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Strategic decision-making in the age of generative artificial intelligence

A mixed-methods study on the role of generative artificial intelligence in enhancing strategic foresight of decision-making

Author:
Louise Hernberg (42566)

Supervisor: Sebastian Krakowski
Date examined: 20.05.2025
Discussant: Hanna Bexell
Examiners: Stefan Haefliger, Henrik Glimstedt

Abstract
This thesis investigates how generative artificial intelligence (GenAI) can improve decision-making within organisations, focusing on its potential to improve strategic foresight, confidence, commitment, and decision quality. While prior research has explored predictive AI in operational settings, little empirical work has examined GenAI's cognitive and organisational impact in strategic contexts. Addressing this gap, the study employs a mixed-methods vignette-based experiment involving knowledge workers making market expansion decisions, both with and without GenAI support. Quantitative results reveal that while GenAI-assisted participants showed slightly higher confidence and commitment, the effects were not statistically significant. However, qualitative findings suggest that GenAI's ability to synthesise complex information and provide diverse perspectives positively influenced participants' sense of preparedness and reduced perceived uncertainty. Importantly, the study highlights that GenAI acts as a cognitive augmentation tool, complementing rather than replacing human judgment. By integrating organisational learning and decision theory, the thesis contributes to the emerging discourse on human-AI collaboration, offering both theoretical insights and practical guidance for organisations seeking to responsibly implement GenAI. The findings underscore the importance of fostering GenAI literacy and organisational trust to unlock GenAI's full potential in enhancing strategic decision-making.

Key words: Generative artificial intelligence, strategic decision-making, strategic foresight, decision commitment, decision confidence, human-AI collaboration

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List of abbreviations

AI	Artificial intelligence
ANOVA	Analysis of variance
B2B	Business-to-business
GenAI	Generative artificial intelligence
LLM	Large language model

1. Introduction

1.1 Background

Decision-making is a fundamental activity for employees in any organisation, involving the selection among alternatives that lead to action or inaction (Cortes et al., 2019). Long-term success depends on strategic foresight, i.e., the ability to anticipate and evaluate the consequences of interconnected choices (Doshi et al., 2024). To avoid detrimental long-term outcomes, improving strategic foresight in decision-making is essential. This thesis defines strategic decisions as choices that set an organisation's overall direction (Cortes et al., 2019). This form of decision-making is at the core of shaping an organisation's course, influencing areas like market entry and customer targeting. In increasingly dynamic environments marked by technological change, traditional decision-making approaches struggle to deliver the strategic foresight needed (Doshi et al., 2024; Leiblein et al., 2018). Simultaneously, the rise of artificial intelligence (AI) presents new opportunities and challenges for augmenting human decision-making capabilities.

With the emergence of generative artificial intelligence (GenAI) in many organisational processes, research has shown it increases human productivity (Mozannar et al., 2022; Peng et al., 2023; Ziegler et al., 2022). With the advancement of GenAI and its ability to process large amounts of unstructured data, i.e., data that is not in a fixed schema such as rows or columns, there is increased attention towards the area of enhanced competitive advantage through human-AI augmentation and how GenAI impacts the decision-making process (Doshi et al., 2024; Duan et al., 2019; Iansiti & Lakhani, 2020; Kaggwa et al., 2024; Shreshtha et al., 2019; Tschang & Almirall, 2021). GenAI can complement human intuition and cognition by managing complexity, while humans remain essential for navigating ambiguity (Raisch & Krakowski, 2021). Understanding this interaction is essential for organisations seeking to strengthen strategic foresight.

The use of GenAI in strategic decision-making is an emerging field with a few published papers within an organisational context (Doshi et al., 2024; Kaggwa et al., 2023; Keding & Meissner, 2021). While there is research on GenAI in general, studies specifically examining its impact on strategic decision-making processes are limited. Keding & Meissner (2021) and Doshi et al. (2024) study on how GenAI can be used in a decision-making process shows the positive effects of AI-human augmentation on strategic choice behaviour. Nevertheless, Keding & Meissner's (2021) study was conducted on senior executives and does not reflect how knowledge workers are impacted by using GenAI in their daily work involving strategic decision-making. Also, the study by Doshi et al. (2024) was focused on evaluating business models by comparing GenAI with human experts' assessment. As the findings from their study are derived from evaluating business models, and research has yet to fully address how GenAI supports complex, multi-variable strategic decisions across diverse organisational roles, this study addresses the gap by focusing on market expansion decisions.

Market expansion differs from business model evaluation since it involves greater risk and complexity due to external uncertainties like regulatory environments and cultural nuances (Ansoff, 1957). By broadening the decision context and sampling knowledge workers across multiple functions, this thesis offers new insights into how GenAI can support multi-layered strategic decision-making processes. The aim is not only to extend theoretical understanding but also to provide practical guidance for organisations seeking to integrate GenAI while recognising potential challenges.

1.2 Problem statement

Prior research has explored the concept of human-AI symbiosis, particularly the division of labour in organisational decision-making, where AI handles data-heavy or routine tasks and humans focus on creative and strategic elements (Jarrahi, 2023; Duan et al., 2019; Iansiti & Lakhani, 2020; Shrestha et al., 2019; Tschang & Almirall, 2021). These studies have largely focused on predictive AI or narrow AI systems that operate within well-defined parameters. There remains a gap in understanding how GenAI, with its capacity for autonomous content creation, ideation, and scenario generation, influences strategic decision-making. Unlike earlier studies that primarily address narrow applications of AI on operational decisions, this study investigates GenAI's potential to enhance strategic foresight. This study addresses the research gap by empirically examining how GenAI influences not just the mechanics of decision-making but the cognitive framing, evaluative confidence, and human judgment processes involved in strategic foresight. Therefore, it contributes an important view to the emerging discourse on GenAI-enabled strategy, focusing specifically on the cognitive and organisational implications of using GenAI as a collaborator in strategic reasoning rather than a tool for tactical support.

This research's unique contribution lies in its empirical examination of how GenAI affects the perceived confidence, commitment, and quality of strategic decisions. In this thesis, the definitions of the three variables are the following: 1) confidence as the belief that a choice is correct (Pouget et al., 2016), 2) commitment as the tendency to persist with a decision that has been made (Ghemawat, 1991), and 3) quality as the perceived thoroughness and effectiveness of the decision that was made (Spetzler et al., 2016). Through a mixed-methods vignette-based experiment, this study provides practical insights into how knowledge workers interact with GenAI tools when navigating ambiguity and high-stakes trade-offs. Whereas traditional AI literature often highlights technological performance, this research focuses on the synergistic relationship between human cognition and GenAI capabilities, uncovering how such interaction may complement, rather than replace, human expertise in strategic contexts.

This study also responds directly to the gaps in the literature for more nuanced, empirically grounded explorations of GenAI in strategic environments. Doshi et al. (2024) demonstrate that while large language models (LLMs) can evaluate strategic alternatives and generate insights that align with expert judgments, their outputs can be inconsistent and biased unless carefully aggregated and interpreted. Similarly, Chaturvedi et al. (2025) emphasise that the success of GenAI in strategic decision-making depends not only on technical performance but also on organisational trust, AI literacy, and the socio-technical systems in which GenAI is embedded. This study addresses not only the opportunities GenAI offers, such as processing unstructured data, simulating outcomes, and expanding decision horizons, but also the ethical and practical challenges it presents, including algorithmic bias, transparency, and the risk of algorithm aversion. In doing so, it offers a holistic framework for understanding how GenAI can be responsibly and effectively integrated to support strategic foresight and decision-making in organisations.

1.3 Research question & hypothesis

Given the limited literature on how GenAI can enhance strategic decision-making processes in organisations, this study addresses the following research question: *How can an organisation leverage generative AI to enhance the strategic foresight of decision-making processes?* While previous research has explored AI's role in decision support more generally, there is still a lack of empirical insight into how GenAI impacts the human dimensions of strategic decision-making, particularly confidence, commitment, and foresight, in real-world organisational contexts. Thus, the independent variable tested in this study is access to a GenAI tool, in this case ChatGPT-4o, and the primary dependent variable is decision commitment. In addition, decision confidence and quality are also measured.

Recent studies (Doshi et al., 2024; Chaturvedi et al., 2025) have evaluated GenAI's ability to assess strategic alternatives, showing that LLMs can approximate expert evaluations when aggregated. Doshi et al.'s (2024) research focuses primarily on model accuracy and prediction alignment rather than the cognitive, behavioural, and organisational effects of using GenAI in decision-making. Likewise, Chaturvedi et al. (2025) provide valuable insights into GenAI implementation challenges, such as trust and AI literacy, but stop short of examining how GenAI affects the quality or experience of making strategic decisions. This study is unique as it directly investigates how GenAI can be integrated into the decision-making workflows of knowledge workers to enhance strategic foresight, i.e., the ability to anticipate, assess, and act on future implications of current choices. Using a vignette-based mixed-method design, this research offers empirical evidence on when and how GenAI augments a decision-maker's clarity, confidence, and commitment in complex scenarios. The study responds to the growing need for practical guidance on incorporating GenAI in a strategic decision-making process rather than focusing solely on model capabilities or technical accuracy.

As the research question being asked in this study examines how GenAI can be used to enhance strategic foresight in an organisational decision-making process, the study hypothesises that GenAI can serve as a cognitive augmentation tool. This tool would enhance the decision-maker's ability to process information, explore alternatives, and anticipate future scenarios more effectively. Specifically, it is expected that the use of GenAI will lead to three concrete improvements in the decision-making process: 1) increased commitment to decisions due to greater confidence in having considered multiple scenarios and alternatives; 2) greater confidence in the quality of the chosen course of action, supported by GenAI's ability to process unstructured data and surface relevant insights; and 3) more informed and timely decision-making, as GenAI accelerates the filtering, synthesis, and presentation of complex information. By providing access to diverse perspectives and challenging initial assumptions, GenAI is anticipated to improve the depth and breadth of strategic analysis, resulting in higher-quality decisions. By hypothesising these specific effects, this study directly tests how organisations can leverage GenAI by positioning GenAI not as a replacement for human judgment but as a tool for augmenting a decision-maker's cognitive capacity, enabling more forward-looking and impactful organisational strategies.

1.4 Scope of the study

This study focuses on exploring how GenAI can enhance strategic foresight in a decision-making process within a business-to-business (B2B) organisational context. It examines knowledge workers' use of GenAI tools to support market expansion decisions, a strategic area requiring high levels of foresight and complexity management. The research specifically targets employees from a single technology-driven company and captures data during a defined period between June and July 2024, reflecting the capabilities of GenAI technologies at that time. The study concentrates on short-term decision outcomes such as confidence, commitment, and perceived decision quality, recognising that strategic decisions often unfold over extended periods. By narrowing its scope to a specific organisational setting, decision type, and technology maturity level, the study provides focused insights that form a foundation for future research into broader and longer-term applications of GenAI in strategic contexts.

2. Literature review

In recent years, the rapid development of GenAI has sparked significant interest in its application across various organisational functions. As GenAI becomes increasingly integrated into everyday business practices, researchers have begun to explore its role in organisational decision-making, mainly through AI-human collaboration (Jarrahi, 2023; Duan et al., 2019). While these studies offer valuable insights into how AI can support routine or operational decision-making by augmenting data analysis and automating tasks, limited research has investigated GenAI's specific impact on strategic decision-making, which is a process characterised by complexity, uncertainty, and long-term implications.

Recent studies (e.g., Doshi et al., 2024; Chaturvedi et al., 2025) focus mainly on GenAI's technical alignment with expert evaluations, treating it as a standalone tool rather than examining its interaction with human judgment. Yet, strategic decisions require more than accurate predictions. They demand foresight, confidence under uncertainty, and critical evaluation. These are dimensions where human expertise remains essential. Also, evidence is mixed. While GenAI improves data synthesis (Doshi et al., 2024), concerns about algorithmic bias, explainability, and over-reliance persist (Ananny & Crawford, 2016; Silva & Kenney, 2018). Gaps in AI literacy further complicate whether users can critically validate GenAI-driven insights (Glikson & Woolley, 2020).

This study addresses the following research gaps: 1) how GenAI shapes strategic foresight and confidence under uncertainty, 2) whether it strengthens decision commitment through enhanced scenario exploration, and 3) how it affects perceived decision quality when human evaluation remains critical. Using the hypothesis with organisational learning theory (Argote & Miron-Spektor, 2011) and decision theory under uncertainty (Fredrickson, 1984), the study moves beyond computation accuracy to assess GenAI's cognitive and behavioural influence on decision-makers. The following chapter will build the theoretical foundation for the study. It first defines GenAI and its technological capabilities, then discusses its intersection with organisational learning and decision theory, and finally examines how GenAI influences strategic decision-making under real-world complexities.

2.1 Defining generative AI

At the core of this study is AI, specifically GenAI. AI is a machine's ability to perform cognitive functions associated with human intelligence, for example, perception, reasoning, learning, environmental interaction, problem-solving, decision-making, and creativity (Rai et al., 2019). AI has been utilised in decision-support systems, automation, and predictive analytics (Hamadaqa et al., 2024). Still, the emergence of GenAI and its ability to handle a vast amount of unstructured data opens possibilities to enhance organisational performance. Doshi et al. (2024)

define GenAI as a category of AI that not only evaluates and processes information but actively generates new content and insights. They specifically highlight LLMs as a subset of GenAI, capable of producing human-like text and generating strategic recommendations. These models enhance decision-making by providing alternative perspectives, scenario-based simulations, and predictive analyses of business outcomes, enabling organisations to navigate complex strategic environments more effectively. Kaggwa et al. (2024) further elaborate that GenAI enhances traditional AI capabilities by fostering creativity and adaptability, making it a powerful tool for organisations navigating complex decision landscapes. Chaturvedi et al. (2025) emphasise that GenAI does not merely automate tasks but interacts dynamically with human decision-makers, reshaping organisational learning and strategic evaluation processes.

GenAI fundamentally alters workplace operations, enabling knowledge workers to analyse large datasets, respond to complex queries, and generate high-quality content in real-time (Brynjolfsson et al., 2023). Examples of widely adopted GenAI applications include OpenAI's ChatGPT and Microsoft's Copilot, which have become integral to business processes across industries. These are forms of LLMs, and unlike AI, which primarily focuses on pattern recognition and decision automation, ChatGPT and Copilot are designed to perform tasks such as text generation, summarisation, and translation, making them a key component of GenAI (Doshi et al., 2024). These developments position GenAI as a highly valuable tool for strategic decision-making and problem-solving, given its ability to synthesise vast amounts of unstructured data.

This optimistic view of GenAI is not without challenge. Several scholars (Bender et al., 2021; Weidinger et al., 2022) caution that LLMs are prone to generating plausible-sounding but factually incorrect or biased outputs. This raises concerns about the reliability of GenAI in complex strategic contexts where precision and contextual understanding are predominant. Also, while GenAI excels at producing coherent narratives and summarising known information, critics argue that it struggles with tasks requiring deep causal reasoning, ethical judgement, or genuine creativity. These are dimensions that are often critical in high-stakes strategic decision-making (Floridi & Chiriatti, 2020). Thus, although the dynamic nature of GenAI holds promise for enhancing strategic analysis, it also introduces new risks, like overconfidence in machine-generated outputs and potential amplification biases. Yet, because of wide GenAI adoption, accessibility, and relevance to knowledge work, ChatGPT has been chosen as the main GenAI tool to study for exploring the hypothesis of this thesis. The choice will be further justified in Chapter 3.

The increasing interest in GenAI's impact on organisational contexts reflects a shift in AI research. Earlier studies (Power et al., 1994; Pomerol, 1997; Robinson et al., 2004) highlighted the benefits of computerised decision-support systems in improving decision accuracy and efficiency. However, GenAI's ability to learn from feedback and self-improve represents a major leap forward, providing organisations with new ways to enhance decision-making processes (Chaturvedi et al., 2025). Doshi et al. (2024) illustrate how GenAI can evaluate strategic alternatives, showing that while individual GenAI-generated rankings may vary, aggregating multiple GenAI assessments aligns closely with human expert evaluations. This suggests that GenAI can be an advanced evaluator in strategic decision-making, helping managers compare business models, predict outcomes, and mitigate decision biases.

Kaggwa et al. (2024) further support this perspective, arguing that firms that are early adopters of GenAI are better positioned for competitive advantage and accelerated growth. Their study introduces a novel measurement of AI adoption at the firm level, analysing how investment in GenAI technologies correlates with improved decision efficiency and organisational performance. Though their study primarily focuses on U.S.-based firms, it provides a compelling argument for the global implications of GenAI adoption. Additionally, recent empirical evidence suggests that GenAI significantly increases productivity among knowledge workers, reinforcing its organisational benefits (Brynjolfsson et al., 2023; Dell'Acqua et al., 2023; Noy & Zhang, 2023). Chaturvedi et al. (2025) note that beyond efficiency gains, GenAI is reshaping the cognitive aspects of decision-making by reducing cognitive biases and enhancing the speed and accuracy of strategic evaluations. This highlights GenAI's dual role as both a technological enabler and an active participant in organisational intelligence.

Despite its transformative potential, challenges remain. AI bias, transparency, and ethical considerations require further research to ensure responsible implementation (Doshi et al., 2024;

Chaturvedi et al., 2025). The tensions between optimistic and sceptical perspectives defines the current research frontier. On the one hand, the trajectory of GenAI's evolution indicates that it will continue to play an integral role in business strategy, organisational learning, and decision optimisation, gradually redefining the boundaries of AI's contribution to human cognition and corporate governance. On the other hand, there remains an urgent need for research that moves beyond technical performance to critically examine how organisations can integrate GenAI responsibly and effectively into decision-making processes. Positioned within this debate, this thesis does not only assume that GenAI's transformative potential will unfold automatically. Instead, it acknowledges the genuine risks and challenges associated with GenAI use and aims to demonstrate that organisations can learn to use GenAI as a cognitive augmentation tool rather than a decision-making substitute. By focusing on the interaction between GenAI support and human strategic judgement, this study contributes to a more nuanced, balanced understanding of how GenAI can enhance strategic foresight while preserving human agency and ethical integrity.

2.2 Organisational learning and decision theory

For an organisation to establish itself as a market leader, strategic foresight is a key factor in its success. A well-structured and high-quality decision-making framework is a strong foundation for competitive advantage. In this context, confidence in decision-making across all levels of an organisation is crucial. Duan et al. (2019) argue that decision-making requires continuous refinement of knowledge, which involves identifying problems, generating and evaluating alternatives, and selecting the best possible option. Fredrickson's (1984) decision theory classifies decisions into decisions made under risk, where probabilities and outcomes are known, and decisions made under uncertainty, where such probabilities remain unknown. In both cases, organisations must integrate structured decision-making frameworks that improve knowledge refinement and alternative evaluations to instil confidence among decision-makers.

Organisational learning plays a crucial role in ensuring high-quality decisions. Transformation occurs when individuals within an organisation gain experience and apply it to their decision-making processes (Argote & Miron-Spektor, 2011). Argote & Miron-Spektor's (2011) theoretical framework distinguishes between the environmental context (external factors like clients, institutions, and regulations) and the organisational context (internal factors such as available information, culture, and technology). Kaggwa et al. (2024) build upon this by asserting that adopting GenAI-driven decision-making technologies enhances organisational learning by reducing cognitive load, improving knowledge accessibility, and increasing decision accuracy. The impact of GenAI on organisational learning is becoming increasingly apparent. Babina et al. (2024) demonstrate that organisations leveraging GenAI empower employees by augmenting their daily workflows with GenAI-enhanced insights, ultimately contributing to overall organisational growth. GenAI's ability to process a vast amount of unstructured data allows employees to focus on more creative work. As a tool, GenAI can handle the more mundane tasks such as summarising reports and helping debug code. This aligns with the perspective that GenAI is an extension of human cognition, providing advanced analytical tools that complement human expertise (Doshi et al., 2024).

Knowledge workers today face an overwhelming influx of data, requiring sophisticated tools to filter and analyse relevant information efficiently. According to Cazzaniga et al. (2024), nearly 40 per cent of global employment is exposed to GenAI-driven transformation, allowing organisations to capitalise on GenAI's potential for enhanced decision-making. Despite the growing prominence of GenAI, limited empirical research exists on its direct impact on employee performance and learning (Brynjolfsson et al., 2023; Chong et al., 2023). Citroen (2011) highlights the importance of information availability in improving decision-making accuracy and efficiency, yet does not link it explicitly to organisational performance. The study by Kaggwa et al. (2024) shows that incorporating GenAI into creating business strategies can enhance corporate performance, demonstrating that when knowledge workers have GenAI available, they can experience a sharper decision-making process.

The emergence of GenAI allows organisations to process vast amounts of data more efficiently, significantly improving decision-making processes. Doshi et al. (2024) highlight that aggregated AI-generated assessments can closely align with human expert evaluations, reinforcing GenAI's potential as an evaluator that reduces decision inconsistencies. Chaturvedi et al. (2025) further argue that GenAI reduces decision biases by offering structured and data-driven evaluations, an essential feature in environments where decision-makers struggle with information overload.

One of the main reasons organisations are increasingly turning to GenAI for decision-making processes is its ability to improve decision accuracy while handling uncertainty. Since decision-making inherently involves uncertain elements, research suggests that GenAI reduces prediction costs by processing large datasets and generating probabilistic insights (Agrawal et al., 2019; Kleinberg et al., 2018). As decision-makers access more accurate and predictive insights, they can align their strategies with long-term organisational goals. Furthermore, when employees make better-informed decisions, organisational learning accelerates, reinforcing the positive feedback loop between decision-making quality and knowledge growth (Argote & Miron-Spektor, 2011).

Kaggwa et al. (2024) emphasise that integrating GenAI-driven decision-making tools fosters a knowledge-based organisational culture, where GenAI augmentation facilitates continuous learning and optimisation. Doshi et al. (2024) further argue that organisations can leverage GenAI-generated strategic assessments to refine business models and mitigate risks, contributing to an enhanced decision-making ecosystem. Chaturvedi et al. (2025) suggest that GenAI's impact extends beyond automation, transforming decision-making into an interactive process that aligns with evolving organisational needs. Thus, the convergence of organisational learning and GenAI-driven decision-making creates a symbiotic relationship where GenAI augments human expertise while organisations refine knowledge frameworks to maximise GenAI’s potential. This reinforces the hypothesis that organisations leveraging GenAI will be effectively better positioned for market leadership, reduce decision-making inefficiencies, and enhance strategic foresight.

2.3 Impact of GenAI on strategic decision-making

The importance of a clear and well-informed decision-making process has long been recognised as a critical factor in achieving organisational success (Ketchen et al., 2004; Trunk et al., 2019). For a decision to be considered strategic, it must be interconnected with other key decisions and capable of influencing broader organisational outcomes (Van den Steen, 2017). One of the central aspects of strategic decision-making is handling uncertainty, which exists in three different modes, requiring decision-makers to adopt adaptive approaches to manage complexity (Mintzberg, 1973). The first mode, planning, is a systematic process that lays the foundation for structured decision-making frameworks (Mintzberg, 1973). This study hypothesises that GenAI significantly enhances strategic decision-making by improving information-seeking efficiency, refining data analysis capabilities, and offering decision-makers more sophisticated predictive insights, i.e., eventually improving strategic foresight capabilities.

Fredrickson (1984) further emphasises the role of systematic decision-making in managing complexity and improving decision quality. However, human cognition is prone to heuristic thinking, leading to biases that affect decision accuracy (Kahneman, 2003; Tversky & Kahneman, 1974). While previous studies have examined the influence of heuristics in decision-making, limited empirical research has been conducted on how GenAI can mitigate these biases. This thesis seeks to fill this gap by exploring GenAI's potential to counteract heuristic-driven errors and optimise strategic decision-making frameworks (Leyer & Schneider, 2021; Pomerol, 1997; Stone et al., 2020; Doshi et al.,2024; Kaggwa et al. 2024). By investigating whether GenAI integration leads to more confident, committed, and higher-quality decisions, this study evaluates GenAI's potential to optimise strategic decision frameworks under conditions of complexity and uncertainty.

Doshi et al. (2024) examined the role of GenAI in strategic decision-making by employing a multi-method approach that leveraged seven LLMs, including OpenAI's GPT-3.5, GPT-4, and Google's Gemini Pro, to evaluate business models. Their methodology involved pairwise evaluations in which GenAI-generated assessments were compared to those of 100 human strategy experts and 150 non-experts, using both base prompting and chain-of-thought prompting to determine how well GenAI could assess business model viability. Their findings indicate that individual AI evaluations were inconsistent and prone to biases, but aggregating multiple GenAI-generated evaluations significantly improved alignment with human expert judgments. GenAI was notably better at identifying weak business models than selecting top-performing ones, indicating limitations in its ability to recognise high-potential strategic opportunities. These results suggest that while GenAI can support strategic decision-making by providing alternative perspectives, simulations, and structured analysis, its inherent biases and inconsistencies necessitate human oversight. As the study highlights, GenAI's ability to assist in complex strategic decisions depends on proper implementation strategies and shows that GenAI's role in strategic decision-making should be viewed as an augmentation rather than a replacement for human expertise, which is a thesis that this study will explore further.

GenAI's capability to reduce uncertainty is particularly valuable in strategic decision-making. Doshi et al. (2024) highlight that GenAI-generated assessments, when aggregated, align closely with human expert evaluations, suggesting that GenAI-enhanced decision-making can improve organisational foresight and reduce inconsistencies in complex evaluations. Moreover, GenAI can generate, compare, and evaluate multiple business models and strategic alternatives, helping organisations refine their strategic options (Doshi et al., 2024). This ability to simulate possible outcomes gives decision-makers a more comprehensive understanding of potential risks and opportunities.

GenAI’s ability to generate nuanced insights and improve decision accuracy makes it a valuable tool for organisations looking to reduce costs associated with strategic uncertainty (Agrawal et al., 2019; Kleinberg et al., 2017; Kaggwa et al., 2024). Prior research has shown that AI outperforms human decision-makers in analytical tasks, offering greater precision in predicting business trends (Brynjolfsson & Mitchell, 2017; Kahneman et al., 2016; Yeomans et al., 2019). However, human judgment remains essential in handling ambiguous situations where data is scarce or requires qualitative reasoning (Mintzberg, 1973; Doshi et al., 2024). Chaturvedi et al. (2025) argue that the optimal approach is a GenAI-augmentation model, where GenAI serves as a support system rather than a replacement for human expertise. This model enables organisations to leverage GenAI-generated insights while retaining human oversight in critical strategic decisions (De Cremer & McGuire, 2022; Jarrahi, 2018; Malone, 2018; Raisch & Krakowski, 2021; Seeber et al., 2018; Doshi et al., 2024; Kaggwa et al., 2024).

One major challenge in integrating GenAI into strategic decision-making is trust. Employees often hesitate to rely on GenAI due to its complexity, lack of transparency, and perceived limitations (Glikson & Woolley, 2020). Kaggwa et al. (2024) suggest that decision-makers are likelier to trust GenAI-generated insights when organisations prioritise GenAI explainability and integrate transparency measures into their decision processes. Hoff & Bashir (2014) developed a three-layered trust model, which provides a theoretical foundation for increasing trust in GenAI-driven decision-making. However, practical applications of this model remain underexplored (Keding & Meissner, 2021). Chugunova & Sele (2022) further emphasise that full automation of strategic decisions may increase mistrust, reinforcing the argument that GenAI should be positioned as an augmentation tool rather than a full replacement for human decision-makers.

The quality of strategic decisions is directly linked to an organisation's long-term performance. Ketchen et al. (2004) stress the need for a comprehensive analysis of competitive environments to reduce uncertainties in strategic planning. Additionally, decision quality has been found to influence firm performance, with studies by Amason (2017) and Dean & Sharfman (1996) demonstrating a direct relationship between high-quality strategic decision-making and organisational success. To improve decision quality, organisations must ensure that decision-makers have access to diverse and high-quality information sources (Rousseau et al., 2018). See et al. (2011) find that seeking input from external sources enhances decision-making quality, which is an insight that supports the argument that GenAI, as a knowledge-generating tool, can improve strategic decision quality by offering broader perspectives and reducing bias.

Studies have shown that GenAI-augmented decision-making leads to higher-quality strategic outcomes by improving information perception and assessment accuracy (Jarrahi, 2018; Miller, 2018; Parry et al., 2016). However, empirical research on how GenAI enhances decision quality within strategic decision-making remains limited (Doshi et al., 2024; Kaggwa et al., 2024). Keding & Meissner (2021) provide evidence that AI-augmented decision-making positively influences managerial choices, suggesting that organisations can benefit from GenAI-driven strategic evaluations. This thesis will further investigate how GenAI augmentation can be scaled across an organisational level to maximise GenAI's potential in strategic planning.

Despite its benefits, GenAI-driven decision-making is not without challenges. Research has demonstrated that GenAI can introduce biases if the underlying datasets are skewed (Silva & Kenney, 2018). Algorithmic bias can affect decision fairness and inclusivity, whether stemming from training data limitations or embedded systemic biases. Doshi et al. (2024) caution that organisations must address GenAI biases by implementing rigorous validation methods and incorporating diverse datasets. Kaggwa et al. (2024) further argue that firms should invest in ethical GenAI frameworks and transparent governance structures to mitigate AI-related biases. Proposals have been made to enhance data fairness (Courtland, 2018), but defining fairness remains a subjective challenge. Additionally, research has suggested that firms must increase transparency in GenAI decision-making (Annany & Crawford, 2016). However, this requires organisations to disclose proprietary algorithms, which may conflict with business interests (Citron & Pasquale, 2016; Lepri et al., 2017).

Existing research has contributed valuable insights into the technical performance of GenAI and its integration into decision-support systems (Doshi et al., 2024; Duan et al., 2019). However, several limitations exist. First, much of the literature focuses on model accuracy, efficiency, or automation, often overlooking the human decision-making experience when augmented by GenAI, such as how it affects users' confidence, engagement, and strategic foresight. Current studies treat AI as an isolated tool rather than examining its role within socio-technical systems, where trust, cognitive load, and organisational context also shape outcomes (Chaturvedi et al., 2024). In addition, many contributions remain conceptual or anecdotal, with limited empirical evidence from real-world or experimentally simulated strategic decision scenarios. This study addresses these gaps by adopting an experimental design that examines the performance implications of GenAI use and the cognitive and behavioural effects of human-AI interaction in complex decision environments.

2.4 Conclusion

This chapter has provided an overview of the role of GenAI in strategic decision-making processes within organisational contexts. Beginning with an introduction to GenAI and its transformative potential in generating new content and aiding knowledge workers, the discussion explored the intersection of GenAI with organisational learning and decision theory. Highlighting the importance of organisational learning for enhancing decision quality and the potential of GenAI to augment human cognition, the chapter underscored the significance of integrating AI technologies into organisational processes to foster sharp decision-making. Moreover, the chapter delved into the specific impact of GenAI on strategic decision-making, emphasising its capacity to reduce uncertainties, enhance decision quality, and influence organisational performance. Recognising the need for human-machine cooperation and the establishment of trust in AI systems, the discussion addressed potential challenges such as biases in AI-generated decisions and the necessity for transparency in data usage. This thesis explores how GenAI can improve strategic foresight while mitigating biases and fostering trust among decision-makers. By addressing these challenges and leveraging the transformative potential of AI technologies, such as GenAI, organisations can unlock new opportunities for sharp decision-making and increase competitiveness in a seemingly complex business environment.

3. Methodological approach

To investigate how GenAI can enhance strategic