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THE IMPACT OF AI ON STRATEGIC DECISION-MAKING IN CRISIS MANAGEMENT

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ABSTRACT

This research investigates the extent to which Artificial Intelligence supports human-based strategic decision-making during supply chain crises. In recent years, supply chains have been increasingly disrupted by geopolitical tensions, pandemics and material shortages. While AI is often positioned as a solution for predictive analytics and scenario planning, little is known about how human decision-makers interact with these tools under pressure. The objective of this study is to explore how AI-generated insights are interpreted, trusted and applied by professionals in crisis contexts. A qualitative research design was adopted, based on eight-semi-structured expert interviews with professionals in supply chain management, AI development and procurement. The Gioia methodology was used to code and analyse the data. Findings indicate that AI plays a supportive rather than an autonomous role. AI enables faster data processing, early risk prediction and improved scenario generation. However, final decisions remain with human actors. Adoption is limited by data scarcity, trust issues and lack of strategic integration. This study contributes to theory by clarifying the boundaries of AI's decision-support role and highlights the importance of human oversight, organizational readiness and ethical awareness. It provides practical recommendations for integrating AI responsibly into strategic supply chains under uncertainty.

Keywords: Artificial Intelligence, Strategic Decision-Making, Supply Chain Crisis Management, Organizational Adoption, Human-AI Collaboration

PREFACE

The research presented in this document explores the effects of AI on strategic decision-making during crisis management. This Master Thesis marks the end of my journey in the Strategic Management master program at Radboud University. The research was conducted between February 2025 and June 2025.

I would like to thank my supervisor from Radboud University, H.S. A Mahmoud, for his guidance throughout my master thesis trajectory. Providing me with valuable feedback and insights while drafting this thesis.

I wish you an insightful and enjoyable reading experience!

Eindhoven, 16th of June 2025
Menno Esvelt

LIST OF ABRIVIATIONS

AI	Artificial Intelligence
ML	Machine Learning
DSS	Decision Support System
LLM	Large Language Model

LIST OF FIGURES

LIST OF TABLES

TABLE OF CONTENTS

1 INTRODUCTION

1.1 PROBLEM FORMULATION

Global supply chains have become increasingly exposed to high-impact disruptions such as geopolitical conflicts, natural disasters and economic volatility (Baryannis et al., 2019). Recent disruptions including the COVID-19 pandemic, the Suez Canal blockage and semiconductor shortage, have exposed weaknesses in traditional supply chain crisis management. These disruptions in supply chains typically relied on reactive strategies and historical data which have failed to provide the speed and adaptability required to respond to the modern fast-moving environment (Frieske & Stieler, 2022; Ivanov & Dolgui, 2020; Tang, 2006; Wan et al., 2023).

Artificial Intelligence (AI) has been identified as a potential enabler of more resilient and responsive supply chains. AI systems can process real-time data, detect anomalies and support decision-making through scenario analysis (Baryannis et al., 2019; Ekellem, 2024; Wang et al., 2023). However, most academic work has focused on the technological capabilities of AI or the contribution to risk identification and operational optimisation. What has been missing is a deeper understanding of how decision-makers interpret, trust and act on AI-generated recommendations in high-pressure crisis scenarios.

Several barriers have limited the practical adoption of AI in crisis management. The main barriers have included the interpretability of AI-generated output, managerial scepticism and concerns over data reliability (Kolbjørnsrud et al., 2017; Stone et al., 2020). The 'black-box' nature of AI models has reduced transparency, which has limited trust and acceptance of AI-generated recommendations (Dwivedi et al., 2021). Governance issues related to accountability, transparency and oversight have further complicate the adoption of AI-driven systems in crisis environments (Cheng et al., 2023).

While existing studies have explored the technological capabilities of AI in risk assessment and supply chain optimisation (Baryannis et al., 2019; Ivanov & Dolgui, 2020), there remains a clear academic gap regarding how AI is used by professionals during real-time decision-making under uncertainty (Dwivedi et al., 2021). Academic insights into how professionals interpret, trust and act upon AI recommendations under pressure remain limited. As a result, practical frameworks that combine predictive analytics with human judgement are still underdeveloped.

This study examines the role of AI in real-time strategic decision-making by human professionals during supply chain crises. By exploring expert insights, the research aims to bridge the gap between the technical capabilities and practical use cases to improve human-AI collaboration in high-stakes environments.

1.2 RELEVANCE

The increasing adoption of AI in supply chain management has introduced new opportunities to improve risk assessment, forecasting accuracy and operational responsiveness (Chandola et al., 2009; Dwivedi et al., 2021). Several existing studies have explored the technological potential of AI in supply chain management. For example, Baryannis et al. (2019) conducted a comprehensive review of AI applications in supply chain risk management highlighted predictive capabilities. Similarly, Richey et al. (2023) provided a roadmap for AI integration in supply chain management. However, these studies focused solely on risk identification and operational resilience, offering limited insights into how AI is used by decision-makers in crisis situations.

Recent studies by Alsakhen et al. (2024) and Maddikunta et al. (2022) acknowledge the limitations of traditional risk mitigation strategies and the lack of speed and adaptability required in dynamic crisis situations. While these studies emphasise the need for predictive capabilities, they pay little attention to how these technologies are interpreted, trusted or challenged by human users. Systematic reviews such as Jahin et al. (2025) mention the potential of AI in decision support but neglect the human-AI interaction under uncertainty. A significant gap exists in the literature concerning the integration of AI-driven analytics into human-based strategic decision-making frameworks (Cheng et al., 2023; Ivanov & Dolgui, 2020). Most studies address technical capabilities but overlook how managers interact with AI-generated recommendations in volatile, high-stakes situations.

This study addresses that gap by exploring how decision-makers interact with AI-generated recommendations in practice with a focus on real-time decision-making during crises. Using expert interviews, this study examines barriers such as trust, interpretability and responsibility and provides insights into how AI can be effectively integrated into human-based decision-making. These areas remain underrepresented in existing literature.

Supply chains are critical to economic stability, availability of goods and the general functioning of industries worldwide. Recent crises like the COVID-19 pandemic have exposed the fragility of existing supply chain structures, leading to disruptions of everyday life (Naz et al., 2022). These crises have demonstrated the necessity of more resilient and adaptive crisis management approaches.

While AI offers the potential to increase resilience, improve response times, and better forecasting accuracy, organizations still face challenges in translating predictive output into effective decisions. They continue to struggle with integrating AI tools in their current decision-making frameworks primarily due to concerns regarding data reliability, transparency and managerial control (Shrestha et al., 2019). While these studies focus on technological integration, they lack the human decision component. This creates the need for research that bridges the gap between AI capabilities and their practical use by decision-makers.

This study offers practical insights by helping organizations understand barriers to AI adoption and requirements for embedding AI into their strategic workflows. By providing practical insights into how AI can be effectively integrated into human-decision-making, this study offers value to organizations seeking to improve their supply chain crisis resilience. It also contributes theoretically by providing clarity on adoption dynamics regarding AI integration in crisis context.

1.3 PROBLEM STATEMENT

This research seeks to address the following research question:

To what extent does Artificial Intelligence support human-based strategic decision-making in supply chain crisis management?

1.4 CONCEPTUAL MODEL

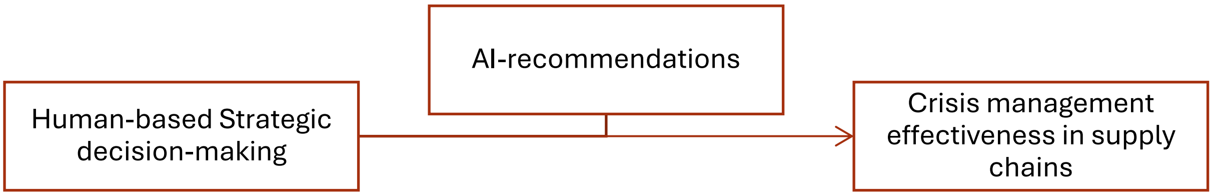

Figure 1 Conceptual model

Figure 1 presents the conceptual model that guides this research. The model illustrates the assumed relationship between AI-generated recommendations, human-based strategic decision-making and the perceived effectiveness of crisis management in supply chain setting. Rather than positioning AI as an autonomous decision-maker, the model conceptualizes it as a support tool that provides predictive insights, scenario simulations and anomaly detection to inform human judgement under uncertainty.

Strategic decision-making has relied on human judgement for a long time. However, in today's complex environments, human decision-makers face challenges that exceed human cognitive abilities (Jarrahi, 2018). This research explores how AI-recommendations affect the effectiveness of human-based strategic decision-making, specifically in supply chain crisis management.

Human decision-making is useful for flexibility and qualitative assessment but is also prone to biases, slower reaction times and information overload; especially in high-stakes environments (Ekellem, 2024; Shrestha et al., 2019). Crises like the Suez Canal blockage demonstrate how sudden disruptions require precise decision-making to manage inventory, logistics and supplier coordination.

AI is increasingly adopted to provide decision support through predictive analytics, anomaly detection and scenario generation. However, the effectiveness depends on trust in the technology, data security and reliability, governance and human oversight (Shrestha et al., 2019).

The adoption of these technologies also presents a significant limitation as not every decision-maker and organization is ready to embrace these systems. This research investigates how AI can complement human judgement, reduce decision-making bias and improve responses in crisis scenarios, ultimately strengthening supply chain resilience.

1.5 THESIS STRUCTURE

The research is structured into six chapters. The first chapter introduces the reader to the research topic, its relevance of the research and presents the central research question. Chapter two presents the theoretical framework, reviewing the key concepts such as strategic decision-making, supply chain crisis management and the role of Artificial Intelligence. The third chapter describes the research methodology, explaining the qualitative approach and design of the data analysis. In chapter 4 the empirical findings derived from expert interviews are presented, organised by aggregate dimensions and thematic themes. Chapter 5 discusses these findings in relation to literature, highlights the theoretical contribution and outlines limitations of the research. The final chapter concludes the thesis by summarizing key insights and answering the central research question.

2 THEORETICAL FRAMEWORK

While the conceptual model in *Figure 1* provides a high-level overview of the relationship between strategic decision-making, AI and crisis management; this chapter further operationalizes these elements by introducing the key constructs that underpin this study. Specifically, it explores how trust, governance, technical capabilities and human-AI collaboration influence the integration of AI in strategic decision-making.

2.1 STRATEGIC DECISION-MAKING

Strategic decision-making is a core function within an organization that shapes the long-term direction by determining resource allocation, competitive positioning and responses to external uncertainties (Teece et al., 1997). Unlike operational decision-making, which focuses more on the short-term efficiency, strategic decision-making involves complex trade-offs and carries significant long-term implications. In the context of global supply chains which are increasingly dynamic and interconnected, strategic decisions play a critical role in building resilience. Decisions made under uncertainty influence the firm's ability to stay resilient and sustain their competitive advantage. According to Christopher and Holweg (2011), structural flexibility is key to navigating volatility effectively.

