementation conditions.

Beyond the market complexity in SCM contexts, competitive dynamics act as central drivers of AI adoption in SCM, as competitive and external pressure motivate firms to keep pace (Pillai et al., 2022; Falayi et al., 2025) and by creating opportunities to outperform industry rivals (Usmani et al., 2023; Chatterjee et al., 2021).

While competitive dynamics create pressure to adopt AI in SCM, external support shapes firms' ability to respond to this pressure. External support, particularly from technology vendors, partners, and SC collaborators, acts as a positive driver of AI adoption by providing technical expertise, integration guidance, and implementation know-how, thereby reducing uncertainty and assimilation barriers (Pillai et al., 2022; Usmani et al., 2023; Chatterjee et al., 2021; van Hoek, 2024). In addition, SC collaboration enhances AI-driven SCM by enabling information exchange and coordinated digital initiatives across SC actors (Wang & Pan, 2022).

Government and legal conditions also represent an environmental factor of AI adoption, primarily through policy incentives and regulatory frameworks. Supportive government measures, such as funding programs, incentives and institutional backing can facilitate AI adoption by reducing perceived risks and easing access to financial and organizational resources (Usmani et al., 2023), although their direct effect on adoption intention appears context-dependent (Pillai et al., 2022). In parallel, regulatory and legal frameworks strongly shape AI adoption by creating either enabling or constraining conditions, as regulatory complexity, governance uncertainty, and unresolved legal issues related to transparency, bias and data protection are consistently identified as major barriers to AI adoption (Fosso Wamba et al., 2024; Singh et al., 2023).

This review further demonstrates the relevance of human-related factors for AI adoption in SCM, as successful implementation at the organizational level depends on human-AI collaboration, integration and user acceptance. Table 12 presents the resulting concept matrix, following Webster & Watson (2002), which synthesizes the identified individual factors influencing AI adoption within the SCM context:

Table 12: Influencing Factors Related to Individual AI Adoption

Factor	[2]	[3]	[8]	[16]	Count
Attitude		✓	✓	✓	3
PU	✓	✓	✓		3
PEOU	✓	✓			2
Behavioral Control		✓	✓		2
Social Influence		✓	✓		2

Attitude constitutes a core determinant of behavioral intention in TAM and consistently emerges as a strong driver of individual AI adoption. Favorable attitudes toward AI significantly increase adoption intention (Alnipak & Toraman, 2025) while attitudes also mediate the effects of task-technology fit on adoption (Chen et al., 2025). In contrast, skepticism toward AI accuracy and opaque algorithmic behavior fosters unfavorable attitudes that hinder adoption (Singh et al., 2023; Nozari et al., 2022), particularly under conditions of low familiarity and uncertainty about AI decision logic (Mishra et al., 2023). This highlights that organizational-level complexity and capability gaps may translate into unfavorable individual attitudes toward AI.

PU, a central TAM construct, consistently emerges as one of the strongest drivers of individual AI adoption. PU directly increases individual adoption (Chatterjee et al., 2021; Alnipak & Toraman, 2025) and indirectly reinforces adoption through its positive effect on attitudes (Alnipak & Toraman, 2025). Moreover, the perceived task-technology fit, referring to the alignment between AI capabilities and SCM task requirements enhances PU and thereby strengthens individual adoption (Chen et al., 2025). Organizational and technological conditions may therefore indirectly influence adoption outcomes by shaping individual usefulness perceptions (Chatterjee et al., 2021; Chen et al., 2025). PEOU, defined as the degree to which individuals believe that using technology will be without effort (Davis et al., 1989), also contributes to individual AI adoption in SCM. PEOU strengthens favorable attitudes and facilitates acceptance of AI-enabled systems (Alnipak & Toraman, 2025; Chen et al., 2025). Furthermore, organizational and technological conditions, such as AI-complexity, technological readiness, and partner support, influence ease-of-use perceptions, thereby linking organizational context to individual adoption outcomes (Chatterjee et al., 2021).

In contrast, perceived behavioral control does not exhibit a significant effect on individual AI adoption in early adoption stages, suggesting that control-related perceptions may become more relevant during later implementation and use phases (Chen et al., 2025). Social influence show mixed effects. Social influence can positively shape attitudes toward AI by signaling peer and organizational approval (Alnipak & Toraman, 2025). However, subjective norms may not necessarily exert a direct effect on adoption intention, particularly when technical fit or individual capabilities are more salient (Chen et al., 2025).

3.5.4 Qualitative Insights on Influencing Factors related to AI Adoption

The qualitative studies were systematically screened, and adoption-related factors were identified and extracted from the text. These factors were subsequently labeled and assigned to the categories previously derived from the quantitative analysis. The qualitative insights thus serve as an additional interpretive layer to the factors derived from quantitative analysis, enriching the empirical patterns, revealing underlying explanatory mechanisms, and highlighting contextual aspects that remain insufficiently captured by quantitative studies.

Each factor was assigned a functional role (complementary, explanatory, contextualizing, or critical). Based on the studies [12], [15], [17], [18] and [19], the following additional insights were derived:

Table 13: Qualitative Insights on Organizational AI Adoption Factors

Level	Factor	[12]	[15]	[17]	[18]	[19]
Organizational	Technological Readiness	Complementary		Complementary		
	Benefits		Complementary & Explanatory		Complementary	Complementary
	Compatibility				Complementary & Contextualizing	Complementary
	Costs	Complementary				Complementary
	AI-Complexity	Complementary	Complementary & Explanatory	Complementary		Complementary
	Cybersecurity Concerns				Critical	
	Employee Capability	Complementary	Complementary	Complementary		Complementary
	Management Support			Complementary & Explanatory	Complementary	
	Organizational Resources	Complementary	Contextualizing		Complementary	Complementary
	Market Complexity			Complementary		
	External Support				Complementary	Complementary
Individual	Attitude	Contextualizing	Explanatory			Complementary

The reviewed qualitative studies largely confirm the organizational and individual adoption factors derived from the quantitative literature, including technological readiness, benefits, compatibility, costs, AI-complexity, employee capability, management support, organizational resources, market complexity, external support and attitude (see Appendix H).

Compatibility is contextualized as an organizational rather than purely technical issue, as qualitative evidence highlights the need for process re-engineering when AI solutions do not fit existing SCM workflows (Rad et al., 2025). AI-complexity is further explained through limitations in AI systems' ability to capture holistic planning dependencies, which reinforces uncertainty and constrains trust despite high technical performance (Fries et al., 2025).

Benefits are illustrated through concrete value-creation mechanisms, such as AI-enabled rework prediction, demonstrating how technical capabilities translate into operational improvements and risk reduction (Fries et al., 2025). Cybersecurity and legal factors are critically reflected, as qualitative findings indicate that strong data governance, regulatory clarity, and transparent compliance structures may function as enabling conditions rather than barriers to adoption (Rad et al., 2025).

Moreover, studies show that management support may be constrained by negative managerial attitudes, indicating that strategic decisions are themselves influenced by individual-level perceptions (Fries et al., 2025) and underscoring the need for multi-level adoption perspectives that explicitly account for managerial factors.

Qualitative evidence also deepens the understanding of individual-level resistance. Perceived threats to worker expertise and established routines reinforce skepticism and reduce trust in AI-supported decision-making, particularly when technical transparence is limited or algorithmic decision logic remains opaque (Fries et al., 2025). Organizational resources and individual attitudes are therefore contextualized through participatory AI design and human-centered implementation approaches (Fries et al., 2025), as well as the broader requirement for sustainable human-machine coexistence (Nitsche et al., 2023). These findings emphasize that AI adoption in SCM requires not only a technological transformation but also the alignment between technical capabilities, organizational structures, and humans, thereby representing a socio-technical process.

3.5.5 Summary and Findings

Across the reviewed 19 studies, a relatively consistent pattern of factors influencing AI adoption in the SCM context emerges at both the organizational and individual levels, thereby contributing to answering RQ2 of this thesis.

Considering the organizational context of TOE, technological readiness, compatibility, and benefits consistently appear as central enablers and drivers, whereas costs, AI-complexity, and cybersecurity concerns are frequently discussed as technological barriers. Management support, employee capabilities, and organizational resources are commonly associated with higher organizational readiness and more favorable adoption conditions. Within the environmental context, market complexity and competitive dynamics are repeatedly identified as relevant external drivers, while stakeholder support may enable firms to respond more effectively to these pressures. Government incentives and regulatory frameworks appear to exert an ambivalent influence, potentially facilitating adoption but also constraining it through regulatory uncertainty and legal risks.

The qualitative evidence largely confirms the relevance of these factors and does not indicate additional factor categories beyond those identified in quantitative literature, suggesting a certain degree of robustness and contextual completeness of the synthesized factors related to AI adoption in SCM.

Beyond consolidation, the SLR suggests the need for AI-specific conceptual refinement. While existing adoption models capture general technological characteristics, they appear to reflect AI-specific properties, such as data quality requirements, explainability, bias, ethical concerns, and cybersecurity risks, only partially. The synthesis therefore indicates that factors such as AI-complexity may play a particularly critical role, as they potentially affect both organizational and individual levels of adoption.

Moreover, the reviewed literature suggests that external pressure in SCM is often discussed in relation to the interplay between market complexity and competitive dynamics rather as isolated environmental factors. The findings further imply the importance of assessing employee skills, development potential, and training resources, as well as evaluating compatibility not solely from a technical perspective but also from process- and employee-related viewpoints. These observations suggest that organizational structures and human factors may jointly condition AI adoption decisions in the SCM context.

At the individual level, PU, PEOU and attitudes consistently emerge as influential drivers of individual adoption. Importantly, the synthesis indicates that organizational and individual factors are interrelated. Organizational conditions appear to shape individual perceptions, while individual acceptance may influence organizational-level adoption outcomes (Gallivan, 2001; Frambach & Schillewaert, 2002). Despite this interdependence, existing SCM studies predominantly examine determinants in isolation, leaving integrated multi-level and multi-perspective adoption models largely underexplored. Future research may therefore benefit from empirically testing models that jointly examine organizational and individual mechanisms across adoption stages.

Figure 6 provides an integrative overview of the organizational-level factors discussed in the literature and structures them into enabling, driving and inhibiting factors related to AI adoption in SCM, thereby addressing RQ3 of this thesis. While the focus remains on the organizational level, the figure indicates potential links to the individual level without implying empirically validated cross-level effects.

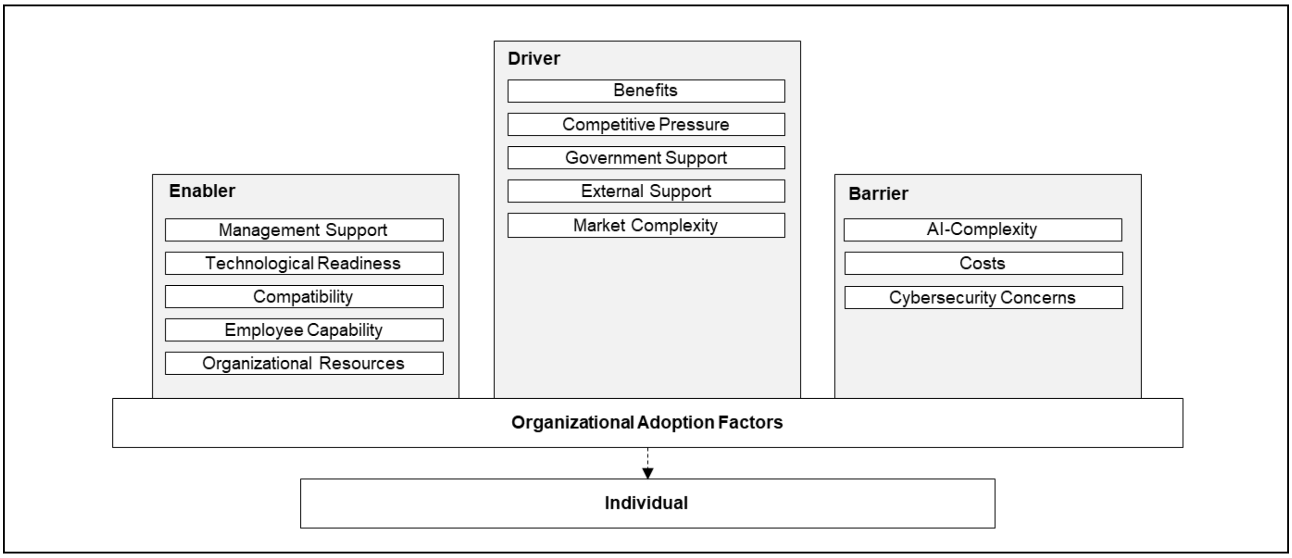


Figure 6: Integrative Overview of Organizational AI Adoption Factors

Note: Author's own illustration

Regarding theoretical foundations, TOE and DOI frameworks continue to appear suitable for analyzing organizational AI adoption, as they capture structural and environmental conditions in the SCM context. At the individual level, TAM-based models remain frequently applied and theoretically relevant. The findings therefore suggest the potential value of integrating TOE, DOI, and TAM in future multi-level adoption research.

The SLR also reveals methodological limitations in the existing literature. Prior studies employ heterogeneous operationalizations of adoption-related factors, limiting comparability. Notably, only Chatterjee et al. (2021) exclusively examine non-adopter organizations, and none of the reviewed SCM studies differentiate between distinct adoption stages. This observation reinforces the need, highlighted by Frambach & Schillewaert (2002), to analyze adoption across separate adoption stages.

Finally, the SLR points to a substantial geographical research gap. Despite comparatively low AI adoption rates and heterogeneous adoption intentions observed in German SCM organizations, empirical evidence for this context remains limited. As adoption factors may vary across national and SC contexts, examining organizational adoption intention within German SCM appears to be a relevant step toward better understanding persistent low adoption rates. Focusing on non-adopter organizations may provide a theoretically grounded and feasible entry point for advancing this research stream.

4 Development of the Conceptual Framework

This chapter presents the conceptual framework guiding the empirical analysis of organizational AI adoption intention in the German SCM context. It introduces the conceptual framework and formulates hypotheses for the subsequent empirical analysis.

Building on the influencing factors identified in the SLR, a conceptual framework is required to systematically structure and explain the factors of AI adoption intention in the SCM context. The TOE framework provides a well-established and flexible structure for analyzing organizational technology adoption by accounting for technological, organizational and environmental contexts. Complementing TOE with characteristics derived from DOI theory enables the assessment of perceived innovation attributes relevant to adoption decisions (Oliveira & Martins, 2011). This perspective therefore captures both structural conditions and perceived technological characteristics that jointly shape organizational adoption intentions.

The factor definitions are adapted and specified based on established adoption theory and recent empirical SCM and AI studies, ensuring conceptual rigor and contextual relevance. The following section introduces the conceptual model and derive the corresponding hypotheses explaining organizational AI adoption intention in the German SCM context.

The framework is illustrated in the figure below:

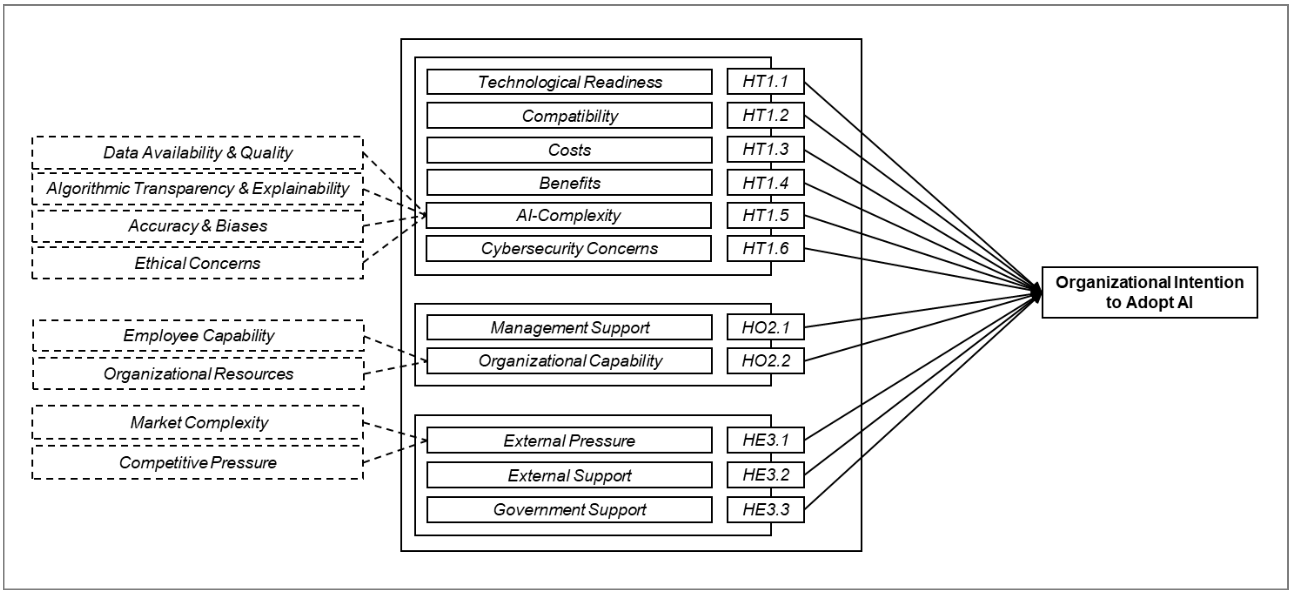


Figure 7: Conceptual Framework for Organizational AI Adoption Intention

Note: Author's own illustration

4.1 Technological Context

As outlined in Chapter 3.5, the main influencing technological factors of AI adoption in SCM include technological readiness, compatibility, costs, benefits, AI-complexity, and cybersecurity concerns.

4.1.1 Technological Readiness

In line with established TOE literature, technological readiness is generally described as the degree to which an organization is equipped with the technological infrastructure and technical expertise required to implement digital innovations (Zhu et al., 2006). Across the reviewed SCM studies, higher technological readiness emerges as a critical enabling condition, as it enhances organizations' ability to deploy and operate AI technologies and reduces technical implementation constraints (Usmani et al., 2023; Chatterjee et al., 2021; Falayi et al., 2025; Pillai et al., 2022). Conversely, insufficient technical infrastructure and expertise may inhibit effective AI implementation (van Hoek, 2024; Singh et al., 2023; Nozari et al., 2022). Accordingly, Technological Readiness is expected to positively influence AI adoption intention.

***Hypothesis HT1.1**:* Technological *Readiness positively influences the AI adoption intention of SCM organizations in Germany.*

4.1.2 Compatibility

According to established TOE literature, compatibility captures the extent to which AI aligns with existing values, beliefs (Rogers, 1983), established processes and technological infrastructures (Chatterjee et al., 2021; Pillai et al., 2022). Across the reviewed SCM studies, higher compatibility facilitates AI adoption by enabling integration into established IT environments, work practices and organizational routines, thereby increasing organizations' willingness to adopt AI (Chatterjee et al., 2021; Pillai et al., 2022; Usmani et al., 2023). Accordingly, Compatibility is expected to positively influence AI adoption intention.

***Hypothesis HT1.2**: Compatibility positively influences the AI adoption intention of SCM organizations in Germany.*

4.1.3 Costs

Adoption literature frequently approaches cost considerations through a "cost-effectiveness" (Premkumar, 1999, p. 471) logic, meaning that organizations evaluate the financial burden of a technology relative to its expected benefits. However, SCM-related AI studies highlight multiple cost components requiring a broader conceptualization. In this thesis, perceived costs refer to the financial requirements for acquiring, implementing and maintaining AI systems (Pillai et al., 2022; Usmani et al., 2023; van Hoek, 2024; Singh et al., 2023; Fosso Wamba et al., 2024). Across the reviewed studies, both direct financial investments and indirect economic uncertainties increase perceived risk and may reduce the financial feasibility of AI adoption (Pillai et al., 2022; Usmani et al., 2023; van Hoek, 2024; Singh et al., 2023; Fosso Wamba et al., 2024). Consequently, Costs are expected to negatively influence AI adoption intention.

Hypothesis HT1.3: *Costs negatively influence the AI adoption intention of SCM organizations in Germany.*

4.1.4 Benefits

According to Rogers relative advantage is “the degree to which an innovation is perceived as being better than the idea it supersedes” (Rogers, 1983, p. 15). This perceived superiority may take economic, performance-related, social or other forms of advantage, depending on adopter characteristics and the nature of the innovation. Building on this conceptual foundation in the SCM and AI context, the factor Benefits refers to the expected operational, strategic or functional advantages that AI technologies offer. Across the reviewed studies, the perceived AI benefits consistently act as a key motivational driver of AI adoption, as anticipated efficiency gains, cost reductions, competitive advantages, and AI-specific functional capabilities increase organizations’ adoption intention (Chatterjee et al., 2021; Pillai et al., 2022; Usmani et al., 2023; Wang & Pan, 2022; Fosso Wamba et al., 2024). Accordingly, Benefits are expected to positively influence AI adoption intention.

Hypothesis HT1.4: *Benefits positively influence the AI adoption intention of SCM organizations in Germany.*

4.1.5 AI-Complexity

Standard adoption literature defines complexity as the “degree of difficulty associated with understanding and learning to use an innovation” (Premkumar, 1999, p. 471), which creates uncertainty in the implementation process and thereby can create perceived risks in the adoption decision stage (Premkumar, 1999; Maduku et al., 2016). AI, however, introduces a distinct form of complexity rooted in its inherent technical characteristics.

AI systems depend on high-quality data, can contain opaque algorithmic processing, may generate biased or inaccurate outputs, and often lack contextual transparency in the SCM context (Culot et al., 2024; Jöhnk et al., 2021). These characteristics increase uncertainty regarding reliability, explainability, and practical usability. As a result, organizations must assess whether their data foundations and AI explainability are sufficient for operational requirements (Fosso Wamba et al., 2024; Singh et al., 2023; Mishra et al., 2023). Accordingly, AI-Complexity is expected to negatively influence AI adoption intention.

HT1.5: *AI-Complexity negatively influences the AI adoption intention of SCM organizations in Germany.*

4.1.6 Cybersecurity Concerns

Cybersecurity concerns refers to the prevention of risks by cyberattacks, data breaches and privacy intrusions associated with AI systems (Nikiforova et al., 2025), which create uncertainty and reduce organizational trust in their use. In the SCM context, such concerns constrain AI adoption by reducing organizations' willingness to rely on AI in SC processes, as heightened exposure to cyber threats weakens confidence in AI-enabled technologies (van Hoek, 2024; Singh et al., 2023; Nozari et al., 2022). Accordingly, Cybersecurity Concerns are expected to negatively influence AI adoption intention.

Hypothesis HT1.6: *Cybersecurity Concerns negatively influence the AI adoption intention of SCM organizations in Germany.*

4.2 Organizational Context

As outlined in Chapter 3.5, the main organizational factors of AI adoption in SCM include employee skills, management support and organizational supporting resources and culture.

4.2.1 Management Support

In line with TOE literature, management support refers to top leadership commitment and resources that create a supportive environment for technology adoption (Premkumar, 1999; Wang et al., 2010 as cited in Low & Chen, 2011). By providing a strategic direction, enabling supporting conditions through skills development and cultural readiness and allocating resources, management support facilitates AI adoption (Chatterjee et al., 2021; Usmani et al., 2023; Falayi et al., 2025; Dey et al., 2023). Accordingly, Management Support is expected to positively influence AI adoption intention.

Hypothesis HO2.1: *Management Support positively influences the AI adoption intention of SCM organizations in Germany.*

4.2.2 Organizational Capability

Many adoption studies conceptualize organizational readiness or competency in terms of financial capacity and IT-related resources (Gangwar et al., 2015; Ajili Ben Youssef et al., 2025; Faustine & Rachmawati, 2024), thereby paying limited attention to employee capabilities that may shape adoption intention (Maduku et al., 2016). In contrast, Zhong & Moon (2023) emphasize employee capability as a central organizational factor, arguing that employees' skills, knowledge, and training conditions fundamentally influence technology adoption success. The reviewed SCM studies similarly indicate that employee capabilities and organizational resources constitute key evaluation criteria in AI adoption decisions, as sufficient skills, readiness, and learning support are required for effective AI deployment (Falayi et al., 2025; Dey et al., 2023; Chatterjee et al., 2021).

Building on Amit & Schoemaker (1993), capabilities refer to a firm's ability to merge resources through organizational processes to achieve desired outcomes. Therefore, building on the SCM evidence, the factor organizational capability conceptualizes the factors employee capability and organizational resources as a combined facilitating factor relevant for AI adoption intention.

Hypothesis HO2.2: *Organizational Capability positively influences the AI adoption intention of SCM organizations in Germany.*

4.3 Environmental Context

As outlined in Chapter 3.5, the main environmental factors of AI adoption in SCM include external pressure, stakeholder support, government and legal conditions.

4.3.1 External Pressure

The reviewed studies suggest that external pressure in SCM arises primarily from competitive dynamics and increasing market complexity. Competitive pressure motivates firms to adopt AI in order to sustain or improve their competitive positioning (Pillai et al., 2022; Usmani et al., 2023; Falayi et al., 2025; Chatterjee et al., 2021). Simultaneously, growing SC volatility and information complexity increase the perceived need for AI-enabled solutions (Wang & Pan, 2022; Falayi et al., 2025). Accordingly, these pressures may constitute a relevant environmental driver of AI adoption.

Hypothesis HE3.1: *External Pressure positively influences the AI adoption intention of SCM organizations in Germany.*

4.3.2 External Support

External support can be defined as “the availability of support for implementing and using an information system” (Premkumar, 1999, p. 472). External support constitutes a key enabler of AI adoption in SCM, as vendor and partner assistance reduce uncertainty and assimilation barriers through technical expertise, collaboration and knowledge transfer, while SC collaboration further facilitates AI adoption by enabling information exchange and coordinated digital initiatives (Pillai et al., 2022; Usmani et al., 2023; Chatterjee et al., 2021; Wang & Pan, 2022). Accordingly, External Support is expected to positively influence AI adoption intention.

Hypothesis HE3.2: *External Support positively influences the AI adoption intention of SCM organizations in Germany.*

4.3.3 Government support

In line with established TOE literature, government support refers to regulatory and policy actions taken by the government that shape the institutional environment for technology adoption (Zhu et al., 2006). This includes establishing regulatory frameworks, shaping a trustworthy technological environment and the provision of financial or strategic incentives that lower uncertainty and encourage innovation uptake. Recent AI adoption research similarly emphasizes the role of institutional support in reducing perceived risks and strengthening organizations’ intention to adopt emerging technologies (Ajili Ben Youssef, 2025; Faustine & Rachmawati, 2024). Within the SCM context, supportive government incentives and clearly defined regulations may also facilitate AI adoption, whereas unresolved legal and regulatory uncertainties hinder it (Usmani et al., 2023; Fosso Wamba et al., 2024; Singh et al., 2023). Therefore, perceived adequacy of government and legal framework conditions is expected to positively influence AI adoption intention.

Hypothesis HE3.3: *Government Support positively influences AI adoption intention of SCM organizations in Germany.*

5 Quantitative Research

This chapter draws on the developed conceptual framework to empirically examine the factors influencing AI adoption intention in German SCM organizations. It outlines the research questions, the target population, the questionnaire design, and the sampling approach. Subsequently, the empirical results are analyzed using descriptive and inferential statistics.

5.1 Research Objectives and Questions

Building on the observed concentration of German SCM organizations in early AI adoption stages and the heterogeneity of intentions to advance toward a strategic long-term adoption decision, this study addresses the limited empirical evidence on influencing factors of AI adoption intention in the German SCM context. Adoption intention is conceptualized as the dependent variable, as it represents a widely accepted and as the nearest predictor of actual adoption behavior (Ajzen, 1991; Frambach & Schillewaert, 2002; Rogers, 1983). In this thesis, adoption intention (also referred to as intention to adopt) refers to the organizational-level willingness of non-adopter organizations to adopt AI before the formal adoption decision, as proposed by Jeyaraj et al. (2023). In addition, the empirical analysis aims to provide an insight about the current AI adoption status of German SCM organizations and the identification of AI applications, that are currently in use or under consideration. In addition to the overarching research question RQ1, the following supplementary research questions are addressed:

RQ4: *“Where do German SCM organizations currently position themselves within the organizational AI adoption process?”*

RQ5: *“Which AI applications are currently applied or considered for adoption in SCM?”*

RQ6: *“How do influencing factors differ across pre-adoption stages?”*

5.2 Research Design

The following chapter outlines the selected population and questionnaire development to address the underlying research questions.

5.2.1 Population

Following Phillips (1981), organizational attributes cannot be directly observed and must therefore be obtained through qualified key informants possessing relevant knowledge and role-specific insight. In SCM contexts, managerial professionals fulfill this criterion, as they are involved in evaluating and shaping technology adoption decisions. Although Gallivan (2001) critiques purely top-down adoption perspectives, he acknowledges that managerial decision-makers remain central in authority-based adoption processes. Accordingly, managerial SCM respondents constitute theoretically appropriate key informants for assessing organizational AI adoption intentions. To ensure the inclusion of knowledgeable informants, the questionnaire applied screening criteria requiring respondents to occupy a managerial role in the SC area within a German organization and to have more than one year of experience in this position (Phillips, 1981). As this study adopts a pre-adoption focus, only organizations that had not yet made a final AI adoption decision were included in the hypothesis testing. In line with Rogers (1983) and Frambach & Schillewaert (2002), non-adopters refer to organizations that have not decided to adopt AI. This includes organizations that are aware of AI (initiation), consider AI for adoption (consideration), evaluate and assess AI for adoption (intention), including tests and experiments to decrease uncertainty. By contrast, adopters refer to organizations that have already made an adoption decision or are partly or extensively using AI in their SC processes (Rogers, 1983). Nevertheless, responses from adopter organizations were collected and used to contextualize and describe the current AI adoption landscape in German SCM context, rather than being included in the hypothesis testing.

5.2.2 Structure of the Questionnaire

At the beginning of the survey, participants were introduced to the study purpose and the applied definition of AI technologies. The survey is structured into four main sections. The first section captures contextual information on the respondents SC domain, identifying the SCOR process area in which the respondent operates and confirming whether the organization is located in Germany. Further exclusion criteria regarding their managerial position and role-specific experience are applied to obtain qualified key informants. In addition, organizational characteristics like the industry and company size are collected. The second section assesses the organization’s AI adoption status by identifying its current stage within the AI adoption process. For organizations that evaluate, decide or actively use AI, additional questions capture the AI use cases to provide deeper insights into the adoption landscape in German SCM. An exclusion criterion terminates the survey if a final AI adoption has already been made, as the study focuses on pre-adoption organizations. The third section measures the conceptual framework structured to the TOE framework to reduce cognitive load. Matrix-based statements were evaluated using a five-point Likert scale from one (strongly disagree) to five (strongly agree). Five-point scales are widely accepted capturing perceptual constructs (Likert, 1932) and provide adequate variance and reliability while minimizing cognitive burden to respondents (Preston & Colman, 2000; Dawes, 2008). A six-point scale was avoided, as forced directional choices may bias responses from non-adopter organizations with limited AI experience (Krosnick, 1991). The measurement items were adapted to the SCM context from established AI and technology adoption studies to ensure construct validity and contextual fit (see Appendix I). Four items per factor were used to balance reliability and respondent effort (DeVellis, 2017). All factors were measured perceptually provided by key informants, consistent with prior adoption research (Rogers, 1983). The term ‘organization’ refers to an overall organizational perspective, whereas ‘supply chain processes’ refer to the respondent’s specific area of responsibility. Brief explanatory notes were provided to ensure consistent interpretation.

5.2.3 Sampling Method

The survey was distributed using a targeted dissemination strategy based on non-probability sampling, as this approach enables efficient access to knowledgeable key informants in the SCM context. Specifically, purposive and snowball sampling were applied through targeted outreach to SCM managers and their contacts, while convenience sampling resulted from voluntary participation via LinkedIn (Ahmed, 2024). However, non-probability sampling may entail self-selection and sampling bias (Ahmed, 2024), thereby limiting generalizing the findings to the wider population of German SCM organizations. At the same time, this approach targeted managers with relevant SC expertise and organizational responsibility while also capturing organizations with varying levels of AI awareness, including those that have not yet actively considered AI.

5.2.4 Sample Size Determination

The required sample size was calculated by performing an a-priori power analysis for multiple linear regression analysis. Following Cohen (1988) and recent adoption research (Abulail et al., 2025; Marfo et al., 2023), a significance level of α = 0.05, a power of .80, and a medium effect size f^2 = .15 were selected. Accounting for 12 variables, the power analysis indicates a minimum required sample of n = 127 complete observations (Hemmerich, 2019).

5.2.5 Sample Overview

The survey was open from December 19 to February 17, 2026, and resulted in 113 respondents. The following table presents an overview of the response characteristics:

Table 14: Sample Overview

Sample	Count
Total	113
Excluded based on non-SCM function	4
Excluded based on non-managerial role	9
Excluded based on non-role experience	1
Excluded post-adopters	16
Incomplete pre-adopters	9
Only opened	7
Complete	67

The regression analysis was conducted using the 67 complete pre-adopter responses. As the collected sample is substantially below the required sample size to reach enough statistical power for the specified model, the results must be interpreted with caution. Nevertheless, the sample size is exceeding the recommended minimum threshold of a ratio of 5:1 (Hair et al., 2019). The 16 excluded post-adopters were only analyzed descriptively to contextualize AI applications in German SCM.

5.3 Statistical Analysis

The following chapter performs descriptive statistics on the collected sample, examines the gathered information in detail, assesses the underlying assumptions of regression analysis, and presents the results of the regression models.

5.3.1 Demographic Statistics

Among the 67 complete pre-adopter responses, most participants are employed in medium-sized companies (38.81%), and small to mid-sized companies (34.33%), followed by large enterprises with more than 5.000 employees (20.90%). A smaller proportion (5.97%) represents companies with 50-249 employees. No organization in the sample employes fewer than 50 employees. Most respondents operate in manufacturing (26.87%), followed by the category ‘Other’ (31.34%), construction (14.93%), and retail and e-commerce (8.96%). Additional sectors include transportation and logistics services (5.97%), wholesale and distribution (5.97%), agriculture, food and natural resources (2.99%), engineering (1.49%) and utilities and energy supply (1.49%). Of the responses categorized as ‘Other’, 71.42% provided specific industry descriptions, including construction and real estate development, gardening equipment, crane and construction technology, plastics processing, healthcare and nursing services, medical technology, optics, semiconductor manufacturing and defense. Due to the applied screening criteria, 97.01% of respondents hold senior management positions and 2.99% occupy executive management roles. With regard to experience in their current position, 31.34% report 6-10 years, 28.36% report 3-5 years, 26.87% report 1-2 years, and 13.43% report more than 10 years, indicating a substantial professional experience across the sample. Respondents primarily operate in end-to-end SCM (37.31%), followed by sourcing (22.39%), deliver (14.93%), plan (13.43%), make (10.45%), and return (1.49%). Thus, all SCOR processes are represented. Participants were instructed to choose the adoption stage that best describes the current status of AI adoption within their SCM function. Among the 67 pre-adopter respondents, 50.75% are in the consideration stage (initial consideration without active evaluation), 34.33% are in the awareness stage (general awareness without concrete consideration), and 14.93% are in the intention stage (active evaluation, optional pilots or experiments). Considering the full sample (n = 113), two respondents report having made an adoption decision without implementation, thirteen report routine AI use in selected SC processes, and one reports widespread routinized usage. Overall, the distribution indicates that German SCM organizations remain in early adoption stages, with only a small proportion classified as post-adopters. The descriptive statistics of the sample are summarized in the following table:

Table 15: Demographics of Respondents (n = 67)

Demographics	Characteristics	Count	Percentage
Company Size	50 - 249 employees	4	5.97%
	250 - 999 employees	23	34.33%
	1.000 - 4.999 employees	26	38.81%
	> 5.000 employees	14	20.90%
Sector	Agriculture, Food & Natural Resources	2	2.99%
	Mining & Raw Materials	0	0.00%
	Construction	10	14.93%
	Manufacturing	18	26.87%
	Engineering	1	1.49%
	Wholesale & Distribution	4	5.97%
	Retail & E-Commerce	6	8.96%
	Transportation & Logistics Services	4	5.97%
	Utilities & Energy Supply	1	1.49%
	Public Sector	0	0.00%
	Other	21	31.34%
Position	Executive Management	2	2.99%
	Senior Management	65	97.01%
Experience	1-2 years	18	26.87%
	3-5 years	19	28.36%
	6-10 years	21	31.34%
	> 10 years	9	13.43%
SCOR	Plan	9	13.43%
	Source	15	22.39%
	Make	7	10.45%
	Deliver	10	14.93%
	Return	1	1.49%
	End-to-end SCM	25	37.31%
Adoption Stage	Awareness	23	34.33%
	Consideration	34	50.75%
	Intention	10	14.93%

Of the 67 respondents, 26.86% voluntary reported AI use cases currently considered, evaluated, or tested. The following statements were reported across the consideration and intention stages and were partially translated from German into English:

Table 16: Reported Use Cases Across the Consideration and Intention Stage

SCOR process	Description
Plan	*“1. Demand forecast 2. Dynamically inventory and safety stocks”*
Source	*“Classically, tools such as Copilot and internal document bots (which can exclusively access internal documents)”*
	“The Supply Chain Due Diligence Act poses certain challenges for our organization; therefore, the implementation of an AI-based tool could be beneficial.”
	“Network and footprint optimization, as well as make-or-buy and nearshoring decisions supported by AI”
	“Coupa for autonomous procurement”
Make	*“Quality control production”*
	“Fully automated production planning”
	“Anomaly detection in production based on data analytics”
	“Predictive maintenance and production planning supported by AI-based forecasting”
Deliver	*“We previously planned to develop a roadmap outlining digital initiatives for our functional area and to present it to executive management. However, due to internal complications, this initiative has been significantly delayed, and at present, no short-term changes are anticipated”*
Return	-
End-to-end SCM	*“Currently, no concrete initiatives have been evaluated yet, but we occasionally gather information and also like to discuss digitalization or AI internally :)”*
	“I occasionally inform myself about such topics and try to stay up to date regarding potential developments (e.g., through newsletters, which are often received via email, or LinkedIn groups); however, at present, no specific initiatives come to mind”
	“No explicit use cases are considered noteworthy”
	“Delivery date forecasting within an integrated software solution.”
	“Customer service bot: Incoming internal orders and inquiries are to be processed and answered by the bot in order to reduce email traffic and long response times for internal stakeholders. At present, however, the department is uncertain whether such a solution would generate tangible added value or be accepted by customers.
	“AI-supported supply chain ‘tower’”
	“S&OP Tool with different AI functions”
	“-Dispatch: automation and planning - Planning and control”

The reported use cases span across the full range of SCOR processes. They include analytical AI applications, such as demand forecasting, as well as software solutions incorporating AI functionalities in sourcing and planning. In addition, respondents report fully automated planning functions within production processes, end-to-end SC monitoring systems, and GAI applications, including customer service chatbots and internal applications such as Copilot. One respondent explicitly linked AI consideration to regulatory pressure stemming from the German SC Due Diligence Act, highlighting AI’s perceived supportive role in managing compliance complexity. Furthermore, the responses suggest that although several participants demonstrate clear interest in AI, internal constraints or the absence of identified uses cases currently hinder further progress. With regard to the use cases reported by post-adopters, analytical AI applications such as demand and inventory forecasting within the SCOR plan step are mentioned. In addition, AI-supported software solutions in sourcing and delivery, as well as the monitoring of production processes, are described. Notably, one respondent reports the use of a self-developed forecasting model for delivery time prediction (see Appendix J). The reported use cases illustrate the diversity and varying levels of complexity of AI applications within the SCM.

5.3.2 Reliability Analysis

To ensure the reliability and internal consistency of the developed measurement instrument, the Cronbach's alpha was calculated for each variable. Cronbach's alpha examines the degree to which multiple factor questionnaire items are interrelated, thereby providing an estimate of internal consistency reliability (Hair et al., 2019). Values of .70 or higher are generally considered acceptable (Nunnally & Bernstein, 1994), whereas coefficients below .70 suggest limited reliability (Swanson & Holton, 2005).

The highest Cronbach's alpha was observed for the dependent variable Intention to Adopt (α = .950). The lowest reliability values were found for Government Support (α = .691) and External Support (α = .705). For Government Support, removing individual items did not meaningfully increase Cronbach's alpha. Given the coefficient is close to the commonly accepted threshold and that the scale was derived from validated measures, all items were retained. Nevertheless, results related to this variable should be interpreted with caution due to its comparatively lower reliability. All remaining variables demonstrated reliability levels above .70, indicating sufficient internal consistency of the measurement instrument (see Appendix K).

5.3.3 Descriptive Statistics

The descriptive statistics indicate moderate mean values across all independent variables, ranging from 2.679 to 3.716 on the five-point Likert scale. Benefits exhibit the highest mean (*M* = 3.716, *SD* = .884), followed by Compatibility (*M* = 3.358, *SD* = .995), and External Pressure (*M* = 3.325, *SD* = .751). In contrast, Government Support shows the lowest mean (*M* = 2.679, *SD* = .441), suggesting comparatively weaker perceived institutional support and relatively low variance in responses. The largest standard deviations were observed for

Compatibility (*SD* = .995) and Management Support (*SD* = .917), indicating higher dispersion in these variables (see Appendix L).

The dependent variable Intention to Adopt (*M* = 3.189, *SD* = 1.149) indicates a moderate tendency toward AI adoption within this sample. The relatively high standard deviation suggests considerable heterogeneity in adoption intentions across respondents. Across adoption stages, a clear upward pattern is observable. Intention to Adopt increases from the awareness stage (*M* = 2.768, *SD* = .901) to consideration (*M* = 3.245, *SD* = 1.280) and reaches its highest level in the intention stage (*M* = 3.967, *SD* = .745). Variability is highest in the consideration stage and lowest in the intention stage, suggesting more homogenous adoption intentions among respondents in more advanced stages (see Appendix L).

5.3.4 Correlation Analysis

The following chapter analyzes the correlations between the dependent and independent variables, as well as the intercorrelations among the independent variables, for the overall pre-adopter sample.

The analysis reveals several significant associations between the dependent variable Intention to Adopt and the independent variables (see Appendix M). Intention to Adopt is positively and significantly correlated with Technological Readiness (r = .400, p < .001), Compatibility (r = .465, p < .001), Benefits (r = .385, p = .001), Organizational Capability (r = .436, p < .001) and Management Support (r = .451, p < .001). In contrast, Costs (r = -.121, p = .329), AI-Complexity (r = -.219, p = .075), Cybersecurity Concerns (r = -.069, p = .578), External Pressure (r = .083, p = .505), External Support (r = .210, p = .088) and Government Support (r = -.230, p = .062) do not show significant relationships with AI adoption intention. The absence of significant negative associations for Costs, AI-Complexity, and Cybersecurity Concerns indicate that these factors are not strongly related to the adoption intention in the overall sample. Likewise, non-significant correlations for External Support and Government Support suggest that adoption intention is not closely associated with external enabling conditions. However, these findings should be interpreted cautiously because of the limited sample size.

Among the independent variables, moderate intercorrelations are observed, particularly between Organizational Capability and Compatibility (r = .523, p < .001), Organizational Capability and Management Support (r = .466, p < .001), Technological Readiness and Management Support (r = .428, p < .001), as well as Technological Readiness and Organizational Capability (r = .434, p < .001). These patterns indicate that technological preparedness, organizational capabilities, and management support tend to co-occur and may reflect an overarching dimension of organizational readiness for AI adoption. Overall, the correlation pattern suggests that AI adoption intention is more strongly related to internal technological and organizational factors than to environmental factors. However, correlations do not imply causality and serve as a preliminary assessment before regression analysis (Swanson & Holton, 2005).

5.3.5 Multiple Linear Regression

The following chapter examines the assumptions underlying the regression analysis and subsequently presents the regression results.

The statistical method multiple linear regression allows to examine the relationship between a dependent variable and multiple independent variables (Hair et al., 2019; Swanson & Holton, 2005; Backhaus et al., 2025). It enables the estimation of the individual influence of each variable while controlling the influence of the remaining variables (Hair et al., 2019). In this analysis, the dependent variable Intention to Adopt is measured using the aggregation of three items with a five-point Likert scale. Although individual Likert-type items are formally ordinal, the mean of multi-item factors can be viewed as approximately interval scaled in quantitative research, thereby allowing the application of parametric methods (Norman, 2010). The regression analysis is applied to test the hypotheses derived from the SLR.

5.3.5.1 Regression Assumptions

Prior to conducting the regression analysis, the underlying assumptions were examined. These include linearity, homoscedasticity, normality of standardized residuals, and independence of errors (Swanson & Holton, 2005; Hair et al., 2019; Wentura et al., 2023). Additionally, the data were examined for influential outliers, multicollinearity, and autocorrelation (Backhaus et al., 2025). Table 17 summarizes the results for n = 67 and indicates that all assumptions were fulfilled. Detailed results of the assumption checks are provided in the appendix (see Appendix N).

Table 17: Overview of Regression Assumptions (*n* = 67)

Assumption	Method	Result	Assumption Check
Linearity	Partial regression plots Residuals vs. Predicted plot	No unusual pattern detected No unusual pattern detected	Fulfilled Fulfilled
Homoscedasticity	Residuals vs. Predicted plot	No unusual pattern detected	Fulfilled
Normality	Q-Q Plot of standardized residuals Shapiro-Wilk test	Approximate normal distribution Minor deviations in the tails Skewness = -.399 Kurtosis = .490 W = .983, p = .502	Fulfilled Fulfilled
Outliers	Standardized Residuals	Min: -2.713 | Max: 2.445 No standardized residual exceeded ±3	Fulfilled
Multicollinearity	Tolerance Variance Inflation Factor (VIF)	Tolerance range: .505 - .891 VIF range: 1.143 - 1.979	Fulfilled Fulfilled
Autocorrelation	Durbin-Watson statistic	DW = 2.261	Fulfilled

5.3.5.2 Regression Analysis and Hypothesis Testing

The regression model resulted in an R^2 of .440 and an adjusted R^2 of .328. While the R^2 indicates that 44% of the variance in the dependent variable is explained by the independent variables (Hair et al., 2019), the adjusted R^2 provides a more appropriate estimate given the relatively small sample size and the number of independent variables, as it accounts for model complexity (Backhaus et al., 2025). The difference between R^2 and adjusted R^2 suggests that part of the explained variance may be attributed to model complexity. Therefore, the results should be interpreted with caution. The overall regression model was found to be statistically significant (F = 3.930, p < .001).

The findings reveal that Compatibility (*ß* = .249, p = .045) and Management Support (*ß* = .273, p = .037) have a significant positive effect on the AI adoption intention of German SCM organizations. This result suggests that higher perceived compatibility of AI with existing values, processes, legacy systems, IT systems and infrastructure is associated with stronger adoption intentions. Moreover, the findings indicate that Management Support, reflected in support and the willingness to allocate resources, awareness of potential benefits, and encouragement of AI usage among employees leads to higher intentions to adopt AI. Accordingly, hypotheses HT1.2 and HO2.1 are supported.

Additionally, the findings reveal that Technological Readiness (*ß* = .111, p = .363), Costs (*ß* = -.159, p = .146), Benefits (*ß* = .176, p = .114), AI-Complexity (*ß* = -.045, p = .684), Cybersecurity Concerns (*ß* = .015, p = .889), Organizational Capability (*ß* = .055, p = .698), External Pressure (*ß* = -.021, *p* = .845), External Support (*ß* = .090, *p* = .417) and Government Support (*ß* = -.086, *p* = .435) show no significant influence on the adoption intention of German SCM organizations in this sample. Consequently, hypotheses HT1.1, HT1.3, HT1.4, HT1.5, HT1.6, HO2.2, HE3.1, HE3.2, HE3.3 are not supported.

Table 18 summarizes the regression results and the status of the hypotheses. A detailed regression output is provided in the Appendix O.

Table 18: Regression Results and Hypothesis Testing

Hypothesis		***ß***	***p***	**Hypothesis Status**
HT1.1	Technological Readiness → Intention to Adopt	.111	.363	Not supported
HT1.2	**Compatibility → Intention to Adopt**	**.249**	**.045**	**Supported**
HT1.3	Costs → Intention to Adopt	-.159	.146	Not supported
HT1.4	Benefits → Intention to Adopt	.176	.114	Not supported
HT1.5	AI-Complexity → Intention to Adopt	-.045	.684	Not supported
HT1.6	Cybersecurity Concerns → Intention to Adopt	.015	.889	Not supported
HO2.1	**Management Support → Intention to Adopt**	**.273**	**.037**	**Supported**
HO2.2	Organizational Capability → Intention to Adopt	.055	.698	Not supported
HE3.1	External Pressure → Intention to Adopt	-.021	.845	Not supported
HE3.2	External Support → Intention to Adopt	.090	.417	Not supported
HE3.3	Government Support → Intention to Adopt	-.086	.435	Not supported

5.4 Exploratory Statistical Analysis of Pre-Adoption Stages

To examine whether the influencing factors of AI adoption intention differ across pre-adoption stages, separate regression analyses were conducted. Given the reduced sample sizes, the findings must be interpreted with caution and are considered exploratory. As the intention stage comprises a substantially smaller sample (*n* = 10), no separate regression analysis was conducted for this stage.

5.4.1 Parsimonious Model Specification

The sample sizes in the awareness (*n* = 23) and consideration stage (*n* = 34) stages fall below the commonly recommended minimum ratio of five observations per variable to ensure stable regression estimates (Hair et al., 2019), given the eleven independent variables included in the original model. To examine potential stage-specific dynamics despite these limitations, a more parsimonious model specification was adopted. The eleven variables were aggregated into theoretically related composite factors, reducing model complexity and improving estimation stability. Accordingly, the stage-specific results are interpreted as exploratory.

Technological Readiness, Compatibility, and Organizational Capability were aggregated into a composite variable Organizational Readiness, capturing overall internal organizational readiness. Conceptually, the three constructs represent complementary dimensions of internal preparedness, including technological infrastructure, process and culture alignment, and human capabilities. Moderate positive intercorrelations within both stages indicate substantial overlap, supporting their aggregation (see Appendix R).

In addition, AI-Complexity and Cybersecurity Concerns were combined, to reflect perceived technological risk and implementation barriers. Both variables capture uncertainty, system vulnerability, and operational challenges associated with AI adoption, justifying their integration into a shared risk dimension.

Finally, External Pressure, External Support, and Government Support were aggregated to represent the broader environmental context influencing adoption intention.

In contrast, Benefits, Costs, and Management Support were retained as separate variables due to their conceptual distinctiveness. Benefits capture expected strategic and operational value, Costs reflect anticipated resource burdens, and Management Support represents internal strategic commitment. Aggregating these variables with readiness-related factors would have reduced conceptual clarity by conflating capability with desirability and feasibility considerations. Retaining them separately therefore preserves theoretical differentiation within the stage-specific models. The following table presents an overview of the parsimonious model specification used in the stage-specific analyses:

Table 19: Mapping of Original Factors to the Parsimonious Composite Factors

Composite Factor	**Original Factor**
Organizational Readiness	Technological Readiness Compatibility Organizational Capability
unaltered	Management Support
unaltered	Costs
unaltered	Benefits
Technological Risk	AI-Complexity Cybersecurity Concerns
Environmental Influence	External Pressure External Support Government Support

5.4.2 Reliability Analysis

To ensure the reliability and internal consistency of the parsimonious model specification, the Cronbach's alpha was calculated for each composite variable within each pre-adoption stage. Values of .70 or higher are generally considered acceptable (Nunnally & Bernstein, 1994; Swanson & Holton, 2005). In the awareness stage, Cronbach's alpha ranged from .533 to .843, whereas in the consideration stage values ranged from .590 to .882 (see Appendix P). Overall, most variables demonstrate acceptable internal consistency. However, some coefficients fall below the recommended threshold of .60 for exploratory research (Hair et al., 2019), indicating limited reliability for specific constructs. Given the exploratory nature of stage-specific analyses and the reduced sample sizes, the results should therefore be interpreted with caution.

5.4.3 Descriptive Statistics

The descriptive statistics indicate noticeable differences across the pre-adoption stages (see Appendix Q). Given the substantially smaller sample size of the intention stage (n = 10), comparisons involving this stage should be interpreted with caution.

Organizational Readiness increases from the awareness stage (M = 2.928, SD = .586) to the consideration stage (M = 3.551, SD = .600) and remains relatively high in the intention stage (M = 3.400, SD = .503), suggesting higher perceived preparedness in more advanced stages. A similar pattern emerges for Management Support and Benefits. Management Support rises from awareness (M = 2.804, SD = .735) to consideration (M = 3.324, SD = .966), while Benefits increase markedly from awareness (M = 3.272, SD = .801) to the consideration stage (M = 3.971, SD = .883). Both variables remain elevated in the intention stage, although with slightly lower mean values.

In contrast, Costs increase only moderately from awareness (M = 2.967, SD = .700) to consideration (M = 3.154, SD = .683) and remain stable in the intention stage (M = 3.175, SD = .906). Technological Risk shows little variation across stages, while Environmental Influence exhibits a slight upward trend.

Overall, stage differences appear to be primarily associated with internal readiness, perceived benefits, and management support, whereas risk perceptions and external environmental influences remain comparatively stable.

5.4.4 Correlation Analysis

Comparing the three pre-adoption stages reveals a shift in the correlational structure of adoption intention. In both awareness (r = .629, p = .001) and consideration stage (r = .564, p < .001), Organizational Readiness shows a strong positive association with Intention to Adopt, indicating that internal capability is consistently linked to adoption intention in early stages. Management Support is also positively related to the adoption intention in both stages, although the relationship weakens from awareness (r = .552, p = .006) to consideration (r = .395, p = .021). A notable structural change emerges for Costs. While no meaningful association is observed in awareness (r = .126, p = .568), Costs become significantly and negatively related to the adoption intention in the consideration stage (r = -.351, p = .042), suggesting that financial considerations may become more salient once organizations move beyond initial awareness.

In the intention stage (n = 10), correlations are interpreted descriptively due to the limited sample size. Benefits exhibit the strongest positive association with Intention (r = .657, p = .039), whereas other relationships remain weak and non-significant.

Overall, the findings suggest that AI adoption intention in early pre-adoption stages is primarily associated with internal readiness and managerial support, while economic considerations become more relevant in the consideration phase (see Appendix R). The intention stage provides only limited additional evidence due to the sample size constraints.

5.4.5 Regression Assumptions

Prior to applying the parsimonious stage-specific regression models, the data for the awareness and consideration stages were examined separately for linearity, homoscedasticity, normality of standardized residuals, independence of errors (Swanson & Holton, 2005; Hair et al., 2019; Wentura et al., 2023). Additionally, influential outliers, multicollinearity, and autocorrelation were assessed (Backhaus et al., 2025). Overall, the regression assumptions were largely satisfied for both stages. For the awareness stage, diagnostic plots indicated a tendency toward heteroscedasticity. Although heteroscedasticity does not bias coefficient estimates, it reduces their efficiency and may lead to biased standard errors and test statistics (Wooldridge, 2009). Consequently, results for the awareness stage are interpreted with appropriate caution. Detailed results of the assumption checks are provided in the appendix (see Appendix S).

5.4.6 Multiple Linear Regression Awareness and Consideration

In the awareness stage, the regression model was statistically significant (F = 3.018, p = .036), with an R^2 of .531 and adjusted R^2 of .355. While the R^2 reflects the variance explained within the sample, the adjusted R^2 provides a more conservative estimate that accounts for model complexity and the small sample size (Hair et al., 2019; Backhaus et al., 2025), indicating that the model is able to explain 35.5% of the variance of the dependent variable.

Organizational Readiness (β = .389) and Management Support (β = .327) exhibit the strongest positive association with Intention to Adopt. Environmental Influence shows a small negative association (β = -.185), whereas Costs (β = .117), Benefits (β = .033) and Technological Risk (β = -.047) show only marginal effects. Given the limited sample size and potential heteroscedasticity, these findings should be interpreted as exploratory.

In the consideration stage, the regression model was statistically significant (F = 4.173, p = .004), with an R^2 of .481 and an adjusted R^2 of .366. This indicates that the model accounts for 36.6% of the variance in the dependent variable (Hair et al., 2019; Backhaus et al., 2025).

Organizational Readiness emerged as a statistically significant factor (β = .408, p = .014), indicating a robust positive effect on Intention to Adopt. Benefits (β = .245, p = .107) and Management Support (β = .223, p = .169) show moderate positive tendencies, while Costs (β = -.253, p = .124) demonstrate a moderate negative tendency. Technological Risk (β = -.033, p = .840) and Environmental Influence (β = -.035, p = .813) appear insubstantial.

The following summarizes the stage-specific regression results. A detailed regression output is provided in the Appendix T.

Table 20: Comparison of Standardized Regression Coefficients (β) for the Awareness and Consideration Stage

Variable	Awareness (β)	Consideration (β)
Organizational Readiness	.389	.408
Management Support	.327	.223
Costs	.117	-.253
Benefits	.033	.245
Technological Risk	-.047	-.033
Environmental Influence	-.185	-.035

Overall, cross-stage comparisons rely primarily on the direction and relative magnitude of standardized coefficients rather than on statistical significance. Given the small sample sizes and the slight heteroscedasticity identified in the awareness stage, these comparisons are interpreted cautiously and considered exploratory. Organizational Readiness shows positive associations in both stages (β = .389) and (β = .408), reaching statistical significance only in the consideration stage. The comparable magnitude suggests a relatively stable positive relationship. Management Support is positively related in both models β = .327 and β = .223, yet remains statistically non-significant. Costs differ across both stages, showing a small positive association in the awareness stage (β = .117) and a moderate negative association in the consideration stage (β = -.253). Although Costs were significantly correlated with the Intention to Adopt at the bivariate level in the consideration stage, the effect does not remain statistically significant in the regression model, indicating that the association may overlap with other variables. Technological Risk and Environmental Influence display small coefficients in both stages, indicating limited associations within the present sample when controlling for the remaining variables.

6 Discussion

This thesis examined the factors influencing the AI adoption intention among German SCM organizations. The following discussion interprets the results and situates the findings within the pre-adoption context.

The distribution of organizations across adoption stages indicates that AI within German SCM is predominantly situated in early-stage engagement. Most respondents locate their organizations in the consideration stage, suggesting that AI has entered strategic reflection and initial assessment, yet has not advanced to formal evaluation or routinized implementation. A substantial proportion remains in the awareness stage, where AI is acknowledged but not yet actively evaluated. Only a small group reports being in the intention stage or beyond. Overall, in regard to RQ4, AI appears broadly recognized within the German SCM context, but not yet institutionalized.

With regard to RQ5, the reported use cases reinforce this pattern. While some organizations describe clearly defined applications, particularly in forecasting, planning, and optimization, others refer to AI engagement in more exploratory or abstract terms. The coexistence of concrete and diffuse use-case descriptions indicates varying levels of concretization across organizations.

Across the pre-adoption context, Management Support emerges as the strongest determinant of AI adoption intention. This suggests that AI adoption intention is closely linked to executive commitment rather than primarily driven by technological characteristics. In this context, Management Support reflects tangible engagement by top leadership, including openly endorsing AI initiatives, allocating the necessary resources, recognizing potential benefits, and encouraging employees to use and apply AI in their daily work. The findings emphasize the role of concrete managerial action over abstract attitudes as it is not merely a favorable view of AI that matters, but the willingness to invest, prioritize, and actively promote its integration within SCM processes. This finding is consistent with prior research emphasizing the importance of top management support as a strong influencing factor of AI adoption and implementation in SCM contexts (Chatterjee et al., 2021; Usmani et al., 2023; Falayi et al., 2025; Dey et al., 2023). Similar effects have been also documented in organizational studies on AI adoption intention across different industry contexts (Thomas et al., 2025; Xu et al., 2025; Widiyanti et al. 2020). Moreover, general research on organizational innovation highlights the role of managerial orientation and organizational configurations that support innovation processes (Hage, 1999).

Compatibility likewise emerges as a significant determinant of AI adoption intention. Organizations are more likely to adopt AI when it is perceived as aligning with existing values, processes, and existing infrastructures, without requiring substantial structural adjustments. In SCM environments, where workflows and systems are highly standardized and interconnected, perceived misalignment may represent a meaningful barrier. Given the substantial long-term investments embedded in SCM infrastructures, compatibility with existing systems becomes particularly salient. Qualitative remarks from individual respondents further illustrate the normative dimension of compatibility. One participant noted concerns that an AI chatbot might face acceptance challenges among internal stakeholders. While anecdotal, such reflections indicate that perceived alignment, whether technical, procedural or normative, can shape the AI adoption intention in German SCM context. This is consistent with prior research emphasizing the importance of alignment with existing values, processes and systems in SCM contexts (Chatterjee et al., 2021; Usmani et al., 2023) to enhance assimilation and acceptance, and to reduce uncertainty. Furthermore, similar effects have been reported in organizational studies on AI adoption across different industry contexts (Ajili Ben Youssef et al., 2025; Badghish & Soomro, 2024).

While organizations recognizing strategic and operational advantages of AI tend to express higher adoption intentions at the bivariate level, Benefits do not retain independent explanatory power when other factors are considered. In contrast to prior research reporting strong effects of strategic and operational advantages (Chatterjee et al., 2021; Pillai et al., 2022; Usmani et al., 2023; Wang & Pan, 2022), the present findings suggest that perceived benefits alone are insufficient to substantially shape AI adoption intention in the German SCM pre-adoption context.

A similar pattern emerges for Technological Readiness. Although organizations with stronger IT infrastructures and AI-related capabilities tend to report higher adoption intentions at the bivariate level, this relationship does not remain statistically robust in the multivariate model. Empirical evidence in prior SCM context is heterogeneous, with some studies identifying significant effects of technological readiness (Chatterjee et al., 2021; Falayi et al., 2025; Usmani et al., 2023) on AI adoption, while others report non-significant findings in comparable operationalizations (Pillai et al., 2021). Within this sample, Technological Readiness does not constitute an independently decisive driver.

Additionally, Costs display a negative but statistically non-significant effect on AI adoption intention. Potential differences across adoption stages are considered in the subsequent stage-specific analyses. Although prior research frequently identifies cost considerations as a negative determinant of AI adoption (Usmani et al., 2023), empirical findings are not uniform. Evidence suggests that costs may be less pronounced or statistically non-significant in certain developed-country contexts (Badghish & Soomro, 2024) or may become more salient during actual implementation and usage phases (Pillai et al., 2022).

Organizational Capability shows a positive bivariate association with AI adoption intention, indicating that organizations with stronger internal competencies tend to express greater adoption intentions. However, its effect does not remain independently decisive when controlling other factors. Given its conceptual proximity to Management Support and Compatibility, Organizational Capability appears embedded within a broader constellation of internal organizational conditions rather than functioning as a distinct driver of adoption intention. This aligns with prior evidence suggesting digital skills and competencies do not necessarily exert a significant effect on the adoption decision of Industry 4.0 technologies in manufacturing contexts (Zhong & Moon, 2023), but may become more salient during implementation and post-adoption phases (Falayi et al., 2025; Dey et al., 2023; Chatterjee et al., 2021).

Similarly, AI-Complexity, Cybersecurity Concerns and environmental influences (External Pressure, External Support, and Government Support) do not emerge as independently decisive determinants in the present pre-adoption context. Although prior research frequently identifies technological risks (van Hoek, 2024; Singh et al., 2023; Nozari et al., 2022) and competitive pressure as relevant drivers of AI adoption in SCM (Chatterjee et al., 2021; Pillai et al., 2022; Wang & Pan, 2022; Falayi et al., 2025), these do not substantially shape adoption intention within this sample. Instead, the findings suggest that AI adoption intention in German SCM is primarily internally anchored rather than externally induced. The slight negative association observed for Government Support further indicates that perceived regulatory or institutional adequacy does not automatically result into stronger adoption intentions in the pre-adoption context. This finding is partly consistent with prior research that did not identify a statistically significant effect on AI adoption intention in SCM contexts (Pillai et al., 2022), despite reporting a positive relationship.

Taken together, the findings indicate that across the pre-adoption context of AI in German SCM, encompassing organizations from initial awareness to active evaluation, adoption intention is primarily associated with managerial support and perceived compatibility. While additional technological, organizational, and environmental factors display directional relationships, they do not demonstrate comparable explanatory relevance. This pattern highlights the selective concentration of determinants shaping AI adoption intention across early adoption stages in this sample.

With regard to RQ6, the exploratory stage-specific analyses indicate a structural shift in how AI adoption intention is formed across the pre-adoption process. In the awareness stage, intention appears to be primarily anchored in internal organizational conditions. Organizational Readiness and Management Support exhibit as the strongest factors of adoption intention, suggesting that early-stage intention is mainly grounded in perceived internal preparedness and leadership alignment rather than in explicit economic reasoning. Although Costs show a small positive association with adoption intention at the bivariate level, their independent explanatory power remains weak. Given that the Costs in this thesis included not only acquisition expenses but also ongoing maintenance and operational costs, it is plausible that such financial implications are not yet fully elaborated in this early stage. Cost perceptions may therefore reflect general engagement with the topic rather than acting as a barrier. At the bivariate level, Environmental Influence displays a negative relationship with adoption intention, indicating that externally driven pressure, governmental and external support may not translate into internally anchored commitment in the awareness stage and could instead reflect reactive positioning. Overall, this stage may appear to be embedded in internal alignment rather than structured by cost-benefit trade-offs. Given the relatively small subsample and slight heteroscedasticity, these patterns should be interpreted cautiously.

In contrast, the consideration stage reveals a more differentiated and evaluative structure. Organizational Readiness remains the strongest determinant, underscoring its consistent centrality across stages. However, Costs assume a clearly negative association, indicating that financial constraints begin to exert an independent influence as adoption intention becomes more concrete. At the same time, Benefits gain relative explanatory importance, suggesting that value expectations are more explicitly integrated into evaluations.

While Management Support remains positively related to adoption intention in the consideration stage, its relative weight is somewhat reduced compared to Organizational Readiness, which may indicate a functional shift in its role. Organizations that have moved beyond mere awareness and initially consider AI adoption have likely already obtained a basic level of managerial support to initiate such considerations. Consequently, variation in intention at this stage is less explained by whether leadership supports AI adoption and more by whether the organization perceives itself as capable of adopting it. Leadership commitment therefore remains important but becomes less differentiated once the consideration stage is entered.

Together, these patterns imply a transition from an orientation-driven logic in awareness toward a more economically grounded and evaluative decision structure in consideration, with Organizational Readiness functioning as structural determinant throughout the pre-adoption stages. The stage-specific differences identified in this thesis support the general process logic proposed by Rogers (1983) and Frambach & Schillewaert (2002) according to which adoption unfolds gradually from awareness to intention in pre-adoption context. At the same time, the findings indicate that the relative importance of determinants may shift across these stages, suggesting that adoption intention is shaped by evolving rather than static decision structures.

In regard to RQ1, the findings indicate that AI adoption intention among German SCM organizations is primarily influenced by internal organizational alignment. More particular, Management Support and Compatibility of AI with existing processes and structures form the central pillars of adoption intention. Other technological, organizational, and environmental factors appear to play a more contextual or supporting role rather than acting as primary drivers within the examined pre-adoption context. Moreover, stage-specific analyses suggest that the relative importance of determinants evolves across the pre-adoption process, with leadership commitment and internal alignment dominating early stages and feasibility and economic considerations gaining importance as adoption becomes more concrete.

7 Implications and Limitations

Building on the preceding discussion, the following chapter synthesizes the theoretical and practical contributions of this thesis and critically highlights its limitations, before recommending directions for future research.

7.1 Theoretical Contributions

The findings of this thesis extend the existing literature on AI adoption in SCM in several ways.

First it introduces and empirically tests a comprehensive conceptual framework consisting out of technological, organizational, and environmental determinants of AI adoption intention in German SCM. By synthesizing fragmented prior research and structuring dispersed factors into a conceptual model, the study provides a comprehensive overview of relevant factors of AI adoption and offers a foundation for further empirical research in comparable organizational contexts. Second, beyond the empirical model, the theoretical framework of this thesis systematically consolidates key foundations of individual-level technology acceptance research. By outlining central concepts of individual adoption processes and embedding them within an organizational adoption perspective, the study provides a conceptual basis that may enable future extensions of the framework toward multilevel analyses combining individual acceptance and organizational adoption research.

Third, the findings highlight the importance of internal organizational alignment for AI adoption intention. Management Support and Compatibility emerge as central determinants, while technological and environmental factors appear more contextual than independently decisive. This shifts the explanatory emphasis from technology-centered to organization-centered interpretations of AI adoption intention in pre-adoption contexts. In addition, by mapping organizations across adoption stages and identifying AI use cases across SCOR-related processes, the study offers insights into the current application areas and adoption maturity of AI in German SCM. The distribution within the examined sample suggests that AI adoption remains predominantly situated in early-stage phases of awareness and consideration. Fourth, by explicitly focusing on adoption intention in the pre-adoption phase and conducting exploratory stage-specific analyses, the study refines diffusion-based process perspectives. The results substantiate the stage logic proposed by Rogers (1983) and Frambach & Schillewaert (2002), while specifying how determinant relevance may vary between awareness and consideration.

7.2 Practical Contributions

Beyond its theoretical contributions, the thesis offers a practical orientation for decision-makers in SCM, digital transformation roles, and AI solution providers.

A central practical implication concerns the role of internal organizational alignment. The AI adoption intention in German SCM appears primarily rooted in management support and perceived compatibility. AI initiatives gain strategic traction through visible executive prioritization and endorsement. Moreover, organizations appear to evaluate AI in terms of its fit with existing structures and processes. For AI solution providers and consultants, this underscores that demonstrating seamless integration and alignment with established SCM processes and structures may be more influential than emphasizing performance gains or technical sophistication alone.

Furthermore, external influences do not constitute primary triggers of early adoption intention in German SCM contexts. Instead, adoption intention appears to be internally motivated and strategically grounded. For practitioners and consultants, this implies that successful positioning of AI initiatives requires the development of a clear internal strategic rationale rather than reliance on external momentum or market narratives. In addition, the stage-specific analyses indicate that the relative relevance of determinants differs across adoption stages, suggesting that communication and positioning strategies should reflect the evaluative focus associated with an organization's current stage within the adoption process.

Finally, the descriptive mapping of adoption stages and AI use cases offers a reference point for practitioners seeking to assess their organization's current level of AI engagement.

7.3 Limitations and Future Research

Although its findings, this thesis is constrained by multiple limitations and identifies areas for further and future research.

The empirical analysis used a relatively small sample of 67 respondents within German SCM-related functions. As the sample lies at the lower range of commonly recommended sample sizes for regression models with eleven variables (Hair et al., 2019), statistical power is inherently constrained, particularly in the stage-specific analyses with substantially smaller subsamples. In addition, the regional focus on German organizations limits the capability to generalize the findings to other regional contexts. Future research could replicate the model with larger and more diverse samples and examine cross-country, industry-specific, or SCOR-process-related differences. Although firm size and industry type were collected, they were not included as control variables. Incorporating such structural characteristics may further clarify whether organizational context moderates the identified relationships.

The study relies on cross-sectional, self-reported survey data. Adoption stages and determinant perceptions were assessed through respondent self-classification, which can lead to the risk of common method variance and perceptual bias. Moreover, the analysis focuses on adoption intention rather than realized implementation or performance outcomes. Longitudinal designs could therefore examine how determinants develop over time and focus on how intention results into actual adoption and implementation success. Additionally, qualitative approaches could provide deeper insights into underlying decision processes shaping AI adoption intention.

A further limitation concerns the broad conceptualization of AI in this study, as adoption intention was assessed at a general level without differentiating between specific AI applications. Given the heterogeneity of AI applications, determinant relevance may vary across use cases, potentially reducing the specificity of the findings.

The exploratory stage-specific analyses were conducted on reduced subsamples, and a heteroscedasticity tendency was observed in the awareness stage, while software limitations precluded the use of robust standard errors. Moreover, selected variables were aggregated in the parsimonious stage-specific model based on conceptual proximity. Although reliability was assessed, some constructs showed limited internal consistency. These aspects suggest cautious interpretation of stage-specific findings. Future research could apply alternative estimation techniques and validate construct structure through confirmatory factor analysis.

Finally, although the sample covered organizations across different engagement levels, potential non-response bias cannot be fully excluded. Moreover, while the theoretical framework integrates insights from individual-level adoption research, the empirical analysis remains at the organizational level. Extending the framework toward multilevel designs may provide deeper insights into cross-level dynamics in AI adoption.

8 Conclusion

This thesis examined the influencing factors of AI adoption intention among German SCM organizations in a pre-adoption context. By empirically testing an comprehensive framework of technological, organizational, and environmental factors, the thesis provides a structured perspective on the determinants shaping adoption intention prior to formal adoption decisions.

The findings suggest that early AI engagement in German SCM is primarily shaped by managerial commitment and the perceived compatibility of AI with existing organizational structures and processes. Moreover, stage-specific findings indicate that determinant relevance evolves as organizations move through the pre-adoption process.

In light of the growing strategic relevance attributed to AI in SCM, the findings underscore that future developments in German SCM will depend not on the awareness or technical ability, but more on the organizational willingness to translate emerging possibilities into strategic commitment. Understanding how adoption intention forms therefore remains central to assessing how AI progresses from strategic consideration to sustained organizational application.

9 References

Abdulla, A., Baryannis, G., & Badi, I. (2023). An integrated machine learning and MARCOS method for supplier evaluation and selection. *Decision Analytics Journal*, *9,* 100342. https://doi.org/10.1016/j.dajour.2023.100342

Abulail, R. N., Badran, O. N., Shkoukani, M. A., & Omeish, F. (2025). Exploring the factors influencing AI adoption intentions in higher education: An integrated model of DOI, TOE, and TAM. *Computers*, *14*(6), 230. https://doi.org/10.3390/computers14060230

Ahmed, S. K. (2024). How to choose a sampling technique and determine sample size for research: A simplified guide for researchers. *Oral Oncology Reports, 12*, 100662. https://doi.org/10.1016/j.oor.2024.100662

Ahn, B., & Ahn, H. (2020). Factors affecting intention to adopt cloud-based ERP from a comprehensive approach. *Sustainability*, *12*(16), 6426. https://doi.org/10.3390/su12166426

Ajili Ben Youssef, W., Bouebdallah, N., & Long, H. (2025). Factors influencing generative artificial intelligence adoption in Vietnam's banking sector: An empirical study. *Financial Innovation, 11*, Article 119. https://doi.org/10.1186/s40854-025-00788-7

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Alnipak, S., & Toraman, Y. (2025). I am ChatGPT – Would you accept me to assist you in logistics management? An empirical study from Türkiye. *LogForum, 21*(3), 473–491. https://doi.org/10.17270/J.LOG.001251

Amit, R., & Schoemaker, P. J. H. (1993). Strategic assets and organizational rent. *Strategic Management Journal*, *14*(1), 33–46. https://doi.org/10.1002/smj.4250140105

APICS (2017). *Quick reference guide: SCOR – Supply Chain Operations Reference Model. APICS.*

Atwani, M., Hlyal, M., & Elalami, J. (2022). A review of artificial intelligence applications in supply chain (2022). *ITM Web of Conferences*, *46*, 03001. https://doi.org/10.1051/itmconf/20224603001

Backhaus, K., Erichson, B., Gensler, S., Weiber, R., & Weiber, T. (2025). *Multivariate Analysemethoden: Eine anwendungsorientierte Einführung* (18th ed.). Springer. https://doi.org/10.1007/978-3-642-14987-0

Backhaus, K., Erichson, B., Pinke, W., & Weiber, R. (2018). *Multivariate Analysemethoden: Eine anwendungsorientierte Einführung* (15th ed.). Springer. https://doi.org/10.1007/978-3-662-56655-8

Badghish, S., & Soomro, Y. A. (2024). Artificial intelligence adoption by SMEs to achieve sustainable business performance: Application of technology–organization–environment framework. *Sustainability*, *16*(5), 1864. https://doi.org/10.3390/su16051864

Baker, J. (2011). The technology–organization–environment framework. In Y. K. Dwivedi, M. R. Wade, & S. L. Schneberger (Eds.), *Information systems theory: Explaining and predicting our digital society* (Vol. 1, pp. 231–245). Springer. https://doi.org/10.1007/978-1-4419-6108-2_12

Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2019). Supply chain risk management and artificial intelligence: State of the art and future research directions. *International Journal of Production Research*, *57*(7), 2179–2202. https://doi.org/10.1080/00207543.2018.1530476

Becker, T. (2024). *Strategische Gestaltung und Digitalisierung der Supply Chain: Wettbewerbsvorteile mit der digitalen Supply Chain erzielen*. Springer Vieweg. https://doi.org/10.1007/978-3-662-68627-0

Bitkom (2025, September 15). *Durchbruch bei Künstlicher Intelligenz. https://www.bitkom.org/Presse/Presseinformation/Durchbruch-Kuenstliche-Intelligenz#ll_unterlagen_pk_ki_2025*

Bitkom e.V. (2022, October 5). *Jedes fünfte Logistikunternehmen setzt Künstliche Intelligenz ein*. https://www.bitkom.org/Presse/Presseinformation/Jedes-fuenfte-Logistikunternehmen-setzt-Kuenstliche-Intelligenz-ein

Bitkom Research. (2021). *Nachhaltig geht nur digital: Wie Deutschland mit KI und Co. die Zukunft gestaltet*. Tata Consultancy Services. https://bitkom-research.de/node/687

Booth, A., Sutton, A., & Papaioannou, D. (2016). *Systematic approaches to a successful literature review* (2nd ed.). Sage Publications.

Bowersox, D. J., Closs, D. J., & Cooper, M. B. (2002). *Supply chain logistics management*. McGraw-Hill Higher Education.

Bundesverband Materialwirtschaft, Einkauf und Logistik e.V. (BME). (2025). *BME-Logistikstudie 2025: Digitalisierung und Künstliche Intelligenz in Supply Chains*. https://www.bme.de/fachinformationen/bme-logistikstudie-2025/

Buxmann, P., & Schmidt, H. (2021). Grundlagen der Künstlichen Intelligenz und des maschinellen Lernens. In P. Buxmann & H. Schmidt (Eds.), *Künstliche Intelligenz: Mit Algorithmen zum wissenschaftlichen Erfolg* (pp. 3–22). Springer Gabler. https://doi.org/10.1007/978-3-662-61794-6

Cannas, V. G., Ciano, M. P., Saltalamacchia, M., & Secchi, R. (2023). Artificial intelligence in supply chain and operations management: A multiple case study research. *International Journal of Production Research, 62*(9), 3333–3360. https://doi.org/10.1080/00207543.2023.2232050

Chatterjee, S., Rana, N. P., Dwivedi, Y. K., & Baabdullah, A. M. (2021). Understanding AI adoption in manufacturing and production firms using an integrated TAM–TOE model. *Technological Forecasting and Social Change, 170*, 120880. https://doi.org/10.1016/j.techfore.2021.120880

Chen, J., Dai, J., Yu, T., & Wang, C. (2025). Factors influencing the adoption of generative AI in supply chain management: An empirical study based on task–technology fit and the theory of planned behaviour. *International Journal of Logistics Research and Applications*. https://doi.org/10.1080/13675567.2025.2520550

Chopra, S., & Meindl, P. (2016). *Supply chain management: Strategy, planning, and operation* (6th ed.). Pearson Education Limited.

Christopher, M. (2016). *Logistics & supply chain management* (5th ed.). Pearson Education Limited.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Council of Supply Chain Management Professionals (CSCMP). (n.d.). *SCM definitions and glossary of terms*. Retrieved February 27, 2026, from https://cscmp.org/CSCMP/cscmp/educate/scm_definitions_and_glossary_of_terms.aspx

Creswell, J. W. (2009). *Research design: Qualitative, quantitative, and mixed methods approaches* (3rd ed.). SAGE Publications.

Culot, G., Podrecca, M., & Nassimbeni, G. (2024). Artificial intelligence in supply chain management: A systematic literature review of empirical studies and research directions. *Computers in Industry*, *162,* 104132. https://doi.org/10.1016/j.compind.2024.104132

Daios, A., Kladovasilakis, N., Kelemis, A., & Kostavelis, I. (2025). AI applications in supply chain management: A survey. *Applied Sciences*, *15*(5), 2775. https://doi.org/10.3390/app15052775

Damanpour, F., & Schneider, M. (2006). Phases of the adoption of innovation in organizations: Effects of environment, organization, and top managers. *British Journal of Management, 17*(3), 215–236. https://doi.org/10.1111/j.1467-8551.2006.00498.x

Damioli, G., Van Roy, V., Vertesy, D., & Vivarelli, M. (2024). Is artificial intelligence leading to a new technological paradigm? *Structural Change and Economic Dynamics*, *72*, 347–359. https://doi.org/10.1016/j.strueco.2024.12.006

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982

Dawes, J. (2008). Do data characteristics change according to the number of scale points used? An experiment using 5-point, 7-point and 10-point scales. *International Journal of Market Research*, *50*(1), 61–104. https://doi.org/10.1177/147078530805000106

DeVellis, R. F. (2017). *Scale development: Theory and applications* (4th ed.). SAGE Publications.

Dey, P. K., Chowdhury, S., Abadie, A., Yaroson, E. V., & Sarkar, S. (2023). Artificial intelligence-driven supply chain resilience in Vietnamese manufacturing small- and medium-sized enterprises. *International Journal of Production Research, 61*(16), 5417–5456. https://doi.org/10.1080/00207543.2023.2179859

ERA Group. (2024). *Langer Weg zum Unternehmen 5.0: Künstliche Intelligenz mit geringem Durchdringungsgrad in Unternehmen*. https://de.eragroup.com/studie-ki/

Ertel, W. (2025). *Grundkurs Künstliche Intelligenz: Eine praxisorientierte Einführung* (6th ed.). Springer Vieweg. https://doi.org/10.1007/978-3-658-44955-1

European Parliament. (2023). *What is artificial intelligence and how is it used?* https://www.europarl.europa.eu/topics/en/article/20200827STO85804/what-is-artificial-intelligence-and-how-is-it-used

European Union (2022). *Directive (EU) 2022/2464 of the European Parliament and of the Council of 14 December 2022 amending Regulation (EU) No 537/2014, Directive 2004/109/EC, Directive 2006/43/EC and Directive 2013/34/EU, as regards corporate* *sustainability reporting (Corporate Sustainability Reporting Directive).* https://eur-lex.europa.eu/eli/dir/2022/2464/oj/eng

European Union (2024a). *Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence and amending Regulations (EC) No 300/2008, (EU) No 167/2013, (EU) No 168/2013, (EU) 2018/858, (EU) 2018/1139 and (EU) 2019/2144 and Directives 2014/90/EU, (EU) 2016/797 and (EU) 2020/1828 (Artificial Intelligence Act).* https://eur-lex.europa.eu/eli/reg/2024/1689/oj

European Union (2024b). *Directive (EU) 2024/1760 of the European Parliament and of the Council of 13 June 2024 on Corporate Sustainability Due Diligence and amending Directive (EU) 2019/1937 and Regulation (EU) 2023/2859.* https://eur-lex.europa.eu/eli/dir/2024/1760/oj

Falayi, T. B., Olugbade, A., Ologun, V., John, S., & Okirikiri, N. (2025). Brains behind the chains: Exploring the drivers of artificial intelligence (AI) in modern supply chain management success. *International Journal of Computer Applications, 187*(40), 8–18. https://doi.org/10.5120/ijca2025925704

Falck, O., Kerkhof, A., & Wölfl, A. (2024). *Künstliche Intelligenz (KI): Verbreitung, Anwendungen und Hindernisse in Deutschland im europäischen Vergleich*. ifo Institut. https://www.ifo.de/publikationen/2024/monographie-autorenschaft/kuenstliche-intelligenz-ki-verbreitung-anwendung

Faustine, P., & Rachmawati, R. (2024). AI adoption determinants and its impacts on HRM effectiveness within MES in Tanzania. *Open Journal of Business and Management*, *12*, 2532–2552. https://doi.org/10.4236/ojbm.2024.124131

Federal Republic of Germany (2021). *Supply Chain Act: Act on Corporate Due Diligence Obligations in Supply Chains (Lieferkettensorgfaltspflichtengesetz – LkSG). https://www.csr-in-deutschland.de/EN/Business-Human-Rights/Supply-Chain-Act/supply-chain-act.html*

Field, A. (2009). *Discovering statistics using SPSS* (3rd ed.). SAGE Publications.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research*. Addison-Wesley.

Fosso Wamba, S., Guthrie, C., Queiroz, M. M., & Minner, S. (2024). ChatGPT and generative artificial intelligence: An exploratory study of key benefits and challenges in operations and supply chain management. *International Journal of Production Research, 62*(16), 5676–5696. https://doi.org/10.1080/00207543.2023.2294116

Foster, L., Sloan, L., Clark, T., & Bryman, A. (2021). *Bryman's social research methods* (6th ed.). Oxford University Press.

Frambach, R. T., & Schillewaert, N. (2002). Organizational innovation adoption: A multi-level framework of determinants and opportunities for future research. *Journal of Business Research, 55*(2), 163–176. https://doi.org/10.1016/S0148-2963(00)00152-1

Fries, M., & Ludwig, T. (2024). "Why are the sales forecasts so low?" Socio-technical challenges of using machine learning for forecasting sales in a bakery. *Computer Supported Cooperative Work (CSCW), 33*(2), 253–293. https://doi.org/10.1007/s10606-022-09458-z

Fries, M., Nießner, J., Ludwig, T., & Kotthaus, C. (2025). Exploring AI integration in SME production planning: Design spaces and the role of workers. *Computer Supported Cooperative Work (CSCW), 34*(2), 293–330. https://doi.org/10.1007/s10606-025-09512-6

Future Today Institute. (2023). *2023 tech trend report* (16th ed.).

Gallivan, M. J. (2001). Organizational adoption and assimilation of complex technological innovations: Development and application of a new framework. *Database for Advances in Information Systems, 32*(3), 51–85. https://doi.org/10.1145/506724.506729

Gangwar, H., Date, H., & Ramaswamy, R. (2015). Understanding determinants of cloud computing adoption using an integrated TAM-TOE model. *Journal of Enterprise Information Management, 28*(1), 107–130. https://doi.org/10.1108/JEIM-08-2013-0065

Gartner. (2022). *What's new in the 2022 Gartner hype cycle for emerging technologies*. https://www.gartner.com/en/articles/what-s-new-in-the-2022-gartner-hype-cycle-for-emerging-technologies

Gartner. (2023). *What's new in the 2023 Gartner hype cycle for emerging technologies*. https://www.gartner.com/en/articles/what-s-new-in-the-2023-gartner-hype-cycle-for-emerging-technologies

Gartner. (2024). *Spotlight on 2024 Gartner hype cycle for emerging technologies*. https://www.gartner.com/en/articles/hype-cycle-for-emerging-technologies

Géron, A. (2022). *Hands-on machine learning with scikit-learn, Keras, and TensorFlow: Concepts, tools, and techniques to build intelligent systems* (3rd ed.). O'Reilly.

Ghobakhloo, M., Arias-Aranda, D., & Benitez-Amado, J. (2011). Adoption of e-commerce applications in SMEs. *Industrial Management & Data Systems*, *111*(8), 1238–1269. https://doi.org/10.1108/02635571111170785

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press. https://www.deeplearningbook.org/

Gursoy, D., & Cai, R. (2025). Artificial intelligence: An overview of research trends and future directions. *International Journal of Contemporary Hospitality Management, 37*(1), 1–17. https://doi.org/10.1108/IJCHM-03-2024-0322

Hage, J. (1999). Organizational innovation and organizational change. *Annual Review of Sociology, 25*, 597–622. https://doi.org/10.1146/annurev.soc.25.1.597

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.

Hakami, T. A., Alginahi, Y. M., & Sabri, O. (2025). Exploring the evolution of big data technologies: A systematic literature review of trends, challenges, and future directions. Future Internet, *17*(9), 427. https://doi.org/10.3390/fi17090427

Handelsverband Deutschland e.V. (HDE), & Safaric Consulting GmbH. (2025). *Künstliche Intelligenz im Handel: Umfrage zum KI-Einsatz 2025*. https://digitalzentrumhandel.de/kuenstliche-intelligenz-im-handel/

Hanne, T., & Dornberger, R. (2017). *Computational intelligence in logistics and supply chain management*. Springer Cham. https://doi.org/10.1007/978-3-319-40722-7

Harland, C. (2024). *Supply chain management: Concepts, challenges and future research directions*. Springer. https://doi.org/10.1007/978-3-031-52247-5

Hemmerich, W. (2019). *StatistikGuru: Poweranalyse und Stichprobenberechnung für Regr ession*. https://statistikguru.de/rechner/poweranalyse-regression.html

INFORM Software. (2025, November 4). *Studie zu KI-Agenten in Logistik und Supply Chain: Hohe Akzeptanz, aber klare Spielregeln gefordert*. https://www.inform-software.com/de/news/addone/studie-zu-ki-agenten-in-logistik-und-supply-chain-hohe-akzeptanz-aber-klare-spielregeln-gefordert

Jeyaraj, A., Dwivedi, Y. K., & Venkatesh, V. (2023). Intention in information systems adoption and use: Current state and research directions. *International Journal of Information Management, 73*, 102680. https://doi.org/10.1016/j.ijinfomgt.2023.102680

Jo, T. (2021). *Machine learning foundations: Supervised, unsupervised, and advanced learning*. Springer. https://doi.org/10.1007/978-3-030-65900-4

Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or not, AI comes—An interview study of organizational AI readiness factors. *Business & Information Systems Engineering, 63*(1), 5–20. https://doi.org/10.1007/s12599-020-00676-7

Jurafsky, D., & Martin, J. H. (2026). *Speech and language processing: An introduction to natural language processing, computational linguistics, and speech recognition with language models* (3rd ed.). https://web.stanford.edu/~jurafsky/slp3/

Kahraman, C., Cebeci, U., & Ulukan, Z. (2003). Multi-criteria supplier selection using fuzzy AHP. *Logistics Information Management*, *16*(6), 382–394. https://doi.org/10.1108/09576050310503367

Kempcke, T. (2021). *KI im Supply-Chain-Management des Handels*. EHI Retail Institute. https://www.relexsolutions.com/de/fachbeitraege/studie-zu-ki-im-handel-das-interesse-ist-gross-die-umsetzung-noch-gering/

Khanfar, A., Kiani, M. R., Iranmanesh, M., & Gengatharen, D. (2024). Determinants of artificial intelligence adoption: Research themes and future directions. *Information Technology and Management.* https://doi.org/10.1007/s10799-024-00435-0

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2017). ImageNet classification with deep convolutional neural networks. *Communications of the ACM, 60*(6), 84–90. https://doi.org/10.1145/3065386

Krosnick, J. A. (1991). Response strategies for coping with the cognitive demands of attitude measures in surveys. *Applied Cognitive Psychology, 5*, 213–236. https://doi.org/10.1002/acp.2350050305

Kutner, M. H., Nachtsheim, C. J., Neter, J., & Li, W. (2005). *Applied linear statistical models* (5th ed.). McGraw-Hill/Irwin.

Lambert, D. M., Cooper, M. C., & Pagh, J. D. (1998). Supply chain management: Implementation issues and research opportunities. *The International Journal of Logistics Management, 9*(2), 1–20. https://doi.org/10.1108/09574099810805807

Likert, R. (1932). A technique for the measurement of attitudes. *Archives of Psychology, 22*(140), 5–55.

Low, C., Chen, Y., & Wu, M. (2011). Understanding the determinants of cloud computing adoption. *Industrial Management & Data Systems, 111*(7), 1006–1023. https://doi.org/10.1108/02635571111161262

Maduku, D. K., Mpinganjira, M., & Duh, H. (2016). Understanding mobile marketing adoption intention by South African SMEs: A multi-perspective framework. *International Journal of Information Management, 36*(5), 711–723. https://doi.org/10.1016/j.ijinfomgt.2016.04.018

Magyar, J. (2025, August 19). *SAP BrandVoice: The next tech supercycle is shaping the future of financial services*. Forbes. https://www.forbes.com/sites/sap/2025/08/19/the-next-tech-supercycle-is-shaping-the-future-of-financial-services

Mahmud, P., Paul, S. K., Azeem, A., & Chowdhury, P. (2021). Evaluating supply chain collaboration barriers in small- and medium-sized enterprises. *Sustainability, 13*(13), 7449. https://doi.org/10.3390/su13137449

Marfo, J., Asamoah, P., Owusu-Bio, M., Marfo, A., & Kyeremeh, K. (2023). *Exploring factors affecting the adoption and continuance usage of drone in healthcare: The role of the environment*. https://doi.org/10.1101/2023.05.04.23289511

Marsland, S. (2015). *Machine learning: An algorithmic perspective* (2nd ed.). Chapman & Hall/CRC. https://doi.org/10.1201/b17476

Maslej, N., Fattorini, L., Perrault, R., Gil, Y., Parli, V., Kariuki, N., Capstick, E., Reuel, A., Brynjolfsson, E., Etchemendy, J., Ligett, K., Lyons, T., Manyika, J., Niebles, J. C., Shoham, Y., Wald, R., Walsh, T., Hamrah, A., Santarlasci, L., … Oak, S. (2025). *The AI Index 2025 annual report*. AI Index Steering Committee, Institute for Human-Centered AI, Stanford University. https://doi.org/10.48550/arXiv.2504.07139

Mayring, Philipp. (2014). *Qualitative content analysis: Theoretical foundation, basic procedures and software solution.* https://nbn-resolving.org/urn:nbn:de:0168-ssoar-395173

McCarthy, J. (2007). *What is artificial intelligence?* https://www-formal.stanford.edu/jmc/

McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (1955). *A proposal for the Dartmouth summer research project on artificial intelligence*. Dartmouth College.

McKinnie, M. (2016). *Cloud Computing: TOE adoption factors by service model in manufacturing.* Dissertation, Georgia State University.

Mediavilla, M. A., Dietrich, F., & Palm, D. (2022). Review and analysis of artificial intelligence methods for demand forecasting in supply chain management. *Procedia CIRP, 107*, 1126–1131. https://doi.org/10.1016/j.procir.2022.05.119

Mentzer, J. T., DeWitt, W., Keebler, J. S., Min, S., Nix, N. W., Smith, C. D., & Zacharia, Z. G. (2001). Defining supply chain management. *Journal of Business Logistics, 22*(2), 1–25. https://doi.org/10.1002/j.2158-1592.2001.tb00001.x

Mishra, D., Muduli, K., Raut, R., Narkhede, B. E., Shee, H., & Jana, S. K. (2023). Challenges facing artificial intelligence adoption during COVID-19 pandemic: An investigation into the agriculture and agri-food supply chain in India. *Sustainability, 15*(8), 6377. https://doi.org/10.3390/su15086377

Mitchell, T. M. (1997). *Machine learning*. McGraw-Hill.

Mockenhaupt, A., & Schlagenhauf, T. (2024). *Digitalisierung und Künstliche Intelligenz in der Produktion*. Springer Vieweg. https://doi.org/10.1007/978-3-658-41935-6

Murphy, K. P. (2012). *Machine learning: a probabilistic perspective.* MIT Press.

Nikiforova, A., Lnenicka, M., Luterek, M., Milic, P., & Bolívar Rodríguez, M. P. (2025). Theorizing the evolution of public data ecosystems: An empirically grounded multi-generational model and future research agenda. *Government Information Quarterly, 42*(3), 102062. https://doi.org/10.1016/j.giq.2025.102062

Nilsson, N. J. (1998). *Artificial intelligence: A new synthesis*. Morgan Kaufmann. https://doi.org/10.1016/C2009-0-27773-7

Nitsche, B., Brands, J., Treiblmaier, H., & Gebhardt, J. (2023). The impact of multiagent systems on autonomous production and supply chain networks: Use cases, barriers and contributions to logistics network resilience. *Supply Chain Management: An International Journal, 28*(5), 894–908. https://doi.org/10.1108/SCM-07-2022-0282

Norman, G. (2010). Likert scales, levels of measurement and the “laws” of statistics. *Advances in Health Science Education, 15,* 625–632. https://doi.org/10.1007/s10459-010-9222-y

Nozari, H., Szmelter-Jarosz, A., & Ghahremani-Nahr, J. (2022). Analysis of the challenges of artificial intelligence of things (AIoT) for the smart supply chain (case study: FMCG industries). *Sensors, 22*(8), 2931. https://doi.org/10.3390/s22082931

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

Oliveira, T., & Martins, M.F. (2011). Literature review of information technology adoption models at firm level. *The Electronic Journal Information Systems Evaluation, 14*(1), 110–121.

Ouyang, L., Wu, J., Jiang, X., Almeida, D., Wainwright, C., Mishkin, P., Zhang, C., Agarwal, S., Slama, K., Ray, A., Schulman, J., Hilton, J., Kelton, F., Miller, L., Simens, M., Askell, A., Welinder, P., Christiano, P., Leike, J., & Lowe, R. (2022). *Training language models to follow instructions with human feedback*. arXiv. https://arxiv.org/abs/2203.02155

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372*, n71. https://doi.org/10.1136/bmj.n71

Pan, H., Zou, N., Wang, R., Ma, J., & Liu, D. (2025). Artificial intelligence usage and supply chain resilience: An organizational information processing theory perspective. *Systems, 13*(9), 724. https://doi.org/10.3390/systems13090724

Petticrew, M., & Roberts, H. (2006). *Systematic reviews in the social sciences: A practical guide.* Blackwell Publishing. https://doi.org/10.1002/9780470754887

Phillips, L. W. (1981). Assessing measurement error in key informant reports: A methodological note on organizational analysis in marketing. *Journal of Marketing Research, 18*(4), 395–415. https://doi.org/10.2307/3151333

Pillai, R., Sivathanu, B., Mariani, M. M., Rana, N. P., Yang, B., & Dwivedi, Y. K. (2021). Adoption of AI-empowered industrial robots in auto component manufacturing companies. *Production Planning & Control, 33*(10–11), 1517–1533. https://doi.org/10.1080/09537287.2021.1882689

Pournader, M., Ghaderi, H., Hassanzadegan, & Fahimnia, B. (2021). Artificial intelligence applications in supply chain management. *International Journal of Production Economics*, *241,* 108250. https://doi.org/10.1016/j.ijpe.2021.108250

Premkumar, G., & Roberts, M. (1999). Adoption of new information technologies in rural small businesses. *Omega, 27*(4), 467–484. https://doi.org/10.1016/S0305-0483(98)00071-1

Preston, C. C., & Colman, A. M. (2000). Optimal number of response categories in rating scales: Reliability, validity, discriminating power, and respondent preferences. *Acta Psychologica, 104*(1), 1–15. https://doi.org/10.1016/S0001-6918(99)00050-5

Rad, F., Oghazi, P., İzmir, O., & Kordestani, A. (2025). Adoption of AI-based order picking in warehouse: Benefits, challenges, and critical success factors. *Review of Managerial Science, 19*(5), 3495–3540. https://doi.org/10.1007/s11846-025-00858-1

Richey, R.G., Chowdhury, S., Davis-Sramek, B., Giannakis, M., & Dwivedi, Y. (2023). Artificial intelligence in logistics and supply chain management: A primer and roadmap for research. *Journal of Business Logistics*, *44*(4), 532–549. https://doi.org/10.1111/jbl.12364

Rogers, E. M. (1983). *Diffusion of innovations* (3rd ed.). The Free Press.

Russell, S. J., & Norvig, P. (2022). *Artificial intelligence: A modern approach* (4th ed., Global ed.). Pearson Education Limited.

Saghafian, M., Laumann, K., & Skogstad, M. R. (2021). Stagewise overview of issues influencing organizational technology adoption and use. *Frontiers in Psychology, 12*, 630145. https://doi.org/10.3389/fpsyg.2021.630145

Saha, R., Shofiullah, S., Faysal, S. A., & Happy, A.T. (2024). Systematic literature review on artificial intelligence applications in supply chain demand forecasting. *Academic Journal on Business Administration Innovation & Sustainability*, *4*(4), 109–127. https://doi.org/10.69593/ajbais.v4i04.136

Sharma, R., Shishodia, A., Gunasekaran, A., Min, H., & Munim, Z. H. (2022). The role of artificial intelligence in supply chain management: mapping the territory. *International Journal of Production Research*, *60*(24), 7527–7751. https://doi.org/10.1080/00207543.2022.2029611

Simchi-Levi, D., Kaminsky, P., & Simchi-Levi, E. (2000). *Designing and managing the supply chain: Concepts, strategies, and case studies*. McGraw-Hill.

Singh, A., Dwivedi, A., Agrawal, D., & Singh, D. (2023). Identifying issues in adoption of AI practices in construction supply chains: Towards managing sustainability. *Operations Management Research, 16*, 1667–1683. https://doi.org/10.1007/s12063-022-00344-x

Somapa, S., Cools, M., & Dullaert, W. (2018). Characterizing supply chain visibility – a literature review. *The International Journal of Logistics Management, 29*(1), 308–339. https://doi.org/10.1108/IJLM-06-2016-0150

Statista. (2024, September). *KI in deutschen Unternehmen: Einsatz von Künstlicher Intelligenz in deutschen Unternehmen in Hinblick auf Potenziale, Herausforderungen und Voraussetzungen*. https://de.statista.com/statistik/studie/id/173446/dokument/ki-in-deutschen-unternehmen/

Swanson, R. A., & Holton, E. F., III (2005). *Research in organizations: Foundations and methods of inquiry.* Berrett Koehler Publications.

Tan, K. C., Kannan, V. R., & Handfield, R. B. (1998). Supply chain management: A survey of current practice in the US. *International Journal of Purchasing & Materials Management, 34*(3), 2–9.

Teixeira, A. R., Ferreira, J. V., & Ramos, A. L. (2025). Intelligent supply chain management: A systematic literature review on artificial intelligence contributions. *Information*, *16*(5), 399. https://doi.org/10.3390/info16050399

Thomas, G., Albishri, N. A., Islam, J. U., & Tanveer, M. (2025). Exploring the determinants of artificial intelligence adoption intention in the SMEs of United Arab Emirates. *SAGE Open, 15*(4), Article 21582440251395561. https://doi.org/10.1177/21582440251395561

Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation.* Lexington Books.

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *British Journal of Management*, *14*(3), 207–222. https://doi.org/10.1111/1467-8551.00375

Ucar, A., Karakose, M., & Kırımça, N. (2024). Artificial intelligence for predictive maintenance applications: Key components, trustworthiness, and future trends. *Applied Sciences*, *14*(2), 898. https://doi.org/10.3390/app14020898

Ullrich, K. (2022, December 22). *Germany's close integration into global trade and value chains*. KfW Research. https://www.kfw.de/About-KfW/Newsroom/Latest-News/News-Details_741120.html

Urban, D., & Mayerl, J. (2018). *Angewandte Regressionsanalyse: Theorie, Technik und Praxis*. Springer VS. https://doi.org/10.1007/978-3-658-01915-0_2

Usmani, A., Sharma, M., Bung, P., Rakesh, D., Ahmad, F., & Gupta, A. (2023). Key variables influencing artificial intelligence (AI) implementation in supply chain management (SCM): An empirical analysis on SMEs. *Migration Letters, 20*(S11), 1284–1307. https://doi.org/10.59670/ml.v20iS11.9083

van Hoek, R. (2024). Insight from industry: Early lessons learned about AI adoption in core procurement processes, directions for managers and researchers. *Supply Chain Management: An International Journal, 29*(4), 794–803. https://doi.org/10.1108/SCM-02-2024-0143

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). *Attention is all you need.* arXiv. https://arxiv.org/abs/1706.03762

Venkatesh, V., Morris, M.G., Davis, G.B., & Davis, F.D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

Wang, M., & Pan, X. (2022). Drivers of artificial intelligence and their effects on supply chain resilience and performance: An empirical analysis on an emerging market. *Sustainability, 14*(24), 16836. https://doi.org/10.3390/su142416836

Webb, A., & Jordan, S. (2024). *The era of living intelligence: Navigating the technology supercycle powering the next wave of innovation*. Future Today Institute.

Webster, J., & Watson, R. T. (2002). Analyzing the past to prepare for the future: Writing a literature review. *MIS Quarterly, 26*(2), xiii–xxiii. https://doi.org/10.2307/4132319

Wentura, D., Wirth, B., & Pospeschill, M. (2023). Multivariate Datenanalyse mit R: Eine kompakte Einführung mit Online Extras (2nd ed.). Springer. https://doi.org/10.1007/978-3-662-65522-1

Werner, H. (2020). *Supply Chain Management: Grundlagen, Strategien, Instrumente und Controlling* (7. Aufl.). Springer Gabler. https://doi.org/10.1007/978-3-658-32429-2

Widiyanti, M., Lestariningsih, M., Irwanto, I., & Rini, E. S. (2020). Customer integration, top management support, organizational structure and supply chain technology adoption. Examining the mediating role of intention to adopt specific supply chain technology. *International Journal of Supply Chain Management*, *9*(4), 1252–1259.

Wohlin, C. (2014). Guidelines for snowballing in systematic literature studies and a replication in software engineering. In *Proceedings of the 18th International Conference on Evaluation and Assessment in Software Engineering* (pp. 1–10). ACM. https://doi.org/10.1145/2601248.2601268

Wooldridge, J. M. (2009). *Introductory econometrics: A modern approach* (4th ed.). South-Western Cengage Learning.

Xu, Z., Ramayah, T., & Shi, Y. (2025). Determinants of generative artificial intelligence adoption in insurance companies. *International Journal of Business and Society, 26*, 272–291. https://doi.org/10.33736/ijbs.9562.2025

Yee, L., Chui, M., Roberts, R., & Smit, S. (2025). *Technology trends outlook 2025* (5th ed.). McKinsey & Company. https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-top-trends-in-tech#/

Zhong, Y., & Moon, H. C. (2023). Investigating the impact of Industry 4.0 technology through a TOE-based innovation model. *Systems*, *11*(6), 277. https://doi.org/10.3390/systems11060277

Zhu, K., & Kraemer, K. L. (2005). Post-adoption variations in usage and value of e-business by organizations: Cross-country evidence from the retail industry. *Information Systems Research*, *16*(1), 61–84. https://doi.org/10.1287/isre.1050.0045

Zhu, K., Kraemer, K. L., & Xu, S. (2006). The process of innovation assimilation by firms in different countries: A technology diffusion perspective on e-business. *Management Science, 52*(10), 1557–1576. https://doi.org/10.1287/mnsc.1050.0487

10 Appendix

List of Appendices

Appendix A: Definitions of SCM

Author	SCM definition
Lambert et al., 1998, p.1	„ […] is the integration of key business processes from end user through original suppliers that provides products, services, and information that add value for customers and other stakeholders.”
Tan et al., 1998, p.4	„ […] addresses materials/supply management from the supply of raw materials to its end of life (and possible recycling or re-use). It focuses on how firms utilize their suppliers’ processes, technology, and capability to enhance competitive advantage.”
Simchi-Levi et al., 2000, p.1	„ […] is a set of approaches utilized to efficiently integrate suppliers, manufactures, warehouses, and stores, so that merchandise is produced and distributed at the right quantities, to the right locations, and at the right time, in order to minimize systemwide costs while satisfying service level requirements.”
Mentzer et al., 2001, p.22	„ […] the systematic, strategic coordination of the traditional business functions within a particular company and across businesses within the supply chain, for the purpose of improving the long-term performance of the individual companies and the supply chains as a whole.”
Bowersox et al., 2002, p.4	„ […] consists of firms collaborating to leverage strategic positioning and to improve operating efficiency. For each firm involved, the supply chain relationship reflects strategic choice. A supply chain strategy is a channel arrangement based on acknowledged dependency and relationship management. Supply chain operations require managerial processes that span across functional areas within individual firms and link trading partners and customers across organizational boundaries.”
Christopher, 2016, p.3	„The management of upstream and downstream relationships with suppliers and customers in order to deliver superior customer value at less cost to the supply chain as a whole.”
Chopra & Meindl, 2016, p.16	„Effective supply chain management involves the management of supply chain assets and product, information, and fund flows to grow the total supply chain surplus. A growth in supply chain surplus increases the size of the total pie, allowing contributing members of the supply chain to benefit.”
Werner, 2020, p.6, own translation	„ […] refers to internal and network-oriented integrated business activities relating to supply, disposal, and recycling, including accompanying cash and information flows.”

Appendix B: Top-Level SCOR Processes

Top Level	Tasks
Plan	Strategic and operational planning of SC Demand and sales forecasting Procurement planning Inventory and stock level planning Production and capacity planning Distribution network planning
Source	Procurement of materials and products Supplier selection and coordination Sourcing to stock, to order, or engineer-to-order Goods receipt and inspection Quality control Storage of procured goods Invoice verification and payment
Make	Make-to-stock production Make-to-order production Engineer-to-order production
Deliver	Customer order management and fulfillment Delivery from stock, make-to-order, or engineer-to-order Shipment of finished and traded goods Picking, packing, and shipping Transportation and distribution management
Return	Return of goods to suppliers Return of goods from customers Handling of defective or excess products

Source: Werner, 2020

Appendix C: Overview of AI Applications in SCM Literature

SCOR	Teixeira et al. (2025)	Culot et al. (2024)	Daios et al. (2025)	Richey et al. (2023)	Sharma et al. (2022)	Pournader et al. (2021)	Atwani et al. (2022)
Plan	DF Inventory optimization Logistics planning Decision-making automation	DF Inventory levels	DF LLM inventory optimization & policies for irregular demand	DF Inventory planning	DF Inventory planning SC network design	SC forecasting Inventory management SC network design	DF Inventory optimization
Source	Procurement automation Supplier (sustainable) evaluation & selection	Supplier scouting & selection Purchasing cost analysis	Support strategic & operational procurement decisions Supplier selection Automation of invoicing/order handling	Supplier (sustainable) evaluation & selection	Supplier selection	Supplier selection & performance evaluation	Supplier selection & evaluation Supplier risk detection
Make	Predictive maintenance Quality control Resource use optimization	Quality control Predictive maintenance Resource optimization	AI-guided robots for picking, packing, counting	Resource use optimization	Production planning Resource use optimization	-	Production scheduling Lot-sizing Order management
Deliver	Logistics planning Inventory planning Routing optimization	Logistic management	Transport route optimization Network analysis Warehouse robotics	Transportation & logistics optimization		-	Vehicle & route optimization
Return	Resource recovery Waste reduction	Warranty claim forecasting	Reverse logistics Returns optimization	-	-	Optimize return logistics	-
Others	Resilience Risk Detection Disruption monitoring ESG monitoring	Improving flexibility, agility and innovation	Customer chatbots Resilience & risk monitoring	Risk management Customer chatbots Marketing & sales strategies Compliance monitoring	Green SCM Risk management	Risk management SC simulation Sustainability management	-

Appendix D: Keyword Strings

PICOC Element	Main Keywords	Synonyms/Related Terms	Search Terms
Intervention *(applied to topic)*	artificial intelligence	AI machine learning deep learning	(("artificial intelligence" OR AI OR "machine learning" OR "deep learning") **AND**
Outcome 1 *(applied to title)*	adopt*	accept*, implement*,integration, usage, use, utili?ation, perceived, usefulness, perceived ease of use, performance expectancy effort, expectancy, social influence, facilitating condition*, organizational readiness, organizational factor* technological, readiness, technological factor* environmental factor*, environmental readiness, innovation diffusion relative, advantage, compatibility, complexity, treatability, observability, intention to use, behavi?ral intention, user behavi?r	(adopt* OR accept* OR implement* OR integration OR usage OR use OR utili?ation OR "perceived usefulness" OR "perceived ease of use" OR "performance expectancy" OR "effort expectancy" OR "social influence" OR "facilitating condition*" OR "organizational readiness" OR "organizational factor*" OR "technological readiness" OR "technological factor*" OR "environmental factor*" OR "environmental readiness" OR "innovation diffusion" OR "relative advantage" OR compatibility OR complexity OR treatability OR observability OR "intention to use" OR "behavi?ral intention" OR "user behavi?r") **AND**
Outcome 2 *(applied to topic)*	factor*	barrier*, challenge*, driver*, enabler*, determinant*, inhibitor*	(barrier* OR challenge* OR driver* OR enabler* OR determinant* OR inhibitor* OR factor*) **AND**
Context *(applied to title)*	supply chain management	SCM, supply chain, logistic*, supply chain operation*, forecast*, production scheduling, demand, planning, inventor*, procurement, purchas*, supplier sourcing, supplier selection, supplier evaluation, manufactur*, production planning, predictive maintenance, quality control, distribution, warehous*, transport*, route optim?ation, reverse logistics, return logistics, recycl*, resource optim?ation, waste reduction, risk management, sustainab*, resilien*, supply chain simulation	("supply chain management" OR SCM OR "supply chain" OR logistic* OR "supply chain operation*" OR forecast* OR "production scheduling" OR "demand planning" OR inventor* OR procurement OR purchas* OR "supplier sourcing" OR "supplier selection" OR "supplier evaluation" OR manufactur* OR "production planning" OR "predictive maintenance" OR "quality control" OR distribution OR warehous* OR transport* OR "route optim?ation" OR "reverse logistics" OR "return logistics" OR recycl* OR "resource optim?ation" OR "waste reduction" OR "risk management" OR sustainab* OR resilien* OR "supply chain simulation"))

Appendix E: Summary of Reviewed Papers

Item	Author	Year	Title	Country	SCOR process	Methodology	Sample	Adoption Model	Main Findings
[1]	Pan et al.	2025	*"Artificial intelligence usage and supply chain resilience: An organizational information processing theory perspective"*	China	All SCOR processes	Quantitative survey using PLS-SEM	231 manufacturing & SCM managers	-	Significant positive effect of AI usage on SC resilience, mediated effect by SC collaboration and SC efficiency, strengthened by higher digital information technology capabilities.
[2]	Chatterjee et al.	2021	*"Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model"*	India	Make (Production and Manufacturing)	Quantitative survey-based study analyzed using PLS-SEM	340 employees of small, medium and large organizations	Integrated TAM-TOE Framework	Leadership support significantly moderates the intention to adopt AI. Technical, social and environmental factors jointly drive adoption of AI, which enhances the productivity, efficiency and competitiveness in manufacturing contexts.
[3]	Alnipak & Toraman	2025	*"I am ChatGPT. Would you accept me to assist you in logistics management? An empirical study from Türkiye."*	Türkiye	Source/Deliver/Return (Logistics)	Quantitative online and face-to-face survey using PLS-SEM	547 logistics students, practitioners and academics	TAM, TBP & Trust	Attitutde emerges as the strongest influencing factor on intention to use ChatGPT, while trust increased PU and PEOU, thereby improving the overall attitude for ChatGPT. Social influence shapes attitude but does not affect intention, and perceived behavioral control shows no meaningful effect.
[4]	Pillai et al.	2022	*"Adoption of AI-empowered industrial robots in auto component manufacturing companies"*	India	Make (Production and Manufacturing)	Quantitative survey using PLS-SEM	460 managers and owners of auto component manufacturing companies	TOE/DOI & Cost issues	Perceived compatibility and benefits, external pressure, and vendor support significantly foster adoption intention of AI-enabled industrial robots, whereas IT infrastructure and government support show no effect. Adoption intention strongly predicts potential use, but high perceived costs reduce this effect.
[5]	Usmani et al.	2023	*"Key variables influencing artificial intelligence (AI) implementation in supply chain management (SCM): An empirical analysis on SMEs"*	India	All SCOR processes	Quantitative survey, exploratory analysis, correlation & stepwise multiple regression	596 employees from SMEs who had used AI at least once in SCM	-; TOE/DOI related variables	Compatibility, relative advantage, managerial support, technical capability, competitive pressure, government support and vendor partnership foster AI implementation, while high costs, market uncertainty and complexity hinder it. AI implementation strongly enhances SCM performance.
[6]	Falayi et al.	2025	*"Brains behind the chains: Exploring the drivers of artificial intelligence (AI) in*	Nigeria	All SCOR processes	Quantitative survey, descriptive statistics,	200 SCM experts, managers and IT	TOE	Management support is the strongest driver of AI adoption; competitive pressure also strongly influences adoption. Workforce digital skills and technology infrastructure positively enable AI-driven

			modern supply chain management success"			correlation analysis and multiple linear regression	personnel in manufacturing companies with digital infrastructure		SCM, while market complexity shows the weakest but still significant effect.
[7]	Fosso Wamba et al.	2024	*"ChatGPT and generative artificial intelligence: an exploratory study of key benefits and challenges in operations and supply chain management"*	USA & UK		Exploratory quantitative survey	300 middle- and upper-level managers	-	AI Adoption in SCM situates in early-stage development (proof-of-concept till implementation). Expected benefits range from operational efficiency, cost savings, decision-making support, and satisfaction of customers. Key challenges relate to data quality, technological integration, organizational readiness, and governance issues. Future anticipated advantages include increased automation, additional cost savings, enhanced customer experience, and sustainability impacts.
[8]	Chen et al.	2025	*"Factors influencing the adoption of generative AI in supply chain management: an empirical study based on task-technology fit and the theory of planned behaviour"*	China	Plan (demand forecasting, capacity planning, inventory & risk management)	Quantitative survey; covariance-based SEM (AMOS)	224 SC experts from various functions and firm sizes	TTF & TPB	SC task requirements and GAI capabilities significantly increase TTF. TTF and subjective norms shape attitudes toward AI. Attitude strongly predicts intention to adopt GAI, while TTF, perceived behavioral control and subjective norms show no significant direct effect on intention. Attitudes fully mediate the effects of TTF and subjective norms on behavioral intention.
[9]	Wang & Pan	2022	*"Drivers of Artificial Intelligence and Their Effects on Supply Chain Resilience and Performance: An Empirical Analysis on an Emerging Market"*	China	All SCOR processes	Quantitative survey using PLS-SEM	318 firms in China	TOE & Resource-based theory (RBT)	AI technology advantages, SC collaboration, and environmental uncertainty all increase firms' willingness to adopt AI, which in turn enhances SC resilience and performance. AI technology advantage improves performance only indirectly through this willingness, while collaboration and environmental uncertainty show both direct and indirect positive effects on resilience and performance.
[10]	Dey et al.	2023	*"Artificial intelligence-driven supply chain resilience in Vietnamese manufacturing small- and medium-sized enterprises"*	Vietnam	All SCOR processes	Quantitative survey; covariance-based SEM	280 operations managers	Knowledge-Based View & Resource Orchestration Theory	Leadership shapes the organizational culture, employee skills and competencies, that significantly influence AI adoption. While culture shows no mediating effect, skills and competencies mediate the effect between leadership and AI adoption. AI adoption enables circular economy processes, agility of the SC, and risk management, which thereby strengthens the overall SC resilience.
[11]	van Hoek	2024	*"Insight from industry-early lessons learned about AI adoption in core procurement*	France, Spain & USA	Source (strategic sourcing, ordering, supplier relationship management)	Exploratory quantitative survey	94 procurement managers	-	AI adoption is low and varies by process; sourcing shows higher consideration, while ordering and supplier relationship management show slightly higher rollout. Key benefits are productivity, visibility and

			processes, directions for managers and researchers"						innovation. Readiness is low, with major barriers related to human sensemaking, supplier readiness and training needs.
[12]	Nitsche et al.	2023	*"The impact of multiagent systems on autonomous production and supply chain networks: use cases, barriers and contributions to logistics network resilience"*	International	All SCOR processes	Delphi-study	18 SCM experts	-	Identifies 11 MAS use cases across multiple SCOR processes and evaluates their potential for resilience, productivity, and implementation complexity. Highlights that MAS can enhance responsiveness and flexibility, but adoption is hindered by technological immaturity, lack of standards, high costs, and change-management challenges.
[13]	Singh et al.	2023	*"Identifying issues in adoption of AI practices in construction supply chains: towards managing sustainability"*	India	All SCOR processes	Literature review and quantitative survey using fuzzy DEMATEL	10 experts from construction, IT/AI, academia and government	-	Key causal barriers include missing trust in AI output, cybersecurity risks, high project cost and risk, unclear benefits, uncertain AI algorithm performance, industry fragmentation, legal/contractual issues, and unstable power or connectivity.
[14]	Nozari et al.	2022	*"Analysis of the challenges of artificial intelligence of things (AIoT) for the smart supply chain (case study: FMCG industries)"*	Iran	All SCOR processes	Systematic literature review and expert interviews analyzed with fuzzy DEMATEL.	40 industry and academic experts	-	Five factors influence AIoT adoption decisions: lack of proper infrastructure, cybersecurity, lack of professionals, connectivity, and transportation management; infrastructure and cybersecurity are the strongest causal drivers.
[15]	Fries et al.	2025	*"Exploring AI integration in SME production planning: design spaces and the role of workers: Exploring AI integration in SME production planning"*	Germany	Plan, Make (production scheduling)	Qualitative interviews, workshops and on-site observations	16 participants (managers, production planners, machine operators) across 3 German metalworking SMEs	-	Identifies prerequisites and three options for AI in SME production planning context (processing time estimation, rework probability, and actual production process), shows data and system heterogeneity as key barriers, and stresses that AI should support, not replace, human planners, requiring participatory, worker-centered design.
[16]	Mishra et al.	2023	*"Challenges facing artificial intelligence adoption during COVID-19 pandemic: An investigation into the agriculture and agri-food supply chain in India"*	India	All SCOR processes	Quantitative survey analyzed through ISM, MICMAC analysis, and SWARA.	543 farmers for survey and 32 domain experts for evaluation	-	Identifies twelve AI adoption challenges and shows that lack of contextual awareness and farmers unwillingness are the key driving factors, while lack of standardization and implementation method act as critical linkage barriers.

[17]	Fries & Ludwig	2024	*“Why are the sales forecasts so low?' Socio-technical challenges of using machine learning for forecasting sales in a bakery”*	Germany	Plan (demand/sales planning)	Qualitative case study combining interviews, workshops and prototype evaluation	Single medium-sized bakery; owner and staff	-	Web-based ordering system was adopted successfully, but the ML forecasting tool was rejected despite high accuracy. Low trust, perceived errors, lack of explainability, and misalignment with work practices hindered adoption; data alone is insufficient without socio-technical alignment.
[18]	Rad et al.	2025	*“Adoption of AI-based order picking in warehouse: benefits, challenges, and critical success factors”*	Türkiye	Deliver (warehouse order picking)	Mixed-methods single case study combining warehouse performance analysis and qualitative interviews	13 participants from warehouse operations, managemen t, and AI/ERP providers	-	AI-based batching reduced travel distance and improved accuracy, documentation, and employee well-being. Adoption was hindered by integration and process issues, communication gaps, costs, and change resistance. Success depended on alignment, clear communication, training, and data-privacy management.
[19]	Cannas et al.	2023	*“Artificial intelligence in supply chain and operations management: a multiple case study research”*	Italy	Make, Plan, Deliver	Qualitative multiple case study using semi-structured interviews, guided by the SCOR model	6 Italian companies	-	AI mainly supports Make processes and improves cost, lead time and OEE, while adoption is hindered by poor data quality and difficult data acquisition, a lack of AI skills and weak change readiness across departments, as well as high investment requirements and unclear ROI.

Appendix F: Factors per Reviewed Quantitative Paper

Item	Item Factor	
[1]	Digital IT capabilities	
[2]	Organizational competency	PEOU
	Organizational complexity	Competitive advantage
	Organizational readiness	Partner support
	Organizational compatability	Leadership support
	PU	
[3]	Perceived usefulness	Trust
	Perceived ease of use	Attitude
	Social influence	Behavioral control
[4]	Perceived compatability	Support from vendors
	Perceived benefits	Government support
	IT infrastructure	Cost issues
	External pressure	
[5]	Compatibility	Managerial support
	Relative advantage	Competitive pressure
	Cost	Government support
	Technical capability	Market uncertainty
	Complexity	Vendor partnership
[6]	Management support	Market complexity
	Workforce digital skill	Competitive pressure
	Technology infrastructure	
[7]	Accuracy, biases and errors	Legacy systems
	Costs and technology access	Legal and regulatory
	Data quality and availability	Staff resistance
	Ethical concerns	Training and skills
[8]	Fitting degree between supply chain and technology	Attitude toward technology
	Supply chain requirements	Subjective norm
	Technology capabilities	Perceived behavioral control of technology
[9]	AI technology advantage	
	Supply chain collaboration	
	Environmental uncertainty	
[10]	Culture	
	Leadership	
	Skills and Competencies	
[11]	Cost of implementing AI in procurement	Leadership support
	Costs of AI technology (licenses etc.)	Suppliers able to invest
	Limited proof of concept	Suppliers trained in AI
	Limited business buy in	Suppliers engaged in AI
	Limited leadership support	Governance of digitalization
	Cyber security risks	Buyer engagement in AI
	Limited technology support	Stable process designs
	Limited technological infrastructure	Technology infrastructure
	Difficulty to integrate automation into existing	Technology team support
	Limited governance of automation	Investment ability
	Limited robustness/stability of process designs	Team members trained in AI
	Limited AI familiarity and ability amongst staff	Stakeholder engagement in AI
[13]	Risk and Costs associated with construction projects	Exploitation by hackers, cybercrimes and privacy intrusion
	Unclear profits and advantages	Uncertain processing and functions of AI algorithms
	Expensive and continuous maintenance requirements	Legal and contractual issues
	Lack of trust in AI outcomes	Frequent interruptions in power and internet connectivity
	Fragmented and project-based nature of industry	
[14]	Lack of proper infrastructure	Managing transportation
	Cybersecurity	Connectivity issues
	Lack of professionals	
[16]	Lack of contextual awareness	Lack of standardization
	Unwillingness	Implementing method

Appendix G: Categorized Factors per Reviewed Quantitative Paper

Dimension	Factor	Factor Name and Item	Count
Technical	Technological Readiness	Digital IT capabilities [1] Organizational competency [2] IT infrastructure [4] Technical capability [5] Technology infrastructure [6] Technology infrastructure [11] Technology team support [11] Limited technological infrastructure [11] Limited technology support [11] Frequent interruptions in power and internet connectivity [13] Lack of proper infrastructure [14] Connectivity issues [14]	8
	AI-Complexity	Organizational complexity [2] Complexity [5] Data quality and availability [7] Accuracy, biases and errors [7] Ethical concerns [7] Uncertain processing and functions of AI algorithms [13] Lack of trust in AI outcomes [13] Lack of trust in AIoT [14] Lack of contextual awareness [16] Implementing method [16]	6
	Compatibility	Organizational compatibility [2] Perceived compatibility [4] Compatibility [5] Legacy systems [7] Stable process designs [11] Difficulty to integrate automation into existing processes [11] Limited robustness/stability of process designs [11]	5
	Costs	Costs and technology access [7] Cost of implementing AI in procurement [11] Costs of AI technology (licenses etc.) [11] Risk and Costs associated with construction projects [13] Unclear profits and advantages [13] Expensive and continuous maintenance requirements [13]	5
	Benefits	Competitive advantage [2] Perceived benefits [4] Relative advantage [5] Automation [7] Business development [7] Content creation [7] Cost savings [7] Customer satisfaction [7] Decision support [7] Efficiency, optimisation and productivity [7] Strategy and competition [7] Time and errors [7] AI technology advantage [9]	5
	Cybersecurity Concerns	Cyber security risks [11] Exploitation by hackers, cybercrimes and privacy intrusion [13] Cybersecurity [14]	3
Organizational	Employee Capability	Workforce digital skill [6] Staff resistance [7] Skills and Competencies [10] Buyer engagement in AI [11] Team members trained in AI [11] Limited AI familiarity and ability amongst staff [11] Lack of professionals [14]	5
	Management Support	Leadership support [2] Managerial support [5] Management support [6] Leadership [10] Leadership support [11] Limited leadership support [11]	5
	Organizational Resources	Organizational readiness [2] Training and skills [7] Culture [10] Governance of digitalization [11] Stakeholder engagement in AI [11] Limited governance of automation [11] Limited business buy-in [11]	4
Environmental	Market Complexity	Market uncertainty [5] Market complexity [6] Environmental uncertainty [9] Fragmented and project-based nature of industry [13] Managing transportation [14]	5
	External Support	Partner support [2] Support from vendors [4] Vendor partnership [5] Supply chain collaboration [9] Suppliers able to invest in AI [11] Suppliers trained in AI [11] Suppliers engaged in AI [11]	5
	Competitive Pressure	Competitive advantage [2] External pressure [4] Competitive pressure [5] Competitive pressure [6]	4
	Government Support	Government support [4] Government support [5] Legal and regulatory [7] Legal and contractual issues [13]	4

Appendix H: Factors per Reviewed Qualitative Paper

Item	Factor Category	Detailed	Evidence/Description	Function	Argument
[12]	AI-Complexity	Application Complexity	Firms doubt AI readiness due to complexity and unclear problem-solving transparency (p. 27)	Complementary	Confirms the perceived high complexity and immaturity of AI/multiagent system applications by specifying that opaque decision logic and unstable system behavior exacerbate firms' concerns about AI readiness and technological barriers.
	Technological Readiness	Lack of qualified experts	Companies often lack skilled multiagent developers to manage complexity and develop AI (p. 27)	Complementary	Confirms that a shortage of AI/ multiagent system expertise hinders adoption due to insufficient capabilities to develop, configure, and maintain these systems.
	Costs	High implementation and data costs	High costs for software and hardware, data preparation, maintenance (p. 27-28)	Complementary	Confirms cost-related barriers by specifying that high software, hardware, data preparation, and maintenance costs increase the perceived financial burden of AI/ multiagent system adoption.
	Organizational Resources	Organizational change challenges	AI cause loss-of-control concerns and require major change management efforts (p. 28)	Complementary	Extends organizational readiness barriers by highlighting substantial change-management requirements and employee loss-of-control concerns not fully captured in quantitative studies.
	Employee Capability	Employee resistance & job replacement fears	Employees fear being replaced; behavioral factors hinder acceptance (p. 28)	Complementary	Confirms individual-level barriers by specifying that emotional resistance and job-replacement fears reinforce low trust and negative attitudes toward AI adoption.
	Attitude	Need for human–machine co-existence	Experts emphasize AI must allow human intervention in early years for trust building (p. 28)	Contextualizing	Contextualizes AI adoption by indicating that maintaining human intervention and shared control in early phases is essential for building trust and acceptance, a condition not addressed in quantitative studies.
[15]	AI-Complexity	Outdated or incomplete data	"An analysis has shown that even though a long history is available, some products were produced more frequently than others. As a result, an AI might accurately learn the production times for frequently demanded products but struggle to forecast those of rarely produced items due to limited examples." (p. 316) "For certain products, there might not be enough examples to identify patterns and hence forecast the rework probability with sufficient accuracy. This could be problematic from an economical point of view, leading to machine reservations and under-utilized capacities, which could have been used to process another product." (p. 318)	Complementary	Confirms that poor data quality blocks meaningful AI use and prevents effective implementation in SMEs.
	AI-Complexity	Lack of contextualized AI outputs	"It does not consider interrelations and dependencies in production planning and therefore cannot tell when production should start and when it exactly ends. For instance, it takes neither tool change into account, which adds additional time needed, nor the current capacity usage or waiting time" (p. 316)	Complementary	Confirms the lack of contextualized AI outputs by specifying that processing-time predictions ignore tool changes, capacity constraints, and interdependencies, limiting their suitability for real production scheduling..
	Attitude	Threat to worker expertise and established routines	"Introducing an AI that provides planners with greater insights disrupts current practices and somehow undermines the workers' expertise, reframing their role and the communication between planners and workers." (p. 317)	Explanatory	Explains negative attitudes toward AI by showing that it disrupts established planner, worker routines and challenges workers' expertise, a social mechanism not captured in quantitative studies.
	Benefits	AI-enabled rework prediction capability	"Considering all these parameters, a heuristic approach like APS overlooks this aspect, as rework is not predefined (in the MD) as a mandatory step in the work plan and therefore is not always scheduled. An AI might infer patterns and rules to make this more manageable." (p. 317) "Similar to Company A, an AI could use machine data that has already been collected to predict the occurrence of dull blades to avoid rework or estimate if the blade will require rework." (p. 317)	Explanatory	Explains perceived performance and quality benefits by showing that AI-enabled rework and tool-wear prediction can reduce scrap and improve planning reliability, thereby clarifying why perceived usefulness drives adoption in quantitative studies.

	AI-Complexity	Difficulty interpreting machine-state data	"The challenge lies in the combination of the data and interpretation of the saw blade's transmitted state. When is a saw blade considered dull? Are there certain vibrations or an increased energy consumption an indicator? The interpretation relies heavily on the workers' experience." (p .318)	Explanatory	Explains output-quality barriers by showing that interpreting machine-state signals (e.g., vibrations, energy consumption) depends on tacit worker knowledge, making AI predictions difficult to trust without human judgment.
	AI-Complexity	High manual data-labeling effort	"Taking this first obstacle leads to the second, which results in the correct labeling of the data, which is a manual and time-consuming task, again demanding the expertise of the workers." (p .318)	Explanatory	Explains persistent data-quality challenges by demonstrating that reliable AI predictions require extensive manual labeling based on worker expertise, creating significant initial effort.
	Benefits	Enhanced process transparency	"AI can use the feedback provided by workers in the PDAS to extract the processes that are actually performed and create a process map. These production flows can then be analyzed in more detail, for example, by product type. This reveals specific production flows and provides a better understanding of the actual production process. The AI could suggest the next work step, as well as the machines required. This information will help planners optimize production planning by bringing it closer to what happens on the shop floor and by finding solutions to problems during the planning phase" (p. 318)	Complementary	Identifies a new perceived benefit by showing that AI can reconstruct actual production flows from PDAS data, making tacit worker practices visible and enabling planners to align schedules more closely with real shop-floor behavior.
	AI-Complexity	Limited holistic planning capability of AI systems	"They do not consider a wide variety of influencing parameters, like tool changes or order sequences. Thus, each space fails to address conflicts between objectives such as delivery time, optimum capacity utilization, or setup optimization. They provide selective support to cover certain partial aspects with additional information to facilitate the work of production planning, even if they do not represent a one-size-fts-all solution for overall production planning and scheduling." (p 319)	Explanatory	Explains insufficient task–technology fit by showing that AI systems fail to integrate key production-planning dependencies, limiting their ability to resolve trade-offs between planning objectives.
	Employee Capability	Low understanding & skills of AI	"For instance, many employees have little understanding of what AI is, what it can do and what it cannot do. The basis that AI requires was also only vaguely known." (p. 320).	Complementary	Confirms skill and knowledge gaps by indicating that employees' limited understanding of AI capabilities and prerequisites reinforces barriers to AI adoption.
	Organizational Resources	Participatory AI design for SCM	"Nonetheless, the development of suitable AI technologies can be specifically tailored to the needs of SMEs. This requires moving in a direction that should aim for a highly participatory approach and ultimately even the democratization of model creation through model development by employees themselves. This requires further research in the areas of CSCW, end-user development, and participatory design" (p. 323).	Contextualizing	Contextualizes AI adoption in SCM by indicating that participatory design and employee involvement in model development enhance acceptance and alignment with SME-specific needs.
[17]	Market Complexity	Demand volatility	"However, she assumed that the bakery is confronted with the problem of oversupplying/undersupplying market demand due to the current ordering process. This circumstance is particularly serious in the food industry, as the goods only have a limited shelf life, and goods from previous days cannot be sold the next day (Wen et al. 2014), at least not at the same conditions and with the same quality" (p. 267).	Complementary	Confirms that high demand uncertainty and perishability pressure in the food sector create strong environmental incentives to adopt AI-based forecasting, aligning with quantitative findings on market complexity as an adoption driver.
	Technological Readiness	Lack of technical infrastructure	"However, as our empirical study and the current process have shown, there is neither a suitable digital data basis nor a technological infrastructure in place to introduce new forms of machine learning-based sales planning. It was therefore first necessary to establish a suitable technological infrastructure to gather data	Complementary	Confirms that missing technological infrastructure blocks the implementation of ML-based systems, consistent with quantitative insights on IT readiness limitations.

			that might enable new forms of sales planning.” (p. 267-268)		
	AI-Complexity	Lack of data	“However, as our empirical study and the current process have shown, there is neither a suitable digital data basis nor a technological infrastructure in place to introduce new forms of machine learning-based sales planning. It was therefore first necessary to establish a suitable technological infrastructure to gather data that might enable new forms of sales planning.” (p. 267-268)	Complementary	Confirms that the absence of a structured digital data foundation prevents ML-based forecasting, reinforcing quantitative findings on data readiness barriers.
	AI-Complexity	Outlier sensitivity	“Although we obtained a high forecast quality for five of the seven days, two outliers led to a complete mistrust and rejection of the results.” (p. 283)	Complementary	Confirms that even isolated AI errors undermine trust and acceptance, reinforcing quantitative findings on error sensitivity and output reliability.
	AI-Complexity	Poor usability and missing UI	“Furthermore, the participants criticized the handling of the module. Currently, data has to be consolidated and prepared in an Excel file from different sources. In addition, the current version of the module does not include a comprehensive user interface.” (p. 284)	Complementary	Confirms that usability barriers, complex workflows and missing UI reduce acceptance, aligning with quantitative PEOU findings.
	Employee Capability	Low technological understanding	“Notably, the owner emphasized that ‘[…] there are no IT experts sitting here,’ to deal with the current module, and no one contradicted his quick, clearly formulated statement. Furthermore, responses clearly showed that a transparent explanation of the results is essential for trust, and the employees said they had too little technological understanding to fully comprehend how the system worked.” (p. 284)	Complementary	Confirms that low AI literacy reduces trust and willingness to use AI, reinforcing quantitative knowledge-related barriers.
	AI-Complexity	Lack of explainability	“We tried to explain the data in more detail through various graphs, but this did not appear to be sufficient. When we were unable to explain Tuesday’s prediction regarding the forecast quantity, the skepticism in the owner’s facial expression increased significantly. Our attempts to get the owner to explore the data to determine possible reasons for deviations were quickly blocked: ‘There is not much interest in this kind of planning.” “Taking the adaptability of ML and the changing behavior of the model into account, it becomes even harder to interpret results, even for experts, such as data scientists, who face issues in trying to correctly interpret explainability models like SHAP (Kaur et al. 2020). Hence, trust issues arise and irritate users (Graaf et al. 2017; Lee et al. 2014).” (p. 284)	Complementary	Explains how missing explainability of AI directly undermine trust even when forecasts are technically sound.
	Management Support	Lack of management support	“Even though we as researchers can see the advantages in terms of production planning using the ML-based application, we quickly accepted that such a ML-based forecasting will not be used because the resistance of the owner is too great.” (p. 284)	Complementary	Confirms that missing managerial support acts as a barrier to AI adoption, reinforcing quantitative findings on the critical role of leadership endorsement.
	Management Support	Negative managerial attitude	“There is not much interest in this kind of planning.” “ML-based forecasting will not be used because the resistance of the owner is too great.” (p. 284)	Explanatory	Explains adoption failure by showing that negative managerial attitudes lead to withheld support for AI-based planning, a management-level mechanism not captured in quantitative studies.
[18]	Costs	Cost reduction	AI reduces energy use, labor effort, stationery cost, machine wear and increases process efficiency (p. 3515)	Complementary	Complements quantitative cost barriers by indicating that users perceive AI-enabled operational cost reductions through lower energy use, labor effort, machine wear, and increased process efficiency.
	Benefits	Increased Employees’ Well-Being	More comfort, less boredom (p. 3515)	Complementary	Complements quantitative adoption constructs by highlighting improved employee well-being through increased comfort and reduced monotony as an additional perceived benefit.

	Benefits	Travel distance and time reduction	Optimal routing solution (p. 3514)	Complementary	Reinforces quantitative findings on perceived usefulness by showing that optimal routing reduces travel distance and task completion time, reflecting established operational efficiency mechanisms.
	Benefits	Higher order simplicity	Less complex documentation (p. 3514)	Complementary	Supports quantitative evidence on ease of use and process efficiency by illustrating how AI reduces documentation complexity and simplifies picking tasks.
	Benefits	Improved documentation	Lower use of order list printouts stationery (p. 3514)	Complementary	Reinforces quantitative insights on performance benefits by demonstrating reduced paperwork and streamlined documentation, without adding a novel theoretical mechanism
	Benefits	Higher order-picking accuracy	Lower number of errors and wrong orders (p. 3514)	Complementary	Aligns with quantitative findings on accuracy and usefulness, confirming that AI improves picking precision.
	Benefits	Positive environmental impacts	Lower energy consumption, longer machine's lifetime, lower paper consumption (p. 3515)	Complementary	Complements quantitative evidence by adding environmental benefits, such as lower energy use, extended machine lifetime, and reduced paper consumption, as an additional operational benefit dimension not captured in perceived usefulness constructs.
	Compatibility	Strategic alignment and process re-engineering for compatability	Functional integration, Strategic fit, Business process re-engineering (p. 3517)	Contextualizing	Specifies the organizational conditions under which AI-based batching can be adopted, showing that functional integration and workflow redesign are necessary for achieving compatibility with warehouse operations.
	Compatibility	Technological integration & interoperability	"The system did not cause us any problems and worked well with other systems" (p. 3518)	Complementary	Confirms quantitative findings that compatibility and system interoperability facilitate AI adoption by showing that stable integration with existing warehouse systems supports acceptance.
	External Support	Vendor and stakeholder support	Communication, Triadic (supply chain) collaboration (p. 3518)	Complementary	Confirms quantitative findings that external vendor and partner support is essential for AI adoption, as effective collaboration between ERP developers, AI providers and warehouse teams enables successful integration.
	Organizational Resources	Education and training	"We were provided with the necessary information through trainings" (p. 3518) "Using the system becomes easier with the training received" (p. 3518)	Complementary	Confirms quantitative findings that training and user education facilitate AI adoption by increasing user competence and reducing effort.
	Cybersecurity	Data privacy management and regulatory compliance	Data sharing permission, Confidentiality Agreement, Privacy and Regulatory Compliance (p. 3518)	Critical	Contrary to quantitative findings where data security and legal issues act as adoption barriers, this case shows that clear privacy management and regulatory compliance can instead enable AI adoption.
	Management Support	Managerial commitment	Willingness to change (p. 3519)	Complementary	Confirms quantitative findings that managerial support facilitates AI adoption, illustrating this effect through positive executive endorsement for technological change.
[19]	Costs	Benefits	Reduction of costs, OEE improvements, Stock rotation improvement (p. 17)	Complementary	Complements quantitative cost barriers by showing that AI can reduce operational costs and improve OEE, challenging predominantly negative cost-related assumptions in prior quantitative evidence.
	Benefits	Speed	Reduction of lead times, process reliability improvement (p. 17)	Complementary	Reinforces quantitative evidence by showing that AI reduces lead times and improves process reliability, reflecting established usefulness and efficiency mechanisms.
	Benefits	Dependability	Service level improvement (p. 17)	Complementary	Supports quantitative findings that AI enhances reliability and service levels, confirming established performance-related usefulness effects.
	Benefits	Quality	Increased product quality (p. 17)	Complementary	Aligns with quantitative evidence by showing that AI enhances product and process quality, reinforcing established usefulness mechanisms.
	Benefits	Safety	Safety improvement (p. 17)	Complementary	Adds practical evidence that AI can reduce workplace safety risks, complementing existing performance-related benefit.
	Benefits	Sustainability	Environmental sustainability improvement (p. 17)	Complementary	Complements quantitative findings by highlighting sustainability improvements as a benefit not captured in perceived usefulness constructs.

	Costs	High investment	"[…] as well as the huge investment needed to conduct the data capture process without a clear return on investment" "Another critical issue is the ability to decide which AI project to develop because the investments are extremely high and take a long time to implement, and subsequently generate an uncertain value and ROI." (p. 18)	Complementary	Confirms quantitative findings that high implementation costs and limited financial resources hinder AI adoption.
	Costs	Lack of clarity regarding the economic benefit	p. 18	Complementary	Aligns with quantitative evidence showing that unclear economic returns and low budgeting experience reduce adoption readiness.
	Employee Capability	Limited skills	"Another critical aspect that was emphasised concerns the availability of specific knowledge and skills, both concerning the internal production processes being addressed and development of AI models." (p. 19) "The last critical issue is finding people who have the skills and abilities to implement such technologies. It is often necessary to turn to external consultancies that can support, at least in the initial stages, the development of the project and provide the appropriate skills that are not available within the company" (p. 19) "From the interviews, it emerges that the path of upskilling and reskilling of figures already present in the company appears to be impractical today, as the skills to be developed are very specific, and for the management of these projects, it is necessary to have already acquired a certain amount of experience because the problems to be faced are often poorly codified." (p. 20)	Complementary	Confirms quantitative findings on the negative impact of limited skills and insufficient training and that even upskilling is not possible due to complexity.
	Organizational Resources	Lack of internal digital culture and training	"The first is the establishment of a change-oriented corporate mindset and culture, as not all internal resources have the skills necessary to manage these new technologies." (p. 18) "Additional evidence emerged from the cases is identified in the absence of an adequate culture of change that can support organisational structures and individuals in the adoption of technological solutions that can also have significant impacts on processes and areas of comfort that have been created over the years." (p. 20)	Complementary	Supports quantitative determinants such as organizational readiness and digital culture, validating that weak cultural support and insufficient training reduce AI adoption likelihood.
	Employee Capability	Lack of employees' readiness	p. 18	Complementary	Confirms quantitative results showing that resistance and low readiness hinder acceptance, reflecting the same individual-level behavioral barriers identified previously.
	External Support	Lack of knowledge and collaboration	"However, there is also an issue of lack of readiness from operators, low integration and collaboration among organisational departments and supply chain partners, difficult process changes, and ineffective change management." (p. 20)	Complementary	Reinforces quantitative evidence that poor internal integration and limited knowledge sharing hinder adoption.
	Compatibility	Compatibility, scalability and interoperability issues	p. 18	Complementary	Matches quantitative findings that compatibility and interoperability problems impede AI adoption.
	AI-Complexity	Challenges in ensuring data quality	"Five companies substantially confirm what emerges from the analysis of the main contributions that have appeared in the literature, highlighting the issue of data quality as the main barrier to implementation due to a low ability to govern the data acquisition processes and the subsequent archiving and processing phases." (p. 20)	Complementary	Confirms quantitative results showing that poor data quality undermines AI performance and adoption.

Appendix I: Survey

Demographic Questions	
Do you currently work in a supply chain management function or a supply chain sub-process?	Yes/No
Which supply chain–related area do you primarily work in?	☐ Plan (e.g., demand and sales forecasting, inventory planning, production or capacity planning, distribution network planning) ☐ Source (e.g., procurement, supplier selection and coordination, sourcing, goods receipt, quality control) ☐ Make (e.g., make-to-stock, make-to-order, engineer-to-order production) ☐ Deliver (e.g., order fulfillment, picking and packing, transportation, distribution management) ☐ Return (e.g., returns to suppliers or from customers, handling defective or excess products) ☐ End-to-end supply chain management (overall responsibility across multiple SCOR processes)
Is the organization you working in located in Germany?	Yes/No
Select your current position.	☐ Executive Management ☐ Senior Management ☐ Other
How long have you been working in your current role?	☐ Less than 1 year ☐ 1–2 years ☐ 3–5 years ☐ 6–10 years ☐ More than 10 years
Organizational Information	
What is the size of your organization?	☐ Fewer than 50 employees ☐ 50–249 employees ☐ 250–999 employees ☐ 1,000–4,999 employees ☐ 5,000 or more employees
What sector does your organization belong to?	☐ Manufacturing / Industrial Production ☐ Construction & Engineering ☐ Agriculture, Food & Natural Resources ☐ Mining & Raw Materials ☐ Wholesale & Distribution ☐ Retail & E-Commerce ☐ Transportation & Logistics Services ☐ Utilities & Energy Supply ☐ Public Sector ☐ Other (please specify)
AI Adoption	
Which best describes your organization's current stage regarding the adoption of AI technologies in supply chain processes?	☐ AI awareness without adoption consideration ☐ Initial consideration of AI adoption (without active evaluation) ☐ Active Evaluation of AI adoption (pilots or small experiments optional) ☐ A decision to fully adopt AI has already been made (AI not yet implemented) ☐ AI is currently being used in some supply chain processes ☐ AI is widely and routinely used across supply chain processes
Which supply chain–related use cases in your area of responsibility is your organization currently evaluating, testing, or using AI technologies for? If your organization is not considering or evaluating any AI technologies in your area of responsibility, please leave this field empty.	Open Question

Appendix

Conceptual Framework					
Factor	**Definition**	**Subdimension**	**Original Item Collection**	**Final Item**	**Source Original Item**
Technological Readiness	Technological Readiness describes the extent to which an organization has the technological infrastructure and technical expertise required to implement digital innovations. (Zhu et al., 2006)	Technical Infrastructure	Your bank has the technical infrastructure to support the implementation of GenAI.	Our organization has the technical infrastructure required for implementing AI technologies.	Ajili Ben Youssef et al., 2025
			Network communication services (e.g., connectivity, reliability, availability, LAN, WAN, etc.)	Our organization has reliable and high-quality network connectivity required for implementing AI technologies.	McKinnie, 2016
		Technical Expertise	I feel that the staff would be equipped with the managerial and technical skills required for InRos.	Our IT staff has the technical skills required to implement AI technologies.	Pillai et al., 2022
			We have experts in the AI domain in our organization.	Our organization has personnel with the expertise in the AI domain.	Chatterjee et al., 2021
Compatibility	Compatibility refers to the extent to which AI fits with existing values and beliefs (Rogers, 1983) and aligns with established processes and technological infrastructures. (Chatterjee et al., 2021; Pillai et al., 2022)	Values	GenAI aligns with your bank's values and culture.	AI technology aligns with our organization's values and culture.	Ajili Ben Youssef et al., 2025
		Processes	InRos would be suitable for our work processes and practices in the organisation.	AI technologies are compatible with our supply chain's work processes and practices.	Pillai et al., 2022
		Technologies	AI technology is compatible with the existing legacy system for production and manufacturing in our firm.	AI technologies are compatible with the existing legacy systems in our supply chain processes.	Chatterjee, 2021
			GenAI easily integrates with IT systems and infrastructure.	AI technologies can be integrated with IT systems and infrastructure in our supply chain processes.	Ajili Ben Youssef et al., 2025
Costs	Costs refer to the financial requirements for acquiring, implementing and maintaining AI systems. (Rogers, 1983; Fosso Wamba et al., 2024; van Hoek, 2024; Singh et al., 2023; Pillai et al., 2022)	Acquiring	The cost of ECTI is high for our company.	The costs of AI technologies are high for our organization.	Ghobakhloo, 2011
		Implementing	The amount of money and time invested in training employees to use these technologies are very high.	The amount of money and time invested in training to use AI technologies is high for our organization.	Premkumar, 1999
			InRos has high cost of installation.	The installation of AI technologies involves high costs for our organization.	Pillai, et al., 2022
		Maintaining	The cost of maintenance and support of these technologies are very high for our business.	The costs of maintenance and support of AI technologies are high for our organization.	Premkumar, 1999
Benefits	Benefits refer to the expected operational, strategic or functional advantages that AI technologies provide. (Rogers, 1983; Premkumar, 1999; Pillai et al., 2022; Usmani et al., 2023; Wang & Pan, 2022; Chen et al., 2025)	Strategic	GenAI gives a competitive Advantage.	AI technology provide a competitive advantage for our supply chain processes.	Ajili Ben Youssef et al., 2025
		Operational	InRos improve the overall productivity of the manufacturing process.	AI technologies improve the overall efficiency of our supply chain processes.	Pillai et al., 2022
			InRos improve the overall productivity of the manufacturing process.	AI technologies improve the overall productivity of our supply chain processes.	Pillai et al., 2022
		Functional	-	AI technologies provide analytical, forecasting or decision-making capabilities for our supply chain processes.	Texeira et al., 2025
AI-Complexity	AI-Complexity refers to the extent to which an organization perceives AI data requirements, limited transparency, algorithmic opacity, and potential biases as complex to manage. (Premkumar, 1999; Maduku et al., 2016; Culot et al., 2024; Jöhnk et al., 2021)	Data Availability & Quality	-	The data requirements of AI technologies are complex for our organization to manage.	Nikiforova et al., 2025
		Algorithmic Transparency & Explainability	I can access a great deal of information which explaining how the AI system works.	AI technologies provide insufficient information to help our organization understand how they work.	Yu & Li, 2022
			I feel that the amount of the available information regarding the AI system's reasoning is large.	AI technologies provide insufficient information to help our organization understand their reasoning processes.	Yu & Li, 2022
		Accuracy & Biases	-	The risk of biased or inaccurate outputs of AI technologies is complex for our organization to manage.	Nikiforova et al., 2025
Cybersecurity Concerns	Cybersecurity Concerns refer to the perceived risks of cyberattacks, data breaches and privacy intrusions associated with AI systems (Nikiforova et al., 2025), which create uncertainty and reduce organizational trust in their use. (van Hoek, 2024; Singh et al., 2023; Nozari et al., 2022)	Concerns	AI adoption in HRM create concerns regarding data security and privacy.	AI technologies create concerns regarding data security and privacy risks for our organization.	Faustine & Rachmawati, 2024
		Access control	Implementing AI in HRM creates vulnerability in access control of the organization's information assets.	AI technologies create vulnerabilities in the access control of our organization's information assets.	Faustine & Rachmawati, 2024
		External dependency	Implementation of AI in HRM create risks through excessive dependency on external vendors (AI tools developers).	AI technologies create risks through excessive dependency on external vendors (AI developers) for our organization.	Faustine & Rachmawati, 2024
		Corporate policies	Implementation of AI in HRM complicate the process of adhering to corporate policies in protecting individual privacy and data security.	AI technologies complicate our organization's adherence to corporate policies protecting individual privacy and data security.	Faustine & Rachmawati, 2024

Appendix

Organizational Capability	Organizational Capability refers to an organization's capacity to combine (Amit & Schoemaker, 1993) employee skills (Falayi et al., 2025; Dey et al., 2023), training resources (Chatterjee et al., 2021) and cultural support (Dey et al., 2023) to enable effective adoption of new technologies.	Employee	Most employees are willing to use these Industry 4.0 technologies.	Most employees in our supply chain processes are willing to use AI technologies.	Zhong & Moon, 2023
			Most employees are able to use these Industry 4.0 technologies after training.	Most employees in our supply chain are able to use AI technologies after training.	Zhong & Moon, 2023
		Training Resources	I have all the readiness resources for learning the AI based manufacturing and production system in my firm.	Our organization provides the necessary resources to support learning for working with AI technologies.	Chatterjee et al., 2021
		Cultural Support	In my organisation, there is strong emphasis on employee skills development.	Our organization has a strong emphasis on employee skills development.	Dey et al., 2023
Management Support	Management Support refers to top leaderships commitment and resources that create a supportive environment and facilitate the adoption of new innovations (Premkumar, 1999; Wang et al., 2010 as cited in Low & Chen, 2011)	Support	The owner or manager enthusiastically supports the adoption of these new technologies.	Top management enthusiastically support the adoption of AI technologies in our supply chain processes.	Premkumar, 1999
		Resources	The owner or manager has allocated adequate resources to adoption of these new technologies.	Top management is willing to allocate adequate resources for the adoption of AI technologies in our supply chain processes.	Premkumar, 1999
		Awareness	Top management is aware of the benefits of these new technologies.	Top management is aware of the benefits that AI technologies could bring to our supply chain processes.	Premkumar, 1999
		Encourage	Top management actively encourages employees to use the new technologies in their daily tasks.	Top management actively encourage employees to use AI technologies in their work.	Premkumar, 1999
External Pressure	External Pressure captures SCM market related forces such as competitive intensity, market complexity and environmental uncertainty that influence AI adoption in SCM. (Premkumar, 1999; Pillai et al., 2022; Usmani et al., 2023; Falayi et al., 2025; Chatterjee et al., 2021)	SC Market	The global business environment is full of challenges.	The supply chain environment we operate in is full of challenges.	Wang & Pan, 2022
			The changing global business environment.	The supply chain environment we operate in is changing rapidly.	Wang & Pan, 2022
		Competitive Pressure	We feel it is a strategic necessity to use these technologies to compete in the marketplace.	AI adoption is perceived as a strategic necessity for our supply chain processes to compete in our sector.	Premkumar, 1999
			The adoption of GenAI is becoming a standard practice in the banking industry.	AI adoption is becoming a standard practice in supply chain processes within our sector.	Ajili Ben Youssef et al., 2025
External Support	External Support refers to "the availability of support for implementing and using an information system" (Premkumar, 1999, p. 472) through vendors and partners (Pillai et al., 2021; Usmani et al., 2023; Chatterjee et al., 2021) and SC collaboration (Wang & Pan, 2022).	Promote	Technology vendors promote these new technologies by offering free training sessions.	There are technology vendors who promote AI technologies by offering free training sessions.	Premkumar, 1999
		Technical Assistance	There are businesses in the community which provide technical support for effective use of these technologies.	There are businesses which provide technical support for effective use of AI technologies.	Premkumar, 1999
		SC Collaboration	Collaboration between supply chain companies to improve production processes.	There is collaboration between our organization and other supply chain companies to support digital and AI-related initiatives.	Wang & Pan, 2022
		Implementation Expertise	There are agencies in the community who provide training on these new technologies.	There are businesses who can provide training for AI technologies in our organization.	Premkumar, 1999
Government Support	Government Support refers to regulatory and policy actions by the government that create favorable conditions by establishing clear frameworks, enabling a trustworthy technological environment and providing incentives for technology adoption. (Zhu & Kraemer, 2005)	Regulatory	The current regulatory environment supports the adoption of GenAI.	The current regulatory environment supports the adoption of AI technologies in our sector.	Ajili Ben Youssef et al., 2025
			Government initiatives and infrastructure support the integration of GenAI.	The current government initiatives and infrastructure support the adoption of AI technologies in our sector.	Ajili Ben Youssef et al., 2025
		Incentives	The government provides incentives/policies encouraging the adoption of GenAI.	The government provides incentives that encourage the adoption of AI technologies in our sector.	Ajili Ben Youssef et al., 2025
			The government financially supports the InRos technology.	The government financially supports the adoption of AI technologies in our sector.	Pillai et al., 2022
Intention to Adopt	Intention to Adopt AI describes an organization's motivated probability to implement AI technologies (Fishbein & Ajzen, 1975; Ajzen, 1991; Venkatesh et al., 2003; Rogers, 1983)		I predict I would use the system in the next <n> months.	Our organization expects that it will adopt AI technologies in our supply chain processes.	Venkatesh et al., 2003
			I plan to use the system in the next <n> months.	Our organization plans to adopt AI technologies in the near future in our supply chain processes.	Venkatesh et al., 2003
			I intend to use the system in the next <n> months.	Our organization intends to adopt AI technologies in our supply chain processes.	Venkatesh et al., 2003

Appendix J: Use Cases of Post-Adopter

SCOR process	Description
Plan	*"For example, we have implemented classical forecasting of demand and inventories within an integrated business planning tool that incorporates various AI-based forecasting models and scenario analysis capabilities, which we use on a regular basis."*
	"Demand forecasting (although I am not entirely certain whether this formally qualifies as AI)"
Source	*"SAP Ariba"*
Make	*"e.g. bottleneck detection in fully automated machines used for lens manufacturing"*
Deliver	*"ETA forecasting using a self-developed model"*
	"Oracle Transportation Management"
Return	-
End-to-end SCM	-

Appendix K: Reliability Analysis

Technological Readiness

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.788*	*.037*	*.716*	*.861*

Compatibility

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.897*	*.021*	*.856*	*.938*

Costs

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.762*	*.045*	*.674*	*.851*

Benefits

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.849*	*.038*	*.775*	*.923*

AI-Complexity

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.723*	*.072*	*.582*	*.863*

Cybersecurity Concerns

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.821*	*.035*	*.753*	*.889*

Organizational Capability

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.717*	*.055*	*.609*	*.825*

Management Support

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.879*	*.021*	*.837*	*.921*

External Pressure

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.734*	*.053*	*.629*	*.838*

External Support

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.705*	*.080*	*.549*	*.861*

Government Support

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.691*	*.116*	*.464*	*.918*

Intention to Adopt

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.950*	*.010*	*.931*	*.969*

Appendix L: Descriptive Statistics

Descriptive Statistics Technological Context ▼

Descriptive Statistics

	Technological Readiness	Compatibility	Costs	Benefits	AI-Complexity	Cybersecurity Concerns
Mean	3.291	3.358	3.093	3.716	3.022	2.963
Std. Deviation	0.741	0.995	0.719	0.884	0.736	0.721
Minimum	1.750	1.250	1.750	1.500	1.750	1.250
Maximum	4.750	5.000	4.500	5.000	4.750	4.500

Descriptive Statistics - Organizational Context

Descriptive Statistics

	Management Support	Organizational Capability
Mean	3.131	3.295
Std. Deviation	0.917	0.719
Minimum	1.250	1.500
Maximum	5.000	4.750

Descriptive Statistics - Environmental Context

Descriptive Statistics

	External Pressure	External Support	Government Support
Mean	3.325	3.187	2.679
Std. Deviation	0.751	0.584	0.441
Minimum	1.250	1.500	1.000
Maximum	4.750	4.500	3.500

Descriptive Statistics - Intention to Adopt ▼

Descriptive Statistics

	Intention to Adopt
Mean	3.189
Std. Deviation	1.149
Minimum	1.000
Maximum	5.000

Descriptive Statistics Technological Context

Descriptive Statistics

	Technological Readiness			Compatibility			Costs		
	Awareness	Consideration	Intention	Awareness	Consideration	Intention	Awareness	Consideration	Intention
Mean	2.924	3.529	3.325	2.946	3.662	3.275	2.967	3.154	3.175
Std. Deviation	0.591	0.783	0.602	0.904	1.005	0.870	0.700	0.683	0.906
Minimum	2.000	1.750	2.500	1.250	1.250	1.500	1.750	1.750	2.250
Maximum	4.000	4.750	4.250	4.750	5.000	4.250	4.500	4.500	4.500

Descriptive Statistics Technological Context 2

Descriptive Statistics

	Benefits			AI-Complexity			Cybersecurity Concerns		
	Awareness	Consideration	Intention	Awareness	Consideration	Intention	Awareness	Consideration	Intention
Mean	3.272	3.971	3.875	3.130	3.007	2.825	2.913	2.941	3.150
Std. Deviation	0.801	0.883	0.729	0.630	0.831	0.624	0.828	0.705	0.516
Minimum	2.000	1.500	2.000	2.250	1.750	2.000	1.250	1.750	2.250
Maximum	4.750	5.000	4.500	4.500	4.750	4.000	4.500	4.500	3.750

Descriptive Statistics - Organizational Context

Descriptive Statistics

	Management Support			Organizational Capability		
	Awareness	Consideration	Intention	Awareness	Consideration	Intention
Mean	2.804	3.324	3.225	2.913	3.463	3.600
Std. Deviation	0.735	0.966	1.003	0.710	0.655	0.637
Minimum	1.250	1.500	2.000	1.500	2.000	2.250
Maximum	4.000	5.000	4.750	4.000	4.750	4.500

Descriptive Statistics - Environmental Context

Descriptive Statistics

	External Pressure			External Support			Government Support		
	Awareness	Consideration	Intention	Awareness	Consideration	Intention	Awareness	Consideration	Intention
Mean	3.022	3.426	3.675	2.978	3.279	3.350	2.750	2.669	2.550
Std. Deviation	0.783	0.692	0.688	0.470	0.586	0.728	0.337	0.484	0.511
Minimum	1.250	2.000	2.000	1.500	2.000	1.750	2.000	1.000	1.750
Maximum	4.500	4.750	4.250	3.750	4.500	4.500	3.250	3.500	3.000

Descriptive Statistics - Intention to Adopt

Descriptive Statistics

	Intention to Adopt		
	Awareness	Consideration	Intention
Mean	2.768	3.245	3.967
Std. Deviation	0.901	1.280	0.745
Minimum	1.333	1.000	3.000
Maximum	4.667	5.000	5.000

Appendix M: Correlation Analysis

Correlation

Pearson's Correlations

Variable		Technological Readiness	Compatibility	Costs	Benefits	AI-Complexity	Cybersecurity Concerns	Organizational Capability	Management Support	External Pressure	External Support	Government Support	Intention to Adopt
1. Technological Readiness	Pearson's r	—											
	p-value	—											
2. Compatibility	Pearson's r	0.293*	—										
	p-value	0.016	—										
3. Costs	Pearson's r	0.071	−0.030	—									
	p-value	0.568	0.808	—									
4. Benefits	Pearson's r	0.280*	0.280*	0.006	—								
	p-value	0.022	0.022	0.958	—								
5. AI-Complexity	Pearson's r	−0.076	−0.138	0.130	−0.024	—							
	p-value	0.539	0.266	0.293	0.850	—							
6. Cybersecurity Concerns	Pearson's r	−0.020	0.040	0.193	-5.101×10^{-4}	0.098	—						
	p-value	0.871	0.747	0.117	0.997	0.430	—						
7. Organizational Capability	Pearson's r	0.434***	0.523***	0.160	0.296*	−0.263*	0.027	—					
	p-value	< .001	< .001	0.195	0.015	0.031	0.828	—					
8. Management Support	Pearson's r	0.428***	0.247*	0.113	0.251*	−0.257*	−0.202	0.466***	—				
	p-value	< .001	0.044	0.361	0.041	0.036	0.102	< .001	—				
9. External Pressure	Pearson's r	0.001	0.084	0.041	0.051	−0.152	0.010	0.162	0.078	—			
	p-value	0.992	0.499	0.740	0.683	0.219	0.933	0.190	0.532	—			
10. External Support	Pearson's r	0.190	0.141	0.014	0.135	−0.160	−0.017	0.165	0.053	0.300*	—		
	p-value	0.124	0.256	0.909	0.276	0.197	0.892	0.183	0.671	0.014	—		
11. Government Support	Pearson's r	−0.194	−0.174	0.009	−0.142	0.133	0.015	−0.285*	−0.059	−0.192	−0.209	—	
	p-value	0.116	0.158	0.941	0.251	0.282	0.902	0.019	0.637	0.119	0.090	—	
12. Intention to Adopt	Pearson's r	0.400***	0.465***	−0.121	0.385**	−0.219	−0.069	0.436***	0.451***	0.083	0.210	−0.230	—
	p-value	< .001	< .001	0.329	0.001	0.075	0.578	< .001	< .001	0.505	0.088	0.062	—

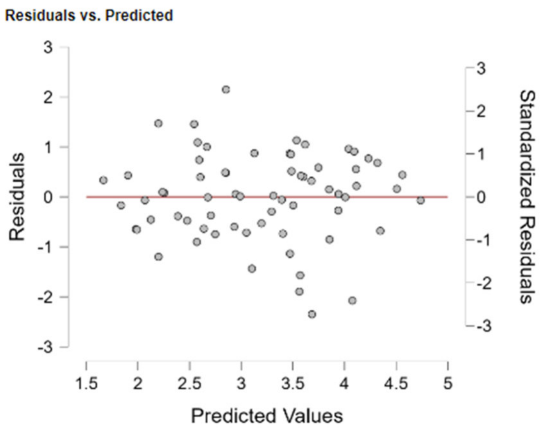
* p < .05, ** p < .01, *** p < .001

Appendix N: Regression Assumptions

The following detailed analysis of the regression assumptions examines the underlying assumptions that must be fulfilled to assure the validity of regression analysis (Hair et al., 2019; Swanson & Holton, 2005; Wentura et al., 2023; Backhaus et al., 2025). The following analysis focuses on *n* = 67 of this thesis.

Linearity

Linearity is described as the “degree to which the change in the dependent variable is associated with the independent variable” (Hair et al., 2019, p. 288). Potential violations were assessed using the “Residual vs. Predicted” and “Partial Regression Plots”. In both plots, residuals should be randomly distributed around zero without systematic patterns (e.g. U-shaped) (Kutner et al., 2005). Visual analysis revealed no evidence of non-linearity. The following figure presents the “Residuals vs. Predicted” plot:



Therefore, the assumption of linearity is fulfilled.

Homoscedasticity

Homoscedasticity exists when “the error terms (residuals) are not constant across the range of the independent variable” (Hair et al., 2019, p. 290). A violation of homoscedasticity assumption would lead to biased standard errors of coefficients, thereby affecting the accuracy of p-values and confidence intervals. To examine if this assumption is violated, the “Residuals vs. Predicted” plot can be observed and is analyzed regarding the existence of unusual patterns for example triangle-shaped (Hair et al., 2019; Backhaus et al., 2025). The residuals show a vertical distribution across the range of independent variables and show no patterns or unusual shapes.

Therefore, the assumption of homoscedasticity is fulfilled.

Normality

The assumption of normality in multiple regression is generally considered relevant to ensure the validity of significance tests and confidence intervals (Hair et al., 2019; Backhaus et al., 2025). In the present analysis, normality was analyzed by viewing the skewness and kurtosis of the standardized residuals, the histogram of the residuals, as well as by conducting a Shapiro-Wilk test and visual analysis of the Q-Q plot.

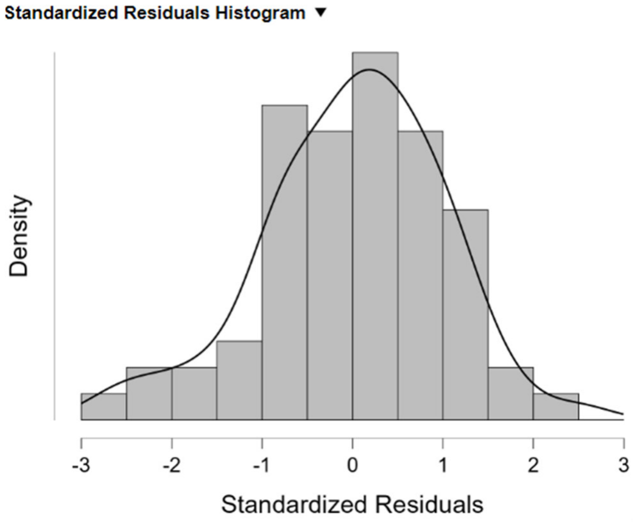
The standardized residuals of the regression model result in a skewness of -.399 and a kurtosis of .490. To further assess normality, z-values were calculated by dividing skewness and kurtosis by using their standard errors. This resulted in a z-value of -1.36 for skewness and .85 for kurtosis. Both values fall within the recommended range of ±1.96, indicating no significant deviation from normality (Field, 2009).

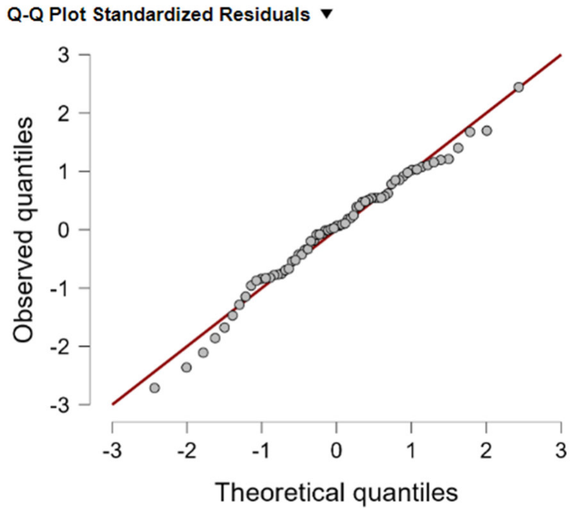
Additionally, the Shapiro-Wilk test yields a p-value of .502, indicating no statistically significant deviation from normality of standardized residuals (Field, 2009).

Skewness, kurtosis and Shapiro-Wilk test of standardized residuals

	Residuals
Skewness	-.399
Std. Error of Skewness	.293
Kurtosis	.490
Std. Error of Kurtosis	.578
Shapiro-Wilk	.983
P-value of Shapiro-Wilk	.502

Furthermore, the standardized residuals were visually analyzed using a histogram and a Q-Q plot (Backhaus et al., 2025). The plot indicates a close approximation of the residuals with normal distribution within the central quantiles, with moderate deviations in the left tail and slight deviations in the upper right tail. Such deviations are common in applied research and are generally not considered critical (Backhaus et al., 2025). Overall, the visual analysis supports the assumption of approximate normality. These results suggest an adequate approximation to normality.





Therefore, the assumption of normality is fulfilled.

Outliers

In addition, the data were examined for potential outliers based on the standardized residuals, as extreme values may disproportionately influence regression results. Standardized residuals exceeding ±3 are commonly considered as substantial outliers (Backhaus et al., 2018). The analysis indicates that the standardized residuals range from -2.713 to 2.445, suggesting the presence of moderate but no critical deviations. Additionally, Cook's distance values were inspected and found to be substantially below the threshold of 1, indicating no evidence of highly influential cases (Backhaus et al., 2025).

Residuals Statistics

	Minimum	Maximum	Mean	SD	N
Std. Residual	-2.713	2.445	.002	.999	67

Multicollinearity

Multicollinearity refers to "shared variance with another variable(s)" (Hair et al., 2019, p. 311) within a multiple regression analysis, which can influence the predictive power of the regression model and the regression coefficients and significance results (Hair et al., 2019; Backhaus, 2025). To assess multicollinearity the tolerance and VIF was analyzed. The VIF values ranged between 1.122 and 1.979 indicating no violation against the recommended threshold of 5 for smaller samples and the maximum VIF threshold of 10 (Hair et al., 2019; Backhaus et al., 2018; Field, 2009). The tolerance was also above the recommended threshold of .25 (Urban & Dieter, 2018).

Tolerance and VIF

	Tolerance	VIF
Technological Readiness	.689	1.452
Compatibility	.690	1.449
Costs	.875	1.143
Benefits	.845	1.184
AI-Complexity	.833	1.200
Cybersecurity Concerns	.891	1.122
Management Support	.624	1.602
Organizational Capability	.505	1.979
External Pressure	.862	1.160
External Support	.838	1.194
Government Support	.856	1.169

Therefore, the assumption of no multicollinearity is fulfilled.

Autocorrelation

Another assumption to be examined concerns the potential autocorrelation of residuals. Autocorrelation occurs when residuals are correlated with one another, a phenomenon that is particularly relevant in time-series analyses (Kutner et al., 2005; Backhaus et al., 2025). Although the present study uses cross-sectional data, the absence of autocorrelation should be verified. The Durbin-Watson test is used to detect autocorrelation of residuals. Values between 1.5 and 2.5 are generally interpreted as indicating no substantial autocorrelation as they are close to 2 (Backhaus et al., 2025).

The analysis results in a Durbin-Watson value of $DW = 2.261$, suggesting no substantial autocorrelation of residuals.

Durbin-Watson

Autocorrelation	Statistic	p
-.184	2.261	.254

Therefore, no extreme autocorrelation exists.

Appendix O: Regression Analysis

Linear Regression ▼

Model Summary - Intention to Adopt

					Durbin-Watson		
Model	R	R^2	Adjusted R^2	RMSE	Autocorrelation	Statistic	p
M_0	0.000	0.000	0.000	1.149	−0.097	2.119	0.625
M_1	0.663	0.440	0.328	0.942	−0.184	2.261	0.254

Note. M_1 includes Technological Readiness, Compatibility, Costs, Benefits, AI-Complexity, Cybersecurity Concerns, Management Support, Organizational Capability, External Pressure, External Support, Government Support

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
M_1	Regression	38.358	11	3.487	3.930	< .001
	Residual	48.803	55	0.887		
	Total	87.161	66			

Note. M_1 includes Technological Readiness, Compatibility, Costs, Benefits, AI-Complexity, Cybersecurity Concerns, Management Support, Organizational Capability, External Pressure, External Support, Government Support

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

							95% CI		Collinearity Statistics	
Model		Unstandardized	Standard Error	Standardized	t	p	Lower	Upper	Tolerance	VIF
M_0	(Intercept)	3.189	0.140		22.715	< .001	2.909	3.469		
M_1	(Intercept)	0.513	1.628		0.315	0.754	−2.750	3.775		
	Technological Readiness	0.173	0.189	0.111	0.917	0.363	−0.205	0.551	0.689	1.452
	Compatibility	0.287	0.140	0.249	2.049	0.045	0.006	0.569	0.690	1.449
	Costs	−0.254	0.172	−0.159	−1.474	0.146	−0.600	0.091	0.875	1.143
	Benefits	0.229	0.143	0.176	1.607	0.114	−0.057	0.515	0.845	1.184
	AI-Complexity	−0.071	0.173	−0.045	−0.409	0.684	−0.417	0.275	0.833	1.200
	Cybersecurity Concerns	0.024	0.170	0.015	0.140	0.889	−0.318	0.365	0.891	1.122
	Management Support	0.341	0.160	0.273	2.134	0.037	0.021	0.662	0.624	1.602
	Organizational Capability	0.089	0.227	0.055	0.390	0.698	−0.366	0.543	0.505	1.979
	External Pressure	−0.033	0.166	−0.021	−0.197	0.845	−0.366	0.300	0.862	1.160
	External Support	0.177	0.217	0.090	0.818	0.417	−0.257	0.612	0.838	1.194
	Government Support	−0.224	0.284	−0.086	−0.787	0.435	−0.793	0.346	0.856	1.169

Appendix P: Reliability Analysis Awareness and Consideration

Organizational Readiness - Awareness

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.843*	*.041*	*.736*	*.923*

Management Support - Awareness

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.788*	*.069*	*.654*	*.922*

Benefits - Awareness

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.729*	*.094*	*.544*	*.913*

Costs - Awareness

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.676*	*.120*	*.440*	*.911*

Technological Risk - Awareness

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.545*	*.144*	*.262*	*.828*

Environmental Influence - Awareness

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.533*	*.214*	*.114*	*.953*

Intention to Adopt - Awareness

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.922*	*.048*	*.827*	*1.016*

Organizational Readiness - Consideration

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.833*	*.037*	*.760*	*.905*

Management Support - Consideration

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.882*	*.034*	*.815*	*.949*

Benefits - Consideration

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.879*	*.052*	*.777*	*.981*

Costs - Consideration

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.746*	*.080*	*.589*	*.903*

Technological Risk - Consideration

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.789*	*.044*	*.703*	*.874*

Environmental Influence - Consideration

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.590*	*.097*	*.399*	*.780*

Intention to Adopt - Consideration

			95% CI	
Coefficient	*Estimate*	*Std. Error*	*Lower*	*Upper*
Coefficient α	*.956*	*.0011*	*.934*	*.978*

Appendix Q: Descriptive Statistics Awareness, Consideration and Intention

Descriptive Statistics - Awareness

Descriptive Statistics

	Organizational Readiness	Management Support	Costs	Benefits	Technological Risk	Environmental Influence	Intention to Adopt
Mean	2.928	2.804	2.967	3.272	3.022	2.917	2.768
Std. Deviation	0.586	0.735	0.700	0.801	0.458	0.324	0.901
Minimum	1.750	1.250	1.750	2.000	2.375	2.167	1.333
Maximum	3.833	4.000	4.500	4.750	4.125	3.583	4.667

Descriptive Statistics - Consideration

Descriptive Statistics

	Organizational Readiness	Management Support	Costs	Benefits	Technological Risk	Environmental Influence	Intention to Adopt
Mean	3.551	3.324	3.154	3.971	2.974	3.125	3.245
Std. Deviation	0.600	0.966	0.683	0.883	0.621	0.351	1.280
Minimum	1.917	1.500	1.750	1.500	2.000	2.250	1.000
Maximum	4.583	5.000	4.500	5.000	4.250	3.917	5.000

Descriptive Statistics - Intention

Descriptive Statistics

	Organizational Readiness	Management Support	Costs	Benefits	Technological Risk	Environmental Influence	Intention to Adopt
Mean	3.400	3.225	3.175	3.875	2.987	3.192	3.967
Std. Deviation	0.503	1.003	0.906	0.729	0.454	0.354	0.745
Minimum	2.750	2.000	2.250	2.000	2.375	2.583	3.000
Maximum	4.250	4.750	4.500	4.500	3.500	3.583	5.000

Appendix R: Correlation Analysis Awareness, Consideration and Intention

Correlation - Awareness

Pearson's Correlations

Variable		Organizational Readiness	Management Support	Costs	Benefits	Technological Risk	Environmental Influence	Intention to Adopt
1. Organizational Readiness	Pearson's r	—						
	p-value	—						
2. Management Support	Pearson's r	0.401	—					
	p-value	0.058	—					
3. Costs	Pearson's r	0.183	−0.007	—				
	p-value	0.402	0.973	—				
4. Benefits	Pearson's r	0.496*	0.273	−0.333	—			
	p-value	0.016	0.207	0.121	—			
5. Technological Risk	Pearson's r	−0.091	−0.168	0.233	0.243	—		
	p-value	0.680	0.443	0.285	0.265	—		
6. Environmental Influence	Pearson's r	−0.361	−0.287	0.209	−0.595**	−0.153	—	
	p-value	0.090	0.185	0.339	0.003	0.485	—	
7. Intention to Adopt	Pearson's r	0.629**	0.552**	0.126	0.375	−0.074	−0.407	—
	p-value	0.001	0.006	0.568	0.078	0.736	0.054	—

* p < .05, ** p < .01, *** p < .001

Correlation - Consideration

Pearson's Correlations

Variable		Organizational Readiness	Management Support	Costs	Benefits	Technological Risk	Environmental Influence	Intention to Adopt
1. Organizational Readiness	Pearson's r	—						
	p-value	—						
2. Management Support	Pearson's r	0.353*	—					
	p-value	0.041	—					
3. Costs	Pearson's r	−0.184	−0.081	—				
	p-value	0.299	0.649	—				
4. Benefits	Pearson's r	0.137	0.023	0.045	—			
	p-value	0.441	0.899	0.798	—			
5. Technological Risk	Pearson's r	−0.015	−0.267	0.430*	−0.053	—		
	p-value	0.933	0.127	0.011	0.765	—		
6. Environmental Influence	Pearson's r	0.081	0.177	0.054	0.287	−0.083	—	
	p-value	0.651	0.317	0.761	0.099	0.639	—	
7. Intention to Adopt	Pearson's r	0.564***	0.395*	−0.351*	0.286	−0.218	0.097	—
	p-value	< .001	0.021	0.042	0.101	0.217	0.587	—

* p < .05, ** p < .01, *** p < .001

Correlation - Intention

Pearson's Correlations

Variable		Organizational Readiness	Management Support	Costs	Benefits	Technological Risk	Environmental Influence	Intention to Adopt
1. Organizational Readiness	Pearson's r	—						
	p-value	—						
2. Management Support	Pearson's r	0.669*	—					
	p-value	0.034	—					
3. Costs	Pearson's r	0.322	0.655*	—				
	p-value	0.364	0.040	—				
4. Benefits	Pearson's r	−0.019	0.622	0.258	—			
	p-value	0.959	0.055	0.472	—			
5. Technological Risk	Pearson's r	−0.786**	−0.793**	−0.526	−0.351	—		
	p-value	0.007	0.006	0.119	0.320	—		
6. Environmental Influence	Pearson's r	0.102	−0.259	−0.499	−0.310	0.053	—	
	p-value	0.778	0.470	0.142	0.384	0.885	—	
7. Intention to Adopt	Pearson's r	0.188	0.433	−0.032	0.657*	−0.412	0.320	—
	p-value	0.603	0.212	0.931	0.039	0.237	0.367	—

* p < .05, ** p < .01, *** p < .001

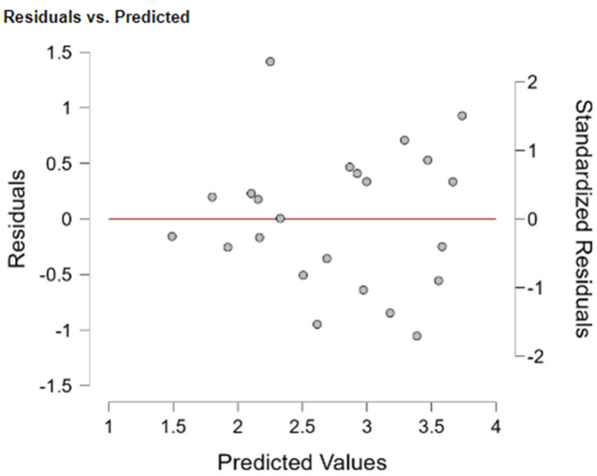
Appendix S: Regression Assumptions Awareness and Consideration

The following detailed analysis of the regression assumptions examines the underlying assumptions that must be met to ensure the validity of regression analysis (Hair et al., 2019; Swanson & Holton, 2005; Wentura et al., 2023; Backhaus et al., 2025). The analysis examines the assumptions for the awareness and consideration stage separately.

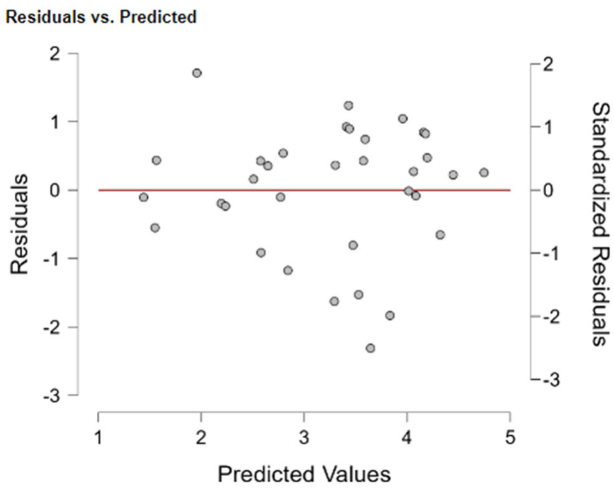
A detailed explanation of the definitions and threshold values for each assumption is provided in the Appendix N.

Linearity

Visual analysis of the "Residual vs. Predicted" and "Partial Regression Plots" for the awareness and consideration stage indicated no evidence of non-linearity as residuals were randomly distributed around zero without systematic patterns.



Awareness



Consideration

Homoscedasticity

The visual analysis of the "Residuals vs. Predicted" plot for the awareness stage showed the existence of a slight triangle-shaped pattern. Although heteroscedasticity does not bias coefficient estimates, it reduces their efficiency and may lead to biased standard errors and test statistics (Wooldridge, 2009). Consequently, results for the awareness stage are interpreted with appropriate caution. The visual analysis for the consideration stage showed no existence of systematic patterns, indicating no heteroscedasticity.

Normality

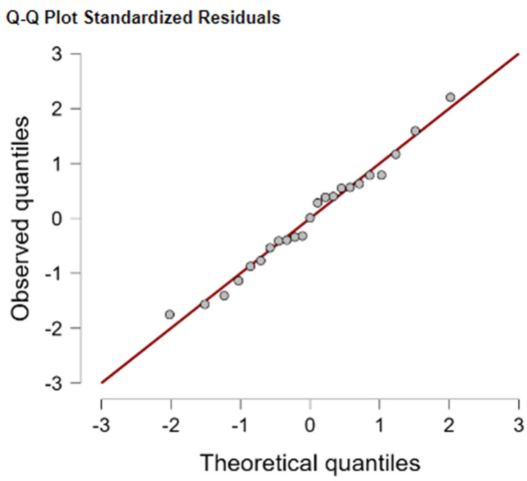
Normality was analyzed by viewing the skewness and kurtosis of the standardized residuals, the histogram of the residuals, as well as by conducting a Shapiro-Wilk test and visual analysis of the Q-Q plot.

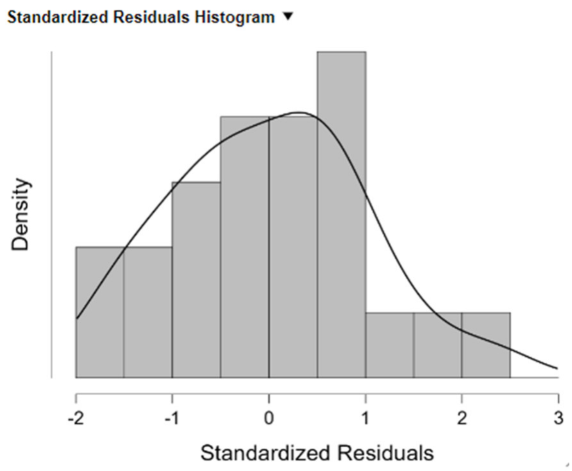
In the awareness stage the standardized residuals result in a skewness of .240 and a kurtosis of -.128. To further assess normality, z-values were calculated by dividing skewness and kurtosis by using their standard errors. This resulted in a z-value of .499 for skewness and -.137. Both values fall within the recommended range of ±1.96, indicating no significant deviation from normality (Field, 2009). Additionally, the Shapiro-Wilk test yields a p-value of .949, indicating no statistically significant deviation from normality of standardized residuals (Field, 2009).

Skewness, Kurtosis and Shapiro-Wilk Test of Standardized Residuals - Awareness

	Residuals
Skewness	.240
Std. Error of Skewness	.481
Kurtosis	-.128
Std. Error of Kurtosis	.935
Shapiro-Wilk	.983
P-value of Shapiro-Wilk	.949

Furthermore, the standardized residuals were visually analyzed using a histogram and a Q-Q plot (Backhaus et al., 2025). The plot indicates a close approximation of the residuals with normal distribution within the central quantiles, low deviations in the tails. Overall, the visual analysis supports the assumption of approximate normality.





Awareness

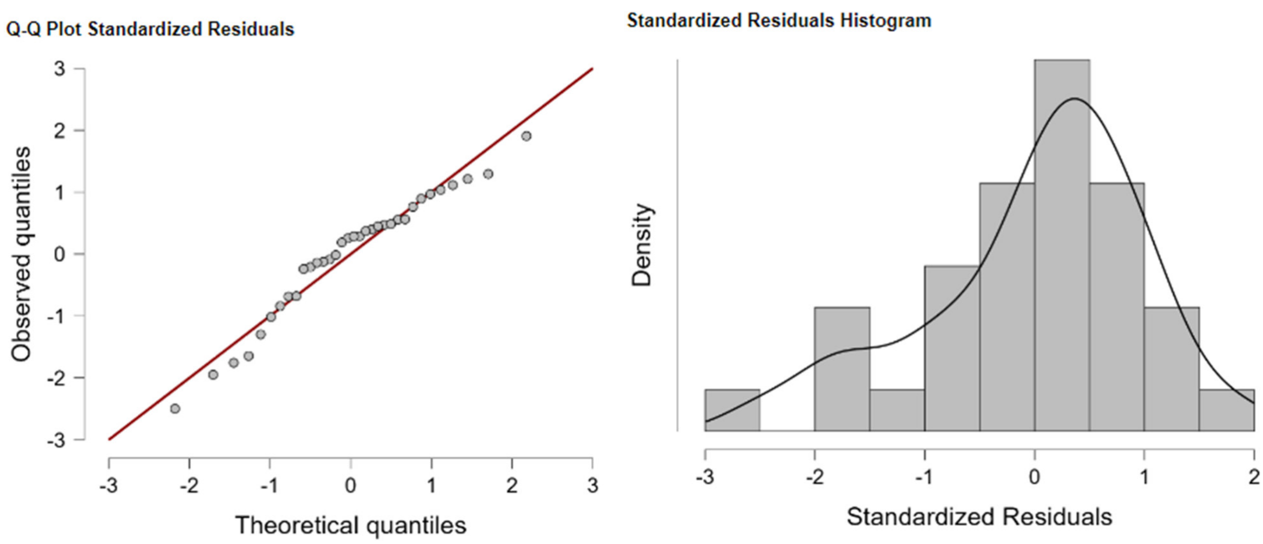
These results suggest an adequate approximation to normality for the awareness stage.

In the consideration stage the standardized residuals result in a skewness of -.740 and a kurtosis of .252. The resulting z-value of -1.84 for skewness and .319 fall within the recommended range of ±1.96, indicating no significant deviation from normality (Field, 2009). Additionally, the Shapiro-Wilk test yields a p-value of .127, indicating no statistically significant deviation from normality of standardized residuals (Field, 2009).

Skewness, Kurtosis and Shapiro-Wilk Test of Standardized Residuals - Consideration

	Residuals
Skewness	-.740
Std. Error of Skewness	.403
Kurtosis	.252
Std. Error of Kurtosis	.788
Shapiro-Wilk	.951
P-value of Shapiro-Wilk	.127

Furthermore, the standardized residuals were visually analyzed using a histogram and a Q-Q plot (Backhaus et al., 2025). The plot indicates a close approximation of the residuals with normal distribution within the central quantiles, with moderate deviations in the tails. Such deviations are common in applied research and are generally not considered critical (Backhaus et al., 2025). Overall, the visual analysis supports the assumption of approximate normality. These results suggest an adequate approximation to normality for the consideration stage.



Consideration

These results suggest an adequate approximation to normality for the consideration stage.

Outliers

In addition, the data were examined for potential outliers based on the standardized residuals, as extreme values may disproportionately influence regression results. The analysis indicates that standardized residuals range from -1.753 to 2.203 in the awareness stage and from -2.497 to 1.906 in the consideration stage. Additionally, Cook's distance values were inspected and found to be substantially below the threshold of 1, indicating no evidence of highly influential cases for the awareness and consideration stage (Backhaus et al., 2025).

Residuals Statistics - Awareness

	Minimum	Maximum	Mean	SD	N
Std. Residual	-1.753	2.203	-.007	1.008	23

Residuals Statistics - Consideration

	Minimum	Maximum	Mean	SD	N
Std. Residual	-2.497	1.906	.009	1.008	34

Multicollinearity

To assess multicollinearity the tolerance and VIF was analyzed. The VIF values ranged between 1.280 and 2.879 in the awareness stage and ranged from 1.124 to 1.376 in the consideration stage, indicating no violation against the recommended threshold of 5 for smaller samples and the maximum VIF threshold of 10 (Hair et al., 2019; Backhaus et al., 2018; Field, 2009). The tolerance was also above the recommended threshold of 0,25 (Urban & Dieter, 2018).

Tolerance and VIF - Awareness

	Tolerance	VIF
Organizational Readiness	.459	2.180
Management Support	.781	1.280
Costs	.529	1.889
Benefits	.347	2.879
Technological Risk	.620	1.614
Environmental Influence	.619	1.616

Tolerance and VIF - Consideration

	Tolerance	VIF
Organizational Readiness	.802	1.246
Management Support	.775	1.291
Costs	.759	1.318
Benefits	.890	1.124
Technological Risk	.727	1.376
Environmental Influence	.882	1.133

Therefore, the assumption of no multicollinearity for the awareness and consideration stage is fulfilled.

Autocorrelation

Autocorrelation occurs when residuals are correlated with one another, a phenomenon that is particularly relevant in time-series analyses (Kutner et al., 2005; Backhaus et al., 2025).

The Durbin-Watson test resulted in *DW* = 1.740 for the awareness stage and in *DW* = 1.890, indicating no substantial autocorrelation.

Durbin-Watson - Awareness

Autocorrelation	Statistic	p
.077	1.740	.628

Durbin-Watson - Consideration

Autocorrelation	Statistic	p
-.007	1.890	.712

Therefore, no extreme autocorrelation exists in the awareness and consideration stage.

Appendix T: Regression Analysis Awareness and Consideration

Linear Regression - Awareness

Model Summary - Intention to Adopt

Model	R	R²	Adjusted R²	RMSE	Durbin-Watson Autocorrelation	Durbin-Watson Statistic	Durbin-Watson p
M_0	0.000	0.000	0.000	0.901	−0.161	2.294	0.473
M_1	0.729	0.531	0.355	0.724	0.077	1.740	0.628

Note. M_1 includes Organizational Readiness, Management Support, Costs, Benefits, Technological Risk, Environmental Influence

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
M_1	Regression	9.490	6	1.582	3.018	0.036
	Residual	8.384	16	0.524		
	Total	17.874	22			

Note. M_1 includes Organizational Readiness, Management Support, Costs, Benefits, Technological Risk, Environmental Influence
Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p	95% CI Lower	95% CI Upper	Collinearity Statistics Tolerance	Collinearity Statistics VIF
M_0	(Intercept)	2.768	0.188		14.728	< .001	2.378	3.158		
M_1	(Intercept)	1.103	2.792		0.395	0.698	−4.816	7.023		
	Organizational Readiness	0.599	0.389	0.389	1.540	0.143	−0.226	1.424	0.459	2.180
	Management Support	0.401	0.238	0.327	1.686	0.111	−0.103	0.905	0.781	1.280
	Costs	0.151	0.303	0.117	0.497	0.626	−0.491	0.793	0.529	1.889
	Benefits	0.037	0.327	0.033	0.113	0.912	−0.656	0.730	0.347	2.879
	Technological Risk	−0.093	0.428	−0.047	−0.218	0.830	−1.001	0.814	0.620	1.614
	Environmental Influence	−0.514	0.606	−0.185	−0.848	0.409	−1.799	0.771	0.619	1.616

Linear Regression - Consideration

Model Summary - Intention to Adopt

Model	R	R²	Adjusted R²	RMSE	Durbin-Watson Autocorrelation	Durbin-Watson Statistic	Durbin-Watson p
M_0	0.000	0.000	0.000	1.280	−0.216	2.363	0.281
M_1	0.694	0.481	0.366	1.019	−0.007	1.890	0.712

Note. M_1 includes Organizational Readiness, Management Support, Costs, Benefits, Technological Risk, Environmental Influence

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
M_1	Regression	26.014	6	4.336	4.173	0.004
	Residual	28.055	27	1.039		
	Total	54.069	33			

Note. M_1 includes Organizational Readiness, Management Support, Costs, Benefits, Technological Risk, Environmental Influence
Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p	95% CI Lower	95% CI Upper	Collinearity Statistics Tolerance	Collinearity Statistics VIF
M_0	(Intercept)	3.245	0.220		14.783	< .001	2.798	3.692		
M_1	(Intercept)	−0.140	2.191		−0.064	0.950	−4.635	4.355		
	Organizational Readiness	0.872	0.330	0.408	2.638	0.014	0.194	1.550	0.802	1.246
	Management Support	0.295	0.209	0.223	1.414	0.169	−0.133	0.723	0.775	1.291
	Costs	−0.474	0.298	−0.253	−1.590	0.124	−1.087	0.138	0.759	1.318
	Benefits	0.355	0.213	0.245	1.667	0.107	−0.082	0.792	0.890	1.124
	Technological Risk	−0.068	0.335	−0.033	−0.204	0.840	−0.756	0.620	0.727	1.376
	Environmental Influence	−0.129	0.539	−0.035	−0.239	0.813	−1.234	0.976	0.882	1.133

11 Disclosure on the Use of Artificial Intelligence

In this thesis AI tools (including generative AI such as ChatGPT or Google Gemini) were used solely for brainstorming, language refinement and structural support. All research design, data analysis, interpretation of results, and academic arguments were developed independently by the author. Full responsibility for the content of this thesis rests with the author.

12 Affirmation

I hereby confirm that I have authored this thesis independently and without illicit assistance from third parties and using solely the aids mentioned. The thoughts that were retrieved directly or indirectly from other sources are marked as such. The work was submitted or published so far in same or similar form of no other test authority.

Buch, 06.03.2026

Place, date

Signature