Traditional frameworks such as the rational decision-making model by Simon (1979) assume that decision-makers evaluate all available information to select the optimal solution. However, this model is based on unrealistic assumptions of complete information and unlimited cognitive capacity, especially in crisis situations where there is significant uncertainty and time pressure. Supply chain crises often involve incomplete data, making it hard to make a rational decision (Christopher & Holweg, 2011; Lerner et al., 2015). Recognizing these limitations, bounded rationality suggests that decision-makers settle for a satisfying solution with incomplete information. Crisis situations increase these constraints by exposing managers to heuristic-based decision-making (Lerner et al., 2015; Tversky & Kahneman, 1974).

While heuristics can accelerate decisions, they can also introduce systematic biases. One of the strongest biases is confirmation bias, which refers to the tendency to seek information that confirms pre-existing beliefs while ignoring contradictory evidence (Nickerson, 1998; Wason, 1960). This bias is problematic in supply chain crisis management as the environment is rapidly changing and requires objective assessment of all available data.

Tversky and Kahneman (1973) introduced the availability heuristic. This is a mental shortcut whereby individuals estimate the probability of events based on how easily they come to mind. In supply chain crisis situations this bias can cause managers to overreact to recent disruptions while neglecting less memorable yet significant risks, resulting in skewed strategic decisions. Closely related is the phenomenon of overconfidence bias, which describes the act of individuals overestimating the accuracy of their knowledge. During supply chain disruptions, overconfidence may lead to undue faith in predictions or strategic choices despite lacking complete information (Tversky & Kahneman, 1974).

While these behavioural limitations show vulnerabilities of human-based decision-making, not all heuristics are detrimental. According to Gigerenzer and Gaissmaier (2011), heuristics can be adaptive and enable quicker decision-making in uncertain environments. Simple rules can be used to classify customer behaviour and anticipate supply chain trends without extensive data analysis (Gigerenzer & Gaissmaier, 2011).

Complementing this behavioural view, the dynamic capabilities theory emphasizes that organizations must develop the ability to sense disruptions (Teece et al., 1997). AI-enhanced decision-making plays a crucial role in strengthening these capabilities. By processing large datasets in real-time, AI is able to augment situation awareness and support adaptive responses (Baryannis et al., 2019). In addition to improving decision speed and pattern recognition, AI can also reduce human biases through scenario modelling and anomaly detection, thus offering more objective and data-driven alternatives (Wang et al., 2023). By offering prescriptive alternatives, AI systems can challenge human limitations and provide more objective decisions (Baryannis et al., 2019).

2.2 CRISIS MANAGEMENT

Crisis management in supply chains refers to the process that organizations adopt to respond to unexpected disruptions that threaten operational continuity (Ponomarov & Holcomb, 2009). Unlike risk management, which focuses on proactive identification of potential threats, crisis management focuses on real-time decision-making during unfolding disruptions. Supply chains are increasingly exposed to external shocks such as natural disasters and pandemics. Events like the COVID-19 pandemic have exposed weaknesses in traditional global supply chain networks by highlighting the need for development in crisis response to balance immediate responsiveness with long-term operational stability (Frieske & Stieler, 2022).

A comprehensive approach to crisis management addresses both immediate response and post-crisis recovery. Foundational frameworks emphasize the need to understand internal risk as well as external risk. Internal risks arise within the organization and include operational inefficiencies, production failures and financial insecurity. External risks stem from political instability, supplier disruption or natural disasters (Baryannis et al., 2019; Christopher & Peck, 2004). Common mitigation strategies include supplier diversification, safety stock and dual sourcing (Tang, 2006).

However, traditional methods alone may not be sufficient in today's highly volatile networks. The complexity of information requires decision-makers to process real-time data, identify threats and react accordingly. Yet, human decision-makers are constrained by cognitive limitations such as information overload and bounded rationality. This is where AI can play a critical role. AI technologies enhance crisis management by enabling predictive analytics, anomaly detection and real-time scenario generation (Ivanov & Dolgui, 2020). As defined by Chandola et al. (2009), anomaly detection refers to the identification of data patterns that deviate from expected behaviour. These can be categorized as point anomalies, contextual anomalies and collective anomalies, all of which can act as early warning signals for emerging disruptions in supply chains.

Nevertheless, AI-generated recommendations alone are not sufficient. Their effectiveness depends heavily on managerial trust, interpretability of the output and appropriate governance mechanisms (Dwivedi et al., 2021).

2.3 SUPPLY CHAIN RESILIENCE

As defined by Ponomarov and Holcomb (2009), supply chain resilience is "the adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function". This definition highlights that resilience requires both proactive preparation and reactive recovery.

The literature identifies multiple dimensions of resilience including agility, visibility, redundancy versus flexibility and dynamic capabilities (Christopher & Peck, 2004; Ponomarov & Holcomb, 2009; Sheffi & Rice, 2005; Teece et al., 1997). Agility refers to the ability to quickly adjust supply chain operations in response to disruptions. Visibility involves real-time insights into supply chain processes which are crucial for anticipating disruptions. Redundancy and flexibility relate to having buffers versus the ability to adapt. Dynamic capabilities with a focus on the ability to sense disruptions are critical to resilience (Teece et al., 1997).

However, human decision-makers may struggle to maintain visibility and adaptability required for these dynamic capabilities. Cognitive overload, limited information-processing capacity and the high speed of disruptions make it difficult to remain resilient. Resilient supply chains must exhibit event readiness, rapid response and recovery mechanisms that enable them to return to a stable operational state (Ponomarov & Holcomb, 2009).

Recent advancements in AI and big data analytics have strengthened supply chain resilience by improving forecasting, risk assessment and disruption response (Ekellem, 2024; Naz et al., 2022). Automated pattern recognition, as described by Wang et al. (2023), enhances this capability by continuously analysing real-time data to flag deviations before they escalate. However, the value of these systems depends heavily on the ability of human actors to interpret AI-generated insights and take appropriate actions (Jarrahi, 2018).

2.4 ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

The integration of AI in supply chain management has significantly increased as firms aim to enhance resilience, efficiency and responsiveness (Richey et al., 2023). AI-driven technologies contribute to decision-making by providing predictive and prescriptive analytics, anomaly detection and real-time scenario generation. These tools enable early disruption forecasting, optimise resource allocation and support data-informed strategies under pressure (Alsakhen et al., 2024; Maddikunta et al., 2022). Predictive analytics enable early detection of potential disruptions by analysing diverse data streams, while prescriptive analytics generate actionable recommendations to mitigate risk (Alsakhen et al., 2024; Wang et al., 2023).

AI refers to systems capable of performing tasks that typically require human intelligence such as pattern recognition, reasoning and decision-making (Kaplan & Haenlein, 2019; Wang et al., 2023). In supply chains, AI enables intelligent forecasting, demand prediction, transport optimisation and autonomous decision support (Richey et al., 2023). AI's relevance in crisis management lies in its ability to detect early warning signs, enhance visibility and provide Decision Support Systems (DSS) that deliver real-time actionable insights (Alsakhen et al., 2024).

Machine learning and big data enable algorithms to learn from historical data improving forecasting accuracy and deviation detection without explicit programming (Baryannis et al., 2019). In supply chains, data analytics processes large and complex datasets to produce accurate forecasts based on consumer behaviour, market trends and supplier performance (Choi et al., 2018; Rahman Mahin et al., 2025). Risk assessment algorithms further enhance resilience by identifying vulnerabilities in advance (Jahin et al., 2025).

DSS provides prescriptive analytics suggesting optimal response strategies based on real-time data inputs (Alsakhen et al., 2024). AI tools also support warehouse management, routing optimisation and digital communication via chatbots (Richey et al., 2023).

Furthermore, the growing reliance on AI creates new vulnerabilities to cyber threats. If data integrity is compromised, decision-making processes may be misinformed. Insufficient network security increases the risk of data breaches which can expose sensitive supplier or operational information (Richey et al., 2023). Therefore, AI must be embedded within a secure, transparent and well-governed environment to realise its full potential. While AI enhances analytical capabilities, human expertise and intuition remain essential, especially in high-stake scenarios to ensure ethical alignment (Jarrahi, 2018).

2.5 HUMAN-AI COLLABORATION IN SUPPLY CHAIN DECISION-MAKING

Rather than replacing humans, AI is best viewed as a collaborator that supports strategic decision-making (Jarrahi, 2018). AI offers speed and scalability in data processing, while humans provide contextual understanding, ethical judgement and ultimate responsibility (Maddikunta et al., 2022). AI systems excel at processing large datasets and generating real-time recommendations, capabilities that often exceed human cognitive limits (Ekellem, 2024).

However, trust in AI remains limited due to barriers such as limited interpretability, perceived loss of control and concerns about data quality (Kolbjørnsrud et al., 2017; Stone et al., 2020). The ‘black box’ nature of many models reduces transparency which makes it difficult for decision-makers to comprehend and verify AI-generated output (Shin, 2021). Managers are afraid to adopt recommendations when they cannot understand how results are produced (Shrestha et al., 2019).

Explainability and causability are essential for overcoming adoption barriers. Explainability refers to the system’s capacity to clarify how decisions are generated, whereas causability reflects the user’s ability to interpret and act upon such explanations (Shin, 2021). Users are more likely to trust and accept AI-generated recommendations when they understand why and how these decisions are made (Shin, 2021).

To foster effective collaboration in the human-AI symbiosis, governance frameworks must define roles, ensure accountability and safeguard decision quality (Cheng et al., 2023). AI systems should serve as an aid and not a replacement, thereby allowing managers to retain control while leveraging the computational strengths (Jarrahi, 2018). Decision-makers should be actively involved in the AI implementation processes, as greater engagement helps build trust, enhances familiarity with AI-driven decision support, and reduces resistance to algorithmic recommendations (Kolbjørnsrud et al., 2017).

3 METHODOLOGICAL APPROACH

Chapter three provides a structured overview of the research design and analysis techniques applied in this study. The research adopted a qualitative approach focusing on expert interviews to investigate how AI supports human-based strategic decision-making in supply chain crisis management. The methodology is based on the theoretical constructs defined in Chapter 2 and directly addresses the research gap identified in Chapter 1: the lack of empirical insight into how decision-makers engage with AI tools during crises.

3.1 RESEARCH DESIGN

Given the exploratory nature of the research question, a qualitative design was chosen. This approach is often used in supply chain crisis management studies that seek to uncover managerial insights and behavioural complexities. Prior studies have employed similar designs. Dwivedi et al. (2021) used expert interviews to investigate AI adoption challenges from multiple managerial perspectives, while Frieske and Stieler (2022) validated their quantitative findings on COVID-19's impact through expert interviews.

This study directly responds to the call by Christopher & Holweg (2011) to explore managerial perspectives in a crisis context. Qualitative research methods were particularly suitable for exploring how decision-makers interpreted and responded to AI-driven recommendations during uncertainty. These methods enable researchers to capture insights into phenomena such as trust and perceived added value (Shrestha et al., 2019; Tong et al., 2007).

While systematic literature reviews have mapped AI applications in risk mitigation and supply chain resilience (Alsakhen et al., 2024; Baryannis et al., 2019; Ivanov & Dolgui, 2020; Naz et al., 2022), these approaches remain theoretical and lack direct engagement with experts. Other studies used case study designs to evaluate decision-making during disruptions scenarios as demonstrated by Cheng et al. (2023). Furthermore, papers such as those by Stone et al. (2020) and Papadakis et al. (1998) applied a mixed methods strategy, combining desk research with expert interviews to validate findings. Despite these contributions, there remains a noticeable gap in empirical research exploring human-AI interaction in crisis management settings.

Although a quantitative research design was considered, it was deemed unsuitable for this study due to limited access to structured datasets on AI adoption during crises and the need for in-depth insights rather than generalizability. In contrast, expert interviews offered the flexibility to explore participants' reasoning, experience and interpretation. These concepts are crucial to understanding how AI recommendations are perceived and applied in real-world decision-making.

The interpretivist epistemological stance of this study supported the qualitative methods, acknowledging that insights emerged from individual experience and expert knowledge. By conducting a targeted set of expert interviews, this study aimed to generate insights into AI-enabled crisis response in supply chains.

3.2 RESEARCH STRATEGY

This study adopted a qualitative approach, focusing on semi-structured interviews to explore the role of AI in strategic decision-making during supply chain crises. The interview data provided rich first-hand insights from industry experts.

The primary data source consists of semi-structured interviews with professionals across three domains: supply chain management, AI development and procurement/logistics. This selection ensured a holistic understanding across strategic, technical and operational perspectives of crisis decision-making. The interviews were designed to gain insights on the perceived value of AI, challenges in human-AI collaboration and organizational conditions that support or hinder adoption in crisis context; these themes directly aligned with the research question and theoretical framework.

Semi-structured interviews allowed for both consistency and flexibility. This format enabled thematic complementarity across participants while allowing for in-depth exploration of themes such as trust, collaboration and governance (Kallio et al., 2016). Tong et al. (2007) emphasise that in-depth interviews allow researchers to investigate not only what participants do, but also how they interpret and understand the situation. This directly aligns with the aim of this research to uncover how decision-makers perceive and engage with AI-generated recommendations under conditions of uncertainty.

During the research, this study maintained a clear focus on its defined scope: understanding the human-AI symbioses in real-life decision-making under pressure, rather than measuring abstract AI capabilities or technical performance. The research strategy thus supports both theoretical and practical relevance.

3.3 DATA COLLECTION

This study is based on eight semi-structured interviews with professionals in the fields of supply chain crisis management and AI development. The participants were selected through purposive sampling based on their domain-specific expertise. Supply chain managers offered strategic insights; AI specialists addressed technical capabilities and limitations while procurement/logistics professionals discussed operational application. Table 1 provides an overview of all interview participants, including their roles and the rationale for their inclusion in this study.

Type of interview	Participant Function	Why?	Date	Specialised field
Physically	(1) Sourcing Coordinator	This interview offers insights into how procurement manages disruptions and applies AI in decision-making.	22-04-2025	Procurement / Logistics
Microsoft Teams	(2) Supply Chain Manager	This interview provides valuable insights into crisis management within supply chains. The participant has hands-on experience navigating the COVID-19 disruptions.	23-04-2025	Supply Chain Management
Microsoft Teams	(3) Partner Consultancy	This interview offers insights into the practical implementations of AI within companies. The	23-04-2025	AI

		participant has extensive experience advising companies on AI adoption.		
Microsoft Teams	(4) Lead Data & AI Engineer	This interview offers insight into how AI is used within a company and on the main advantages.	29-04-2025	AI
Microsoft Teams	(5) Partner Data & Analytics	This interview provides insights into practical AI applications and barriers in analytics and supply chains.	12-05-2025	AI in Supply Chain
Physically	(6) Engagement Manager	This interview provides insights into practical AI applications in operational tasks and focussing on benefits for improved decision support.	15-05-2025	AI
Microsoft Teams	(7) Production Supply Coordinator	This interview provides information on how AI is used as a supportive tool for brainstorming and general use cases in supply chain management.	22-05-2025	Supply Chain Management
Microsoft Teams	(8) Inbound Material planner	This interview shows data is used in decision-making for planning applications and explores the potential of AI to detect supply risks and support scenario planning.	23-05-2025	Supply Chain Management

Table 1, Overview of interview participants

Although the original target was 10-12 interviews, eight expert interviews proved sufficient for capturing rich and thematically saturated data. As Guest et al. (2006) noted, data saturation in homogenous expert groups often occurs within the first six to twelve interviews. Although more extensive meaning saturation requires additional interviews (Hennink et al., 2017), the current sample size is justified by both the quality of insights and practical constraints.

The interview questions were derived from the theoretical framework in Chapter 2 and are organized around the core constructs such as technical capabilities, trust and human-AI collaboration. Domain-specific interview guides (see Appendix 1: semi-structured Interview guide) alongside a mapping of theoretical variables to research questions (see Appendix 2: Interview questions mapped to theoretical framework). This structure allowed for targeted questioning across different expert domains while preserving thematic consistency.

3.4 DATA ANALYSIS

The qualitative data collected through expert interviews were analysed using the Gioia methodology (Gioia et al., 2013), which is particularly suited for exploring complex, socially constructed phenomena. This makes it an appropriate fit for the aim of this study: exploring how AI affects strategic decision-making in the context of supply chain crisis management. The strength of the Gioia approach lies in its capacity to generate inductive insights grounded in participants' experience.

The Gioia method involves a three-step coding process that structures the path from raw data to conceptual insights, these are: (1) identifying first-order codes based on participants'' language, (2) creating second-order themes that reflect broader conceptual patterns, and (3) consolidating these into aggregate dimensions that form the foundation for the theoretical contribution.

The initial coding in ATLAS.ti yielded a total of 798 first-order codes, reflecting the breadth and complexity of expert perspectives. This number was reduced to 183 recurring concepts through iterative consolidation. These 183 codes were grouped into nine second-order themes and further synthesised into three aggregate dimensions: AI as a support tool in decision-making, Organizational readiness and adoption barriers, and Human role and responsibility in decision-making.

This approach enhanced the credibility and transparency of the research findings, while ensuring they remained closely tied to the voices of participants. The analysis followed an iterative cycle of coding, memo-writing and constant comparison across interviews. While full interview transcripts are not included due to length constraints, they are available upon request. Interview summaries can be found in Appendix 3: summary of interviews. A visual overview of the data structure and coding hierarchy is provided in Figure 2.

3.5 RESEARCH ETHICS

All interviews were conducted in line with ethical research principles. Prio to participation, all interviewees received a clear explanation of the purpose of the study and informed consent was obtained. Participation was entirely voluntary and participants had the right to withdraw at any point.

Interviews were recorded via Microsoft Teams or mobile devices. Audio recordings were transcribed using WhisperTranscribe and are anonymized to protect the identity and privacy of all participants. No personal identifiers were collected and the data was stored securely in compliance with data protection standards.

Participants were recruited through professional networks and LinkedIn, ensuring that all interviewees had relevant domain expertise. While the sample size was limited to eight participants due to practical constraints, thematic saturation was achieved. Nonetheless, the reliance on expert perspectives introduces the possibility of socially desirable answers.

4 RESULTS

Chapter 4 presents the empirical findings derived from thematic analysis of expert interviews using the Gioia method as outlined in Chapter 3. Each aggregate dimension consists of multiple second-order themes and representative first-order concepts. Rather than presenting all 183 codes, this chapter highlights the most salient patterns that illuminate how AI contributes to strategic decision-making in supply chain crisis contexts.

4.1 OVERVIEW OF CODING STRUCTURE AND THEME DEVELOPMENT

To build an understanding of how AI supports strategic decision-making during supply chain crises, a structured coding process was applied using the Gioia methodology (Gioia et al., 2013). As outlined in section 3.4, this approach enables the systematic transformation of raw textual data into abstract conceptual insights. A visual representation of the coding structure is presented in Figure 2. While not all first-order codes are included, the figure highlights the most salient and recurring patterns that informed the development of central themes. Emphasis was placed on conceptual clarity and thematic relevance, rather than exhaustive listing. The full set of codes is available upon request.

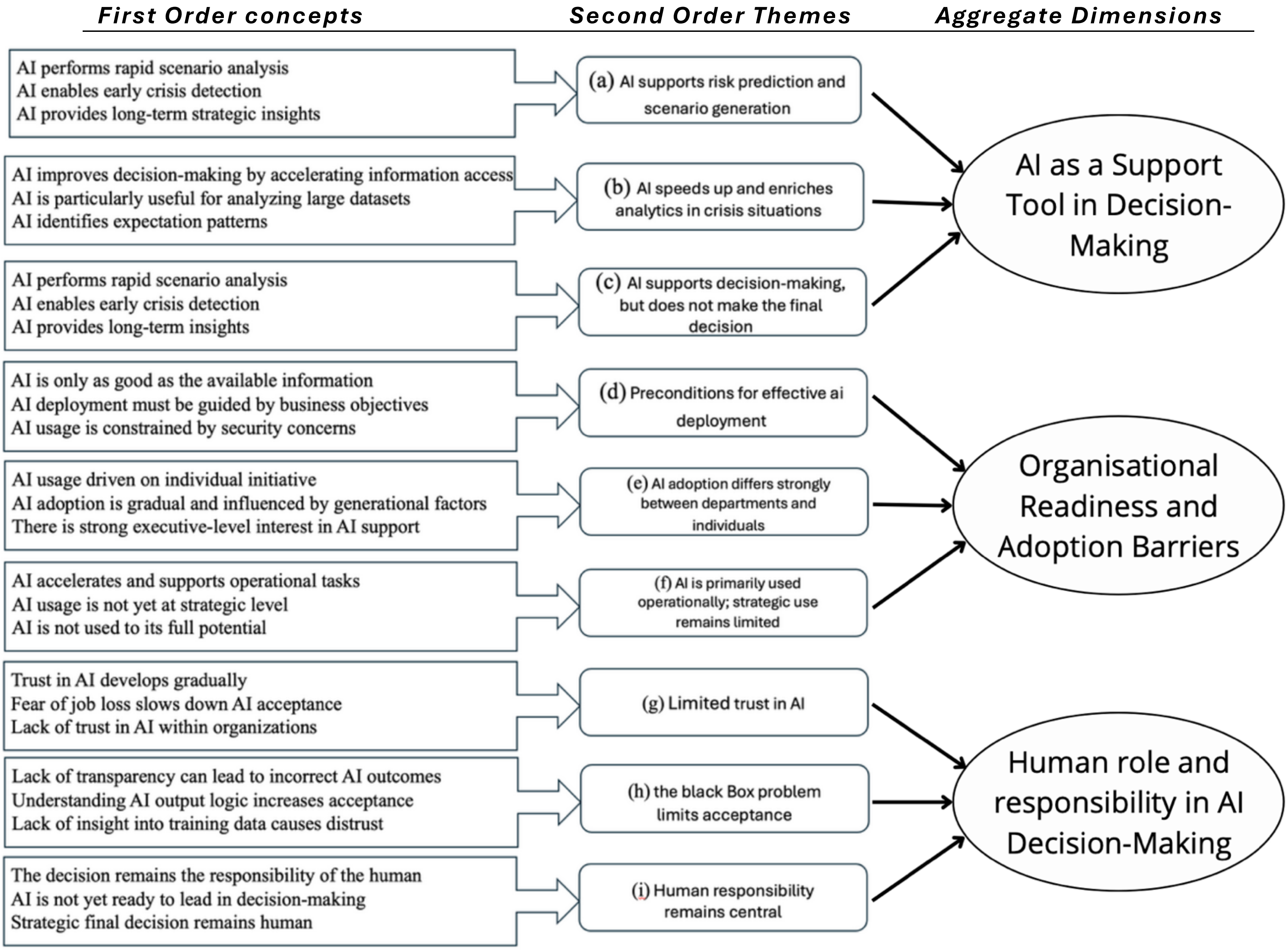

Figure 2, Code Tree First-Order Codes, Second-Order Themes, Aggregate Dimensions

4.2 AI AS A SUPPORT TOOL IN DECISION-MAKING

The first aggregate dimension reflects how AI is currently used to support rather than replace decision-making in supply chain crisis context. Based on the interviews it became clear that AI is not perceived as a fully autonomous decision-maker, but as a tool to enhance the capacity of humans and act more quickly. AI offers potential in processing large volumes of data, identifying patterns and provide predictive and analytical insights under time pressure. The following themes describe how AI enables early risk detection, accelerating the generation of scenarios and strengthens analytical processes.

4.2.1 AI supports risk prediction and scenario generation

One of the best ways in which AI supports crisis response is by enabling early risk prediction and generating potential scenarios based on real-time data. Several participants emphasized that AI allows organizations to anticipate disruptions more effectively. These disruptions often remain hidden until they escalate which makes predictive capability a valuable asset.

AI can help humans to detect weak signals and early warning sings as indicators that may point to a to-be crisis. For example, one participant explained how AI can identify suppliers that lack proper certification or show signs of financial instability. Others noted that global incidents such as the Suez Canal blockage or natural disasters in Asia have shown how vulnerable supply chains are to unexpected external events. Being able to have predictive insights allow for companies to act earlier and mitigate the effects of these disruptions before they happen and escalate.

Despite the clear potential, some participants said that predictive capabilities are still underused in practice. One AI expert stated: “You already have predictive capabilities – companies are still really bad at that, by the way” (R3). This reflects the gap between technical capabilities and the actual adoption of AI in organizations.

In addition, participants often mentioned the ability of AI to generate decision scenarios. Participants described how AI tools can simulate various responses on current data which helps managers to choose between alternatives more quickly and with more insights. One participant described this as: “a sort of preparation so that people can make better choices” (R4). The ability to generate scenarios was viewed as a key tool to accelerate and improve strategic decision-making.

Next to the forecasting and simulation capabilities, AI also contributes to detecting deviations and inefficiencies in lead times and inventory flows. Several participants gave examples where AI tools revealed abnormal patterns or hidden delays by comparing actual and expected data. This helps companies reduce bottlenecks more effectively.

These findings indicate that AI has the ability to enhance crisis preparedness by offering predictive insights, fast scenario analysis and deviation detection. However, the degree to which these capabilities can be used heavily depend on the AI-readiness of the organization.

4.2.2 AI speeds up and enriches analytics in crisis situations

An often-recurring insight from the interviews is that AI significantly enhances both the speed and quality of data analysis. In high-pressure situations the ability to process and interpret information can directly affect the effectiveness of the response. Participants highlighted that AI enables quicker access to information, supports timely decision-making and helps move beyond symptom-driven approaches.

Traditional crisis response was frequently described as slow and reactive with problems often reaching senior levels when it is too late. One participant illustrated: “Right now we still work in a very symptom-driven way … you’re basically always looking in the rear-view mirror” (R3). Others highlighted that when AI is embedded effectively it allows critical signals to reach the right people much faster allowing for a more proactive approach.

The strengths of AI hides in its ability to analyse large volumes of data and extract insights that humans might overlook. Participants described how AI tools are not only used for streamlining data and information gathering but also help interpret symptoms and causes of disruption more effectively. One participant explained: “AI is mainly valuable in the analytical part, processing large datasets and providing good explanations for what’s happening and why: (R2).

In supply chains, AI was seen as a valuable tool for profiling suppliers, identifying risk factors and triggering interventions. Participants shared examples of how AI can flag suppliers with a history of poor delivery performance or emerging risks such as upcoming shortages. This allows for earlier contract negotiations, inventory adjustments or pre-emptive actions that reduce crisis impact.

Beyond speed, AI also has a precision advantage over humans. Several participants noted that AI provides more complete and objective insights that help decision-makers act more confidently and faster. As one participant put it: “I am more complete, faster, more to the point, and that makes me more effective” (R6).

AI contributes to crisis decision-making by enriching the analytical foundation and accelerating data processing. The shift from reactive to structure and data-driven insights illustrate the growing potential for AI to be integrated in daily operations and enhance supply chain resilience.

4.2.3 AI supports decision-making, but does not make the final decision

Across interviews it became clear there was a strong consensus that AI serves as a valuable assistant in decision-making, but the final responsibility continues to rest with humans. AI is seen as a supportive tool that provides suggestions and helps evaluate alternatives but does not replace humans.

Participants frequently described AI as ‘sparring partner’ or ‘personal assistant’ that presents options and helps reflect. One participant explained: “It advises me, and I choose the best alternative. It presents me with decision moments, but I make the final call” (R6). This dynamic reflects the collaboration between humans and AI.

AI is able to enrich and support decision-making by presenting out-of-the-box suggestions or insights from large datasets. However, participants said that it still lacks contextual awareness. AI recommendations must be interpreted with a slight pinch of salt and for this reason many participants hesitate to use AI during crisis situations.

Next to idea generation, AI is also used to validate and justify decisions that are made by humans. AI helps decision-makers reflect critically and communicate them though with more confidence by delivering data-backed reasoning. Yet, the ability to challenge AI's output and verifying its factuality remains a human task.

As one participant summarized: "I don't think people will ask AI to make strategic decisions for them, but they do let themselves be informed and advised by AI" (R4). Another added: "It's not a colleague thinking long with you, it's a tool that transforms data into suitable insights" (R5).

In summary, AI has a significant role in decision support but does not have full control of the final decision. Decision-making continues to rely on human oversight and contextual understanding.

4.3 ORGANIZATIONAL READINESS AND ADOPTION BARRIERS

The successful integration of AI into strategic decision-making during supply chain crises depends not only on the technological capabilities, but also on the organizational readiness and internal adoption. Many firms acknowledge the potential of AI, though various barriers hinder its deployment. Interview data revealed that organizations struggle with basic preconditions such as privacy, data availability and internal alignment. Adoption differs widely between departments and individuals as there are often no strict guidelines. The following themes elaborate on these findings.

4.3.1 Preconditions for effective AI deployment

A recurring theme across interviews was the importance of organizational conditions for AI to function effectively. Participants emphasized that AI cannot offer value in times of crisis if it has not been embedded and tested in stable conditions. One participant put it best: *"If it works well outside of crisis time, then they might be able to use it to act faster during a crisis, but it has to happen in that order"* (R5).

Security concerns were frequently mentioned, mostly regarding the risk of data leakage and misuse of private information. Interviews described how organizations hesitated to use large language models (LLMs) unless they could guarantee secure handling of internal data. As a result, many firms opted for private environments such as Microsoft Copilot installations, to ensure data privacy. This was seen as a necessary step to build trust internally. This was explained clearly by a participant: *"That's why we use a Copilot license where we can input contract-specific information that doesn't leave the environment"* (R6).

Another key theme was the availability of high-quality data. Participants noted that AI systems can only function as intended if they receive good input data. One participant summarized this clearly: *"Without reliable data, there is no reliable AI"* (R5). In some cases, companies had already started training programs focused on improving prompt quality, underlining that good AI output depends on well-structured input. It is very important to ask the right question and align AI tools with the business goals.

Despite these investments, a lot of organizations still struggle to implement AI at a central level. Fragmentation, differing maturity levels and the absence of a unified strategy were cited as obstacles. An AI expert explained: *"If you really want to use AI effectively in decision-making, you may need ten or twenty different models, each with its own strength- but making that work together is incredibly difficult"* (R3). These insights suggest that although some companies are taking steps to build secure and data-driven environments, the integration remains limited due to coordination and trust.

4.3.2 AI adoption differs strongly between departments and individuals

The next key theme that emerged is the uneven adoption of AI across organizations, departments and individuals. Participants emphasized that willingness and ability to adopt new technologies vary depending on personal attitudes and organizational structure. In many of the interviews, resistance to change was not limited to AI but reflected broader inertia in adapting to new situations.

High-tech environments and large corporations with skilled people are likely to embrace AI faster, because data-driven thinking is already embedded in their systems. Smaller or less digitally mature organizations have more difficulties to adopt this new technology. One participant explained: *"In a large company with a lot of young, highly educated people and data scientists, things get picked up quite quickly. But in small or medium-sized company, with maybe one person capable of leading such efforts, adoption will be much slower "*(R7). Several interviews showed that awareness of the need to evolve is gradually growing within companies. This is driven by pure competitive pressure.

Currently, the use of AI in many firms is driven by personal initiative rather than company policy. One participant observed: "It's mainly from personal initiative. The organization itself currently applies little AI" (R1). While some noted that the adoption of AI is accelerating, the lack of coordinated efforts continues to hinder the consistent use.

4.3.3 AI adoption remains task-focused

Across interviews participants emphasized it became clear that AI is mostly used for operational purposes rather the strategic applications. Participants explained that many AI tools are currently applied to automate repetitive tasks, reduce manual load or enhance efficiency in current workflows. The integration of AI into strategic decision-making is still rare.

Interviews pointed out how AI supports tasks such as document processing, image recognition and writing assistance. One participant provided a striking example: *"We used to have 15 people spending a year on visual rail analysis. Now we do it with AI in 11 days"* (R3). Another said: *"You translate small task faster; you handle invoices automatically. That's all manual work that can now be done by robots"* (R5). This illustrates that the current benefits of AI are mostly seen in time savings, and productivity and efficiency gains.

The strength of AI in operational use also lies in its reliability and scalability. AI systems, unlike humans, do not fatigue and can work continuously with consistent performance. Several participants talked about inventory management as an area where AI provides clear advantages, especially in forecasting demand or identifying reorder points.

However, the strategic potential of AI remains underutilised. Participants agreed that while tools like ChatGPT have raised awareness, most firms are far from embedding AI in their decision-making processes. There was a shared recognition that the journey towards meaningful AI integration is still at a very early stage. Leveraging the full AI potential requires more than only the technical capability; it requires alignment with long-term strategic goals.

4.4 HUMAN ROLE AND RESPONSIBILITY IN AI DECISIONS-MAKING

This aggregate dimension highlights how the human role remains central in the adoption and application of AI in strategic decision-making. Across the interviews, participants emphasized the importance of remaining in control and human oversight. Many experts expressed concerns about adopting AI due to the limited understanding of how these systems operate. People have concerns about data security and keeping their intellectual property safe. The findings show that trust in AI is still in its early stages and is influenced by broader human resistance to change. The following themes explore how limited trust, ethical boundaries and human accountability influence the integration of AI in human decision-making.

4.4.1 Trust barriers to AI integration

A recurring theme across the interviews was that trust in AI is limited both on an individual and organizational level. This stems from a combination of unfamiliarity, fear of losing control and concerns about job replacement. Many professionals encounter uncertainty about security and ethical use.

Participants described how emotional reactions to AI are the same as historically seen with other disruptive technologies. One participant compared the current fears to past fears around the industrial revolution*: "Like when the steam train was introduced, people feared it would upset the cows or spoil milk. Disruptive technologies often evoke fear – and that fear reflects how significant the change might be"* (R3). All participants agreed that we are still at the beginning of this revolution and AI is still in its beginning stages.

The organizational trust issues are closely tied to the protection of intellectual property and use of confidential data. Several participants mentioned the use of internal policies to not use AI tools when dealing with sensitive information. As one participant explained: *"The main guideline is: no sharing of sensitive company information, passwords, or specific designs ... those are part of our unique selling point"* (R1). These types of concerns limit how AI can be embedded in critical business systems.

Furthermore, the participants emphasized that there is fear regarding job loss due to AI. While few believed that AI would completely replace human roles, there was a shared sentiment that I would complement complex tasks. Despite these concerns participants were optimistic that this period of uncertainty is not for ever, trust is not static and can evolve over time. As one participant put it: *"It's also about trust, and that takes time. Gradually, trust builds as AI starts to take over certain tasks"* R3).

These insights underline that trust in AI is a gradual process that takes time. However, those concerns must be addressed before AI can be fully integrated into human-decision-making processes.

4.4.2 the black Box problem limits acceptance

One of the main barriers to adopt AI in strategic decision-making is the lack of transparency in how AI systems generate their output. This is called the 'black box' problem. Participants emphasized that without insight into how AI models operate, the trust in AI output remains limited.

Even when models provide relevant results, users often do not understand how or why these outputs were generated. This is particularly true for LLMs where the underlying training data remains vague. One participant explained: "In the case of a LLM, it's effectively always a black box. You don't know the architecture, and the parameters alone don't tell you anything about potential biases or data sources" (R4). Other participants concluded that as a user you simply do not know how the AI arrives at their answer and that lack of transparency is dangerous in decision-making.

Not being able to verify how results are produced affects the quality of decisions. Several participants highlighted how the need for AI to explain not just the outcome but also the reasoning. Interviews showed that AI outputs must be contextualized in a way that supports interpretation and action. As one participant said: “If AI gives an answer, you want to know what it’s based on – ideally with references, so you can click through and verify it yourself” (R4).

Some interviewees suggested solutions to solve this transparency gap. These include more interactive systems that display reasoning steps.

The black box nature of AI remains a big barrier for full-scale adoption. As long as users cannot understand and validate how models arrive at certain outputs, organizations will be hesitant to embed AI into their core decision-making processes.

4.4.3 Human responsibility remains central

A recurring theme across the interviews was that despite the increasing use of AI in supply chain management, participants thought that human responsibility remains essential. Especially in high-stake cases like crisis situations. Here participants emphasized that humans must remain accountable for the decision made.

Participants frequently said that AI is not inherently intelligent but operates within the boundaries set by human input. It is effective in processing large volumes of information and generating quick responses but often lacks contextual awareness and ethical judgement. As one participant said nicely: “That intelligence isn’t really there – it’s imposed by humans. So you have to ask the right question, and understand the problem well enough to know whether AI can even help solve it” (R3).

Crises situations are unpredictable and require contextual knowledge to solve. This implicit knowledge is not stored in datafiles. Many participants shared the opinion that organizations fall back on their most experienced employees in times of crisis rather than relying on experimental technologies. One participant explained: “You’re not going to gamble your future on an experimental AI when the stakes are high. The natural reflex is to fall back on your most trusted people” (R5).

In addition, there was broad agreement that human judgement must always rule over AI suggestions, especially when outcomes deviate from human expectations. While AI might present alternative perspectives, decision-makers must critically assess the generated output. A few participants stressed the importance of remaining in control and aim for traceable AI output. This includes keeping records of AI performance, understanding where it failed and determining when oversight can be loosened safely. As one participant summarized: “You have to keep your grip. Without grip, it [AI] derails. You need to keep records of what went well and what went wrong and gradually learn where AI can be trusted without supervision” (R3).

These insights show that AI can inform and support decision-making but does not replace the human role. Trust in AI can grow over time but in strategic context the final accountability remains human.

5. DISCUSSION

This chapter addresses the central research questions of the study: *To what extent does Artificial Intelligence support human-based strategic decision-making in supply chain crisis management?* The findings indicate that AI contributes to strategic decision-making in a supportive rather than autonomous role. Interview data revealed that AI is particularly valued for its ability to enable early risk prediction, generate decision scenarios and accelerate processing of large data volumes under pressure. These capabilities help organizations respond more quickly and confidently to disruptions.

However, the effectiveness of AI remains highly dependent on contextual factors. Trust in AI systems, the quality and structure of underlying data, cultural readiness to embrace new technologies and the ability to interpret AI-generated insights all emerged as critical conditions for success. Rather than replacing human judgement, AI is seen as a complementary tool that can enhance strategic reasoning.

The following sections interpret these findings through the lens of the theoretical framework presented in Chapter 2. Each of the three aggregate dimensions identified in Chapter 4 is examined in relation to existing academic perspectives. This discussion highlights where theory and practice align, where gap persist and what contributions this study makes to both academic and practical understanding.

5.1 KEY FINDINGS AND THEORY

5.1.1 AI as a Support tool in decision-making

The first key dimension concerns how AI functions as a support tool in strategic decision-making. This is essential to understand the role of AI in supporting decision-making during supply chain crises, particularly in relation to theories of dynamic capabilities, bounded rationality and prescriptive analytics.

A central finding from the interviews is that AI is not perceived as a replacement for human decision-makers but rather as a tool that improves strategic responses. This aligns with the view of Teece et al. (1997), who argue that organizations with strong dynamic capabilities are better able to maintain resilience in volatile environments. These dynamic capabilities consist of the ability to sense, seize and reconfigure resources. Participants often described AI as useful in early risk detection, real-time disruption monitoring and the identification of hidden vulnerabilities in supplier performance.

These finding also aligns closely with literature on the predictive and prescriptive power of AI in supply chain risk management. Ivanov and Dolgui (2020) and Alsakhen et al. (2024) highlight how AI is able to detect anomalies and simulate scenarios to inform strategic decision-makers. These capabilities repeatedly emerged during the interviews. For example, multiple participants emphasized that AI tools are used to simulate disruptions and create scenarios or compare strategic alternatives based on real-time data. One participant explained that AI offers a sort of preparation so people can make better choices," this directly reflects that concepts of prescriptive analytics discussed in Wang et al. (2023).

However, noticeable gap emerged between theory and practice regarding the ability of AI to reduce cognitive bias. While the literature suggests that AI supports rationality by mitigating human biases such as confirmation bias and availability bias (Baryannis et al., 2019; Wang et al., 2023), this role was not acknowledged by any of the participants. Instead, their focus remained on time pressure and data insufficiency, suggesting that while AI offers speed and scale, it does not address the deeper behavioural limitations of human decision-making.

The interviews also confirmed theoretical insights related to bounded rationality (Simon, 1979). Participants described operating under pressure, limited information and short timeframes, often relying on intuition and experience. In such conditions, decision-makers satisfice rather than optimise. AI has a valuable role in compressing the time needed to reach an acceptable decision through timely data support. This supports the theory that AI complements human limitations but does not eliminate them.

Finally, the role of AI in forecasting and resource planning was identified as a core strength. Participants described how AI systems were used to flag inventory deviations, analyse lead times and detect changes in demand patterns. These findings are consistent with Maddikunta et al. (2022), who argue that AI enhances resource allocation and predictive maintenance by revealing hidden patterns.

In summary, the empirical findings strongly support the literature regarding the role AI plays in supporting strategic decision-making through prediction, scenario planning and analytical speed. However, they reveal that the supposed role in bias reduction is not yet acknowledged by experts. Decision-makers continue to rely on experience and intuition when operating under uncertainty.

5.1.2 Organizational readiness and adoption barriers

The second key finding concerns the organizational conditions that shape the integration of AI in strategic-decision-making. This dimension is essential in understanding not only the technical requirements for AI implementations but also the social and cultural factors that determine adoption.

The interviews revealed that adoption of AI is inconsistent, decentralised and often depends on individual initiative rather than institutional strategy. This observation supports Cheng et al. (2023) and Shrestha et al. (2019), who argue that strong governance and formal engagement are necessary for complete successful integration. This decentralized and individual-driven approach reveals a gap between structured models of AI governance in the literature and the fragmented reality in practice.

The literature highlights the importance of data quality, data security and AI infrastructure (Alsakhen et al., 2024; Richey et al., 2023). These subjects frequently emerged during the interviews. Multiple participants mentioned the use of Copilot environments to protect sensitive data. This confirms the call made by Richey et al. (Richey et al., 2023) to proactively address cybersecurity. This also supports the theoretical emphasis on secure infrastructure as requirement for responsible AI deployment by (Alsakhen et al., 2024).

However, a critical barrier emerged in the form of data scarcity. While Baryannis et al. (2019) suggest that AI can learn from historical data to support forecasting and decision-making, many participants explained that their organization lack the structured data needed to give these models the necessary input. As a result, AI models often operate below their potential. This mismatch between theoretical assumptions of data abundance and the real-world limitation of data availability highlights a significant challenge that needs further academic attention.

In addition, the theoretical framework presents AI as a transformative force in strategic decision-making while the participants indicated that AI is currently solely used for operational purposes. Examples made by participants include invoice processing, document classification, anomaly detection. These findings support the view of Jarrahi (Jarrahi, 2018) that AI adoption begins at the task level and only gradually moves into more strategic domains.

Another important finding lies in emphasising the human and cultural dimensions of organizational readiness. While the literature discusses governance and readiness mostly in structural terms (IT infrastructure, policies), the interviews emphasized the social and cultural aspects of readiness. This suggests that readiness for AI adoption should not only be assessed by structural indicators but must also include acceptance by employees. The perception that “people have trouble changing in general” underlines the need to address emotional resistance in AI integration strategies.

5.1.3 Human role and responsibility in AI decision-making

The final dimension centres on the human role in AI-supported decision-making. This dimension addresses how accountability, trust and judgement remain control to strategic decision-making despite the added value of AI in data analytics and forecasting.

Several participants emphasized that while AI adds value as support, the final decision is always made by a human. In times of crisis the organization prefers to rely on experienced professional rather than experimenting with autonomous systems. This view supports the theory of human-AI symbioses by Jarrahi (2018), who argues that AI offers computational advantages while humans contribute situational awareness and ethical reasoning.

Participants described AI as a tool that suggests options, offers data-driven insights and proposes scenarios but never as a tool that will make autonomous decisions. One participant stated: “It advises me, and I choose the best alternative,” and another emphasized that “AI is not a colleague thinking along, it is a tool that transforms data into suitable insights.” These arguments support the finding of Shrestha et al. (2019) who argue that the effectiveness of AI depends on how well humans can interpret and act upon that output. This confirms that while AI can support decision quality, responsibility and authority remain with human actors.

The black box problem emerged as a significant barrier to trust and adoption. Several participants expressed concern over the lack of transparency in how AI systems reach their conclusion. They cited vague training data, inaccessible model architectures and a general inability to interpret reasoning as major issues. As one participant explained: “You don’t know the architecture, and the parameters alone don’t tell you anything about potential biases or data sources. “These concerns reflect the arguments made by Stone et al. (2020), Maddikunta et al. (2022) and Dwivedi et al. (2021), all of whom highlight transparency and explainability as a critical requirements for AI adoption.

The interviews also revealed that trust is closely tied to control and accountability. Multiple participants indicated that they would not delegate final decision-making authority to AI, as this would compromise accountability towards customers and stakeholders. This reflects the idea of Kolbjornsrud et al. (2017), who argue that clear governance frameworks are necessary to assign responsibility in a human-AI collaboration.

One element that emerged from the interviews but was underdeveloped in the theoretical framework concerns the perceived lack of ethical judgement and emotional intelligence in AI systems. While this was not deeply discussed in the cited literature, participants identified it a s a key reason for having humans in control of decision-making. They felt that AI lacks the ability to weigh ethical values or understand soft signals under ambiguity. These findings suggests that human values, intuition and soft skills remain irreplaceable in moments of strategic ambiguity.

In summary, this study confirms that the human role in decision-making remains central, particularly when trust, ethics and accountability are at stake. While AI supports and enhances decision processes through data insight and scenario simulation, limitations in transparency, interpretably and ethical reasoning reinforce the necessity of human oversight. These insights underscore the importance of integrating governance, trust-building and ethical awareness into any future AI deployment strategy.

5.2 THEORETICAL CONTRIBUTIONS

This study offers multiple contributions to the academic literature on AI-supported decision-making and supply chain crisis management. First, it confirms the relevance of existing theoretical frameworks such as bounded rationality (Simon, 1979), dynamic capabilities (Teece et al., 1997) and human-AI collaboration (Jarrahi, 2018). It validates these theories by explaining how organizations respond to disruptions. Specifically, the empirical findings demonstrate that AI enhances the sensing and analysis phases of decision-making. Furthermore, the results confirm that decisions remain bounded by limited time and incomplete data.

Second, the study extends current theory by identifying discrepancies between theoretical assumptions and practical realities. Literature frequently suggests that AI reduces cognitive biases such as confirmation bias and overconfidence (Baryannis et al., 2019; Wang et al., 2023). Interestingly, these theories were not confirmed by the expert interviews. Instead, decision-makers still rely heavily on intuition and personal experience, even when supported by AI systems. This challenges the assumption that AI alters cognitive bias in high-pressure environments.

Next, this research highlights an underexplored barrier to AI adoption in data scarcity. The literature often assumes that organizations have access to clean, structured and comprehensive data sets for AI input (Baryannis et al., 2019). However, several participants pointed out that their organizations lack the data necessary to make effective use of AI systems for decision-making. This reveals a gap in current theoretical models, which underestimate the operational challenges deploying AI in supply chains.

In addition, the findings suggest that emotional intelligence and ethical judgement remain an important part of decision-making. Participants observed that AI lack these capabilities which affects the trust and acceptance. This highlights the need for theoretical models to incorporate not only structural factors but also the effective and ethical dimensions of human-AI interaction.

Finally, the findings emphasize the importance of organizational readiness beyond technical infrastructure. Cultural openness and trust-building appear to be equally, if not more, essential for successful AI implementation.

5.3 PRACTICAL IMPLICATIONS

This research offers several implications for organizations seeking to apply AI in strategic supply chain decision-making. First, organizations should see AI as a support tool rather than a substitution. AI should be implemented to enhance decision speed and scenario generation, rather than to fully automate strategic choices. This approach aligns with current capabilities and support trust among users.

Second, investment in data infrastructure is essential. The findings emphasise that without structured and reliable input data, even the most advanced AI systems are likely to underperform. Therefore, improving data architecture is a critical requirement for effective AI deployment.

In addition, organizations must prepare not only technically but also culturally. Resistance to AI adoption is often rooted in cultural barriers rather than technological limitations. Change management strategies should focus on trust-building and promoting openness to experimentation.

Fourth, it is crucial to define accountability and authority. Effective AI governance requires clearly defined roles and responsibilities, ensuring that AI recommendations are embedded in decision support systems where humans retain ultimate accountability.

Next, a strategic and incremental implementation is crucial. Interviewees noted that AI adoption often begins with operational use cases such as invoice processing and anomaly detection. These easy applications can help build trust and gradually grow to a more strategic integration.

Finally, organizations must not overlook the human factor. While AI is able to process data at scale, leaders should remain cautious about over-reliance and ensure room for human judgement and intuition, particularly in high-stakes contexts.

5.4 LIMITATIONS AND FUTURE RESEARCH

Although this study offers valuable insights into how AI can support strategic decision-making in supply chain context, several limitations must be acknowledged. These limitations do not undermine the validity of the findings but highlight areas for improvement and further research.

5.4.1 Limitations of this research

A primary limitation concerns the conceptual overlap between Artificial Intelligence, Machine Learning and data analytics. Although the theoretical framework clearly defines these constructs, this distinction was not always upheld during the interviews. Participants often referred to AI although they meant data analytics or automation systems. This ambiguity limits the precision with which conclusions about AI adoption can be drawn. In retrospect, this could have been mitigated by discussing the meaning of AI at the start of each interview to create a shared understanding. In addition, the interviewer could have intervened during the conversation to clarify that the topic being discussed does not actually concern AI but data analytics.

Second, the research design primarily focused on identifying adoption barriers and perceived value rather than on developing actionable solutions. While this was a design choice to remain exploratory, it restricts the study's practical applicability. More focus on improvements in handling with AI could might have strengthened the practical implications.

Third, the interview structure was broad, which enabled thematic richness but limited the depth on certain emerging technologies such as digital twins or sector-specific use cases. These concepts are present in the academic literature but were not addressed by participants. This limitation was partly due to the open-ended form of the interviews which could have been mitigated by asking targeted questions.

Additionally, the concepts of emotional intelligence and psychological resistance were underdeveloped in the theoretical framework, despite their presence in the interviews. This reflects a missed opportunity to integrate behavioural science literature more systematically into the theoretical framework. This was a trade-off made during the scoping phase to maintain conceptual focus but is now limits the completeness of the research.

Finally, while the sample of eight experts was sufficient for thematic saturation, more participants would have enhanced the generalizability of the findings.

5.4.2 Future research possibilities

Building on the limitations discussed above, several possibilities for future research emerge. First, there is a need to clarify the conceptual boundaries between Artificial Intelligence, Machine Learning and data analytics. Future research should examine how practitioners define and use these technologies in real-world context. This would help reduce confusion and support more precise adoption strategies.

Second, the findings suggest a need for the development of structured implementation frameworks for strategic AI use. Many organizations remain restricted to operational applications, and future studies could design phased models that guide the transition from task-specific tools to integrate strategic applications. These frameworks should include trust-building, governance structures and clearly defined responsibilities.

Another possibility lies in further exploration of the behavioural and psychological dimensions of human-AI interaction. The interviews showed that emotional resistance, perceived loss of control and ethical concerns form key barriers to adoption. Applying behavioural theory may help design interventions that enhance trust, explainability and accountability.

A fourth important direction lies in investigating data maturity as a requirement for effective AI deployment. Participants frequently mentioned data scarcity and quality issues. Research should focus on how organizations can improve their data infrastructure.

Finally, the actual impact of AI on cognitive biases remains unclear. Although the literature assumes that AI reduces decision biases such as confirmation bias, this was not confirmed in practice. Controlled studies are needed to test whether AI tools support objective decision-making during crises.

In conclusion, future research should move beyond technical capabilities and focus more deeply on the organization, behavioural and contextual conditions that determine whether AI is able to support strategic decision-making under uncertainty.

6. CONCLUSION

This study set out to answer the central research question: "*To what extent does Artificial Intelligence support human-based strategic decision-making in supply chain crisis management?*"

The findings suggest that AI supports human-based decision-making to limited but growing extent. Its main contributions lie in accelerating data analysis, enabling early detection of supply chain disruptions and supporting scenario planning under time pressure. These capabilities align with the concept of prescriptive analytics, which aims to offer informed recommendations based on real-time data (Alsakhen et al., 2024; Wang et al., 2023). However, the strategic value of AI remains conditional on several factors, including human judgement, data quality, organizational readiness and trust.

Rather than replacing decision-makers, AI currently acts as a support tool that augments but does not substitute human-based reasoning and accountability. These findings support the theory of Jarrahi (2018), who argues that professionals rely on AI for enhanced insights but fall back on experience and contextual awareness in high-stakes situations. In doing so, the study challenges the more deterministic assumptions that AI will eventually replace human judgement in crisis decision-making (Dwivedi et al., 2021).

Organizational readiness emerged as both a technical and cultural enabler of AI effectiveness. While prior research focuses on IT infrastructure, data maturity and system integration (Richey et al., 2023), this study highlights that trust, resistance to change and managerial scepticism are equally important. These findings support Kolbjornsrud et al. (2017), who argue that AI adoption depends on user engagement and clearly defined governance structures. In many cases, decentralised activities and lack of shared understanding were barriers to the integration of AI into strategic workflows.

Another critical insight relates to conceptual ambiguity surrounding AI. Participants frequently used the term 'AI' when referring to traditional data analytics or automation tools. This misalignment in terminology complicates adoption strategies and further distances theoretical assumptions from practical application.

In conclusion, AI holds substantial promise in supporting more effective strategic decisions during supply chain crises. Especially, by improving visibility, response speed and scenario analysis. However, its impact is determined not only by technical capabilities but by how well it is embedded within organizational decision routines, supported by trust and aligned with human values. Future progress depends on addressing the human, structural and cultural foundations that enable AI to function as a truly strategic assistant.

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APPENDICES

APPENDIX 1: SEMI-STRUCTURED INTERVIEW GUIDE

General opening

Thank you for participating in this interview. The aim of this study is to explore how AI and ML influence strategic decision-making in supply chain crisis management. The findings will contribute to a master thesis at Radboud University in the field of strategic management.

Before we begin, I would like to state the following: The interview will take approximately 30 – 45 minutes. The information provided will be transcribed and only used for research purposes. This is only available for the interviewer and the supervisor.

With permission, I would like to record the interview. The audio will only be used for transcription analysis and will not be shared externally. Do you give permission to record?

a. Yes: start recording
b. No: start taking notes

Appendix 1.1 AI specialist – Interview questions

1. **Background and experience**
   a. Can you tell me about your current role and experience with ML and AI systems.
   b. Have you worked on AI projects that were applied in supply chain or crisis-related contexts? What was the goal and what was the biggest challenge you face in applying it?
2. **Technical capabilities and limitations**
   a. In your view, what are the main strengths of using AI and ML in supporting decision-making under crisis?
   b. What technical limitations or risks do you currently see in applying AI for such purposes?
3. **Trust and Interpretability**
   a. How do stakeholders respond to AI-generated recommendations in your experience?
   b. How do you address concerns related to explainability or the black-box effect in your line of work?
   c. Have you encountered any resistance due to trust issues? If so, what where the causes and how where they addressed?
4. **Human-AI collaboration**
   a. How would you describe the ideal relationship between human judgement and AI outputs in high stakes or time-sensitive decisions?
   b. Are current systems in your view more supportive or autonomous and what is the ideal balance in your opinion.
5. **Governance and responsibility**
   a. Are there clear governance structures in your organization that define accountability for AI-generated decisions?

   b. How is responsibility handled in situations where AI outputs lead to wrong or suboptimal decisions?

6. **Future perspectives**
   a. Where do you see the most promising developments in AI for decision-making over the next 3-5 years?
   b. What changes are needed to improve the integration of AI in strategic decision process?

Closing question

Thank you for your time and valuable input. Is there anything else you think is important about AI in strategic decision-making that we haven't yet discussed?

Appendix 1.2: Supply chain manager – interview questions

1. **Background and Crisis experience**
   a. Can you tell me about your role within the supply chain and how you are involved during crisis situations?
   b. Can you describe a recent supply chain disruption you encountered and how decisions were made during that event?
2. **Use and prediction of AI**
   a. Have you had any experience using ML or AI-based tools to support decision-making?
   b. What do you perceive as the main added value of AI in supporting supply chain resilience and decision-making during crisis management situations?
   c. In your experience, does AI improve the speed or quality of decision-making? Why or why not?
3. **Barriers and practical challenges**
   a. What challenges have you encountered when using AI tools in crisis situations?
   b. Have there been instances where AI outputs were not followed or even contradicted by human decision-makers? Why?
   c. What would be necessary to make AI recommendations more actionable or trustworthy for decision-makers?
4. **Human-AI interaction and trust**
   a. To what extent you rely on your own judgement versus automated recommendations during disruptions?
   b. How do you view the balance between human experience and AI-based recommendations in crisis situations?
   c. Would you prefer AI to act more as an assistant or as an autonomous decision-maker? Why?
5. **Governance and implementation**
   a. Are there formal processes in place to evaluate or monitor AI usage in decisions-making?

   b. Who holds final responsibility for decisions when AI is involved?
   c. Have there been discussions about ethics, bias or accountability within the organization?

6. **Looking ahead**
   a. Where do you see the role of AI evolving within supply chain management over the next 3-5 years?
   b. What would be your ideal vision for integrating AI into crisis decision-making process?
   c. To what extentdo you believe AI contributes to enhancing supply chain resilience after a disruption?

Closing question

Thank you for your contribution. Is there anything else you would like to add about the use of AI in strategic supply chain decision-making?

Appendix 1.3: Procurement/ logistics expert – interview questions

1. **Role and crisis Involvement**
   a. Can you describe your current role in procurement or logistics and how often you deal with disruptions or crises?
   b. What type of decisions are typically required from your side when a supply chain crisis occurs?
   c. Can you give an example of a recent disruption where quick decisions had to be made?
2. **Exposure to AI and Digital tools**
   a. Have you used or been exposed to any AI-driven or decision support tools in your role?
   b. What was your impression of how helpful these tools were in supporting real-time decision-making?
   c. Do you feel AI is well integrated into procurement/ logistic process during crises? Why or why not?
3. **Responsiveness and operational barriers**
   a. What are the main bottlenecks or limitations in your response to sudden disruptions?
   b. To what extentdo you think AI could help overcome these challenges?
   c. What are the practice benefits to implementing AI tools in your daily operation?
4. **Trust, communication & adoption**
   a. Do you or your colleagues typically trust AI-based suggestions during a disruption? Why or why not?
   b. Is there enough communication between technical/ AIteams and operational teams to make use of the technology effectively?
   c. What would be needed to increase trust and adoption of AI-generated insights in your role.
5. **Responsibility and accountability**
   a. Who holds the final responsibility for decisions made during disruption in your domain?

b. If AI provides a wrong recommendation, how is that handled in terms of accountability?
c. Are there clear policies or governance structures in place around using AI in operational decision-making?

6. **Outlook and recommendations**
   a. Where do you see the most promising use cases of AI in procurement/ logistics crisis management in the next few years?
   b. What would your main recommendation be for improving the collaboration between AI tools and human decision-makers in your domain?

Closing question

Thank you for your input. Is there anything else you believe should be considered regarding the use of AI in procurement and logistics during times of disruption?

APPENDIX 2: INTERVIEW QUESTIONS MAPPED TO THEORETICAL FRAMEWORK

This table provides an overview of the key variables from the theoretical framework linked to the corresponding interview questions.

Theoretical variable	Definitiond/ link to theory	Interview questions	Target group
Strategic Decision-Making Effectiveness	Effectiveness of strategic decisions in crises (chapter 2.1); includes bias reduction, bounded rationality and decision speed.	AI: 1b, 2a SCM: 2b, 2c PRO/LOG: 2b	All
Crisis Responsiveness & Supply Chain Resilience	Capacity to anticipate, respond to and recover from disruptions (chapter 2.2, 2.3).	SCM: 1b, 6c PRO/LOG: 1c, 3a, 6a	SCM, PRO/LOG
AI Technical Capabilities	Technical strengths and limitations of AI systems (chapter 2.4)	AI: 2a, 2b PRO/LOG: 2a, 2b	AI, PRO/LOG
Trust and Interpretability	Extent of trust in AI outputs, influenced by explainability and user familiarity (chapter 2.5)	AI: 3a, 3b, 3c SCM: 4a, 4b PRO/LOG: 4a, 4c	ALL
Human-AI Collaboration	How humans and AI systems interact and complement each other in decision-making (chapter 2.5).	AI: 4a, 4b SCM: 4a, 4b, 4c PRO/LOG: 4a	ALL
Governance & Accountability	Clarity of roles, responsibility and oversight when using AI in decision-making (chapter 2.5).	AI: 5a, 5b SCM: 5a, 5b, 5c PRO/LOG: 5a, 5b, 5c	ALL
Barriers to AI adoption	Organizational, technical or human factors limiting AI adoption (chapter 2.4, 2.5)	SCM: 3a, 3b, 3c PRO/LOG: 3a, 3b, 3c	SCM, PRO/LOG
Future Perspectives	Expectations and visions for AI's role in strategic supply chain management (chapter 2.4, 2.5).	AI: 6a,6b SCM: 6a, 6b PRO/LOG: 6a, 6b	ALL

Table 2, *Interview questions mapped to theoretical framework*

Appendix 2.1 Visual mapping figure relation variable with interview questions

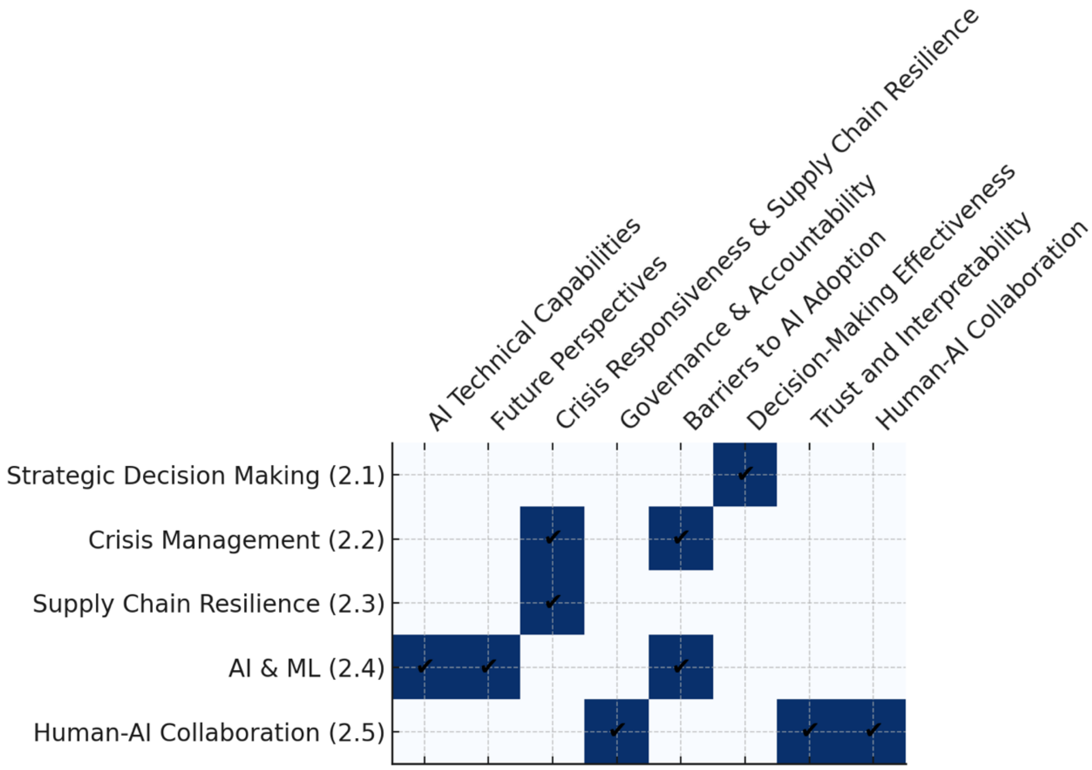

Figure 3, Visual mapping of relation theoretical framework to interview questions

APPENDIX 3: SUMMARY OF INTERVIEWS

3.1: participant #1 – Sourcing coordinator

Duration 15 minutes

The participant works as a sourcing coordinator and is responsible for design coordination, supplier management, pricing and contracts. Disruptions are relatively rare but can occur due to late deliveries of defective components, sometimes caused by broader supply chain risks such as geopolitical events or natural disasters. In response to disruptions, the focus lies on supplier contact and escalation through personal networks or negotiation tactics while alternatives are explored via internal inventory systems.

AI tools are used occasionally and on personal initiative, mainly to search inventory, support prioritisation arguments and perform market pricing research. There is little collaboration between the AI and executive branches within the company and current guidelines discourage sharing sensitive data with AI systems.

Key bottlenecks include a lack of standardized data storage and difficulty accessing historical information. The participant sees potential for AI to assist in predicting risks, analysing supplier KPI's and enhancing decision support trough visualisation and quick scans. Additionally, AI could help optimise inventory decisions and suggest better contractual strategies in the future.

3.2: Participant # 2 – supply chain coordinator

Duration 20 minutes

The participant works as a supply chain manager at a company where AI is primarily used as an analytical tool to process large volumes of data and detect potential disruptions. AI serves as a support mechanism that enables operational efficiency, allowing supply chain professionals to dictate more time to strategic decision-making and long-term planning.

A good example of AI use was during the Suez Canal blockage where the system was used to rapidly assess which shipments would be delayed and to identify alternative suppliers. Another application involved analysing internal production processes to identify products that could be outsourced to free up capacity. These use cases demonstrate the value AI has in crisis response and operational optimisation.

The company emphasises the need for ethical and secure AI usage. Tools like Microsoft Copilot are preferred due to better data protection, and there is a push to standardise AI use across teams. Key challenges include ensuring consistency in tools, trending and data handling practices.

Despite AI's growing role, the final responsibility for decisions remains with human users. Critical assessment of AI outputs is essential and deviations from AI recommendations are accepted when aligned with broader business goals or supplier relationships. AI is expected to increasingly support operations decisions this will free up capacity for strategic planning.

3.3 Participant # 3 – Partner consultancy Data specialist

Duration 40 minutes

The participant leads the AI department at a consultancy firm and works closely with large corporates on embedding AI into both operational processes and strategic decision-making. He emphasized the importance of aligning AI implementation with governance, security and business vision. In crisis context, the value of AI is in the scenario analysis, rapid data interpretation and highlighting critical pressure point across the supply chain.

Examples include optimizing packaging lines, detecting production microstops and helping clients automate previously manual visual inspections. AI improves both the operational efficiency and management responsiveness by surfacing early indicators of disruption.

However, organizational adoption is often hindered by distrust, lack of understanding and fears over job loss or displacement and loss of control. The participant compares AI maturity to raising a child, trust and autonomy must be earned over time, with careful supervision and fallback mechanisms. Even in advanced AI use cases the human oversight remains essentials.

He also stresses the importance of explainability (avoiding the black-box effect), well designed implementation and hybrid skills sets that combine business, ethical and technical knowledge. Successful AI integration requires a clear top-down visions, the right models per use case and long-term organizational learning.

3.4 Participant # 4 – Lead DATA & AI engineer

Duration 35 minutes

The participant leads the AI department at a consultancy firm and has background in mechanical and computational engineering. His work focuses on applying AI across industries. With the main focus on engineering-heavy domains such as automotive by accelerating simulation processes and improving decision-making through custom AI tooling. He supports companies in moving from traditional engineering cycles to AI-augmented processes, enabling faster time-to-market.

The participant highlighted that AI is already indirectly involved in strategic decision-making. Particularly through scenario creation and decision support. Tools built around Large Language models help gain insights from large datasets, such as assessing hundreds of CVs based on role criteria or simulating alternative product development paths. However strategic decisions still remain human-driven, with AI acting as an advisor.

In supply chain crisis context, adoption is limited by trust issues, particularly in technical departments where accuracy and traceability are vital. Concerns around hallucinations, misuse of company data and loss of control are very common. Explainability is very important next to context-driven implementation and developing guardrails to improv e data relevance and transparency.

According to the participant, most companies will not train their own models but will adopt open-source systems embedded within customized internal workflows. The future of AI in strategic environments lies in responsible deployment, explainable outputs and integration into decision-making structures without removing human accountability.

3.5 Participant #5 – Partner Data & analytics

Duration 30 min

The participant leads the Data & analytics practice at a big consultancy firm and brings over a decade of experience embedding AI into both public and private processes. He explained that AI currently adds the most value in data transformation and scenario analysis. AI is primarily used to accelerate insights generation by converting unstructured data, such as supplier offers, into structured and comparable information. For example, a procurement tool developed for a public sector client enables users to extract and analyse supplier data in a matter of hours rather than weeks, significantly speeding up decision preparation.

Despite these advancements, he emphasized that adoption of AI in high-stakes strategic decision-making, especially during crises, remains limited. In such moments, organizations instinctively revert to human expertise or bring in experienced consultants rather than rely on experimental technology. He stressed that AI can only be effective if the underlying data infrastructure is in place, and in many organizations, that remains a major obstacle. Trust in AI is further complicated by concerns over bias in training data and the opacity of generative AI models. The participant referred to these limitations as both technical and ethical in nature, and emphasized the importance of data quality, governance and transparency as essential conditions for successful implementation.

The participant outlined a typology of five AI applications: personal AI (tools like copilots that support individual productivity), process AI (automate repetitive tasks), agentic AI (autonomous, end-to-end process execution), embedded AI (features built into enterprise systems such as ERP or CRM) and specialized AI (custom solutions like drone inspections or visual infrastructure analysis. According to him, the most realistic and impactful use cases lie in process optimization and embedded functionalities were clear business cases and measurable outcomes support adoption.

Looking ahead, the participant sees potential in technologies such as digital twins, which could enable real-time simulations of supply chain disruptions and guide strategic responses. However, he emphasized that most supply chains, particularly those involving physical goods are not yet digitally mature enough to fully leverage these tools. He concluded by stating that AI should first prove its value in non-critical operational environments before being trusted in high-impact crisis-related decisions. In his words, “without reliable data, there is no reliable AI. Adoption in crisis comes later – only after AI has proven itself operationally.

3.6 Participant # 6 – Engagement manager

Duration 25 minutes

The participant works as a project manager at a client-facing position within a consultancy firm and uses AI tools such as Microsoft Copilot primarily for operational support. One of the key applications is processing large volumes of candidate CVs, where Copilot assists in matching profiles to specific job criteria and generating tailored interview questions. The participant emphasizes AI’s strengths in speed, completeness and consistency which significantly enhances productivity and focus during interviews. Currently, AI is not used for strategic decision-making within the participant’s scope. Instead, it serves as a personal assistant or advisor, supporting scenario development and improving task execution. The participant remains responsible for final decisions and treats AI suggestions critically. This approach reflects the broader sentiment that AI should augment, not replace, human judgement; especially given the current limitations in explainability and contextual understanding.

The organization ensures data privacy by using isolated environments for AI interaction, especially when handling sensitive client data in the defense industry. A dedicated Copilot license is used within secure SharePoint environments, enabling AI to understand and process contextual information without risking data leakage.

The participant notes that adoption is uneven, influenced by factors such as age and digital habits. While young professionals embrace AI more easily, others struggle with integrating it into their workflows. Although the company offers extensive AI training and prompt engineering support, the success of AI integration still depends on individual willingness to change.

Client interest in AI integration is high, especially in tech-forward sectors like defense. In response, some clients are investing heavily in secure, proprietary AI infrastructure to retain control over data and avoid dependency on public models. Strategic use of AI remains limited, but there is growing recognition of its potential in future decision environments.

The participant foresees AI evolving into a more autonomous decision-maker, especially when context-specific data is available. However, emotional intelligence, non-verbal communication, and human nuance remain outside AI's current capabilities. These are essential in high-stakes environments where AI lacks the capacity to assess tone, intent, or non-verbal cues—highlighting the need for human oversight and a hybrid model of collaboration.

3.7 Participant # 7 – Production supply coordinator

Duration 30 minutes

The participant is a manufacturing supply chain coordinator at a large technology company. Their role bridges the gap between sourcing and operations, focusing on improvement projects and handling escalations within the factory. Although not involved in daily operations, the participant plays a key role in decision-making related to sourcing, outsourcing, and selecting suppliers, especially in crisis situations that can result in significant penalties if deliveries are delayed.

Disruptions occur daily, with more severe incidents emerging weekly or monthly. In many cases, data is insufficient or unavailable, and decisions are made based on experience, especially when disruptions involve unique suppliers or non-standard products. While the participant does not currently use AI in active crisis management, they do employ AI for brainstorming, information gathering, and comparing suppliers—particularly when dealing with unfamiliar domains like new machinery acquisition.

AI is mainly used in a support role, not for autonomous decision-making. It helps synthesize large amounts of information, serves as a sparring partner, and provides alternative perspectives. According to the participant, AI could evolve into a more proactive decision-support tool—identifying risks earlier, enabling scenario-based thinking, and detecting patterns in supply disruptions. However, current limitations include lack of company-specific context, inconsistent output reliability, and restricted use of sensitive data due to company policy.

There is a general awareness of the importance of cybersecurity and compliance. While informal use of tools like ChatGPT is widespread, company policy restricts sharing proprietary data, and official AI use is aligned with Microsoft-based internal systems. Training is still limited, and much of the learning is left to individual initiative.

AI adoption varies across demographics, with younger professionals exploring its capabilities more actively. Older employees tend to be more sceptical, viewing AI as a black box or an unrealistic tool. The participant notes that trust in AI builds over time, especially once users begin to understand its reasoning process. They advocate for a balance between critical evaluation and gradual confidence building through repeated successful interactions.

Although AI is not yet used in acute escalations or high-pressure decisions, its role as an analytical and advisory tool is growing. The participant envisions future use in crisis prevention, through predictive analytics and long-term pattern recognition—shifting supply chain management from reactive to proactive.

3.8 Participant # 8 – Inound material planner

Duration 20 minutes

The participant is an Inbound Material Planner operating at the regional level, responsible for ensuring mid- to long-term material availability across multiple European production sites. Their role includes placing orders, maintaining supplier relationships, and managing materials such as flavors and sweeteners for specific factories.

Supply disruptions occur regularly, especially for volatile materials like color additives. While data from SAP is used to monitor inventory versus demand, decision-making in crisis situations remains largely manual. The participant notes that data signals such as negative stock levels trigger human interventions, but these are not yet automated or AI-driven.

AI is currently not used for direct decision-making, but the participant sees value in its potential for pattern recognition, risk profiling, and predictive analytics. For example, identifying recurring supplier delays could enable proactive adjustments. AI's ability to analyse large datasets quickly could provide dashboards and insights that humans might overlook, particularly for strategic supplier management.

The company is actively exploring AI through internal initiatives, including a dedicated ChatGPT team and secure environments where AI can be used with sensitive data. However, AI adoption remains voluntary and depends on personal initiative. Training resources are available but not enforced.

Looking forward, the participant believes AI could play a greater role in decision support, particularly in complex planning situations involving high-value goods like cocoa butter. However, human oversight remains essential due to the financial stakes and the need for accountability. The participant cautions against blindly trusting AI, especially when the reasoning behind its suggestions is opaque—highlighting the persistent "black box" issue.

Ultimately, AI is seen as a useful assistant rather than a decision-maker. While its current role is limited, the participant expects that, with better transparency and reliability, AI will become a valuable tool for faster and more informed supply chain decisions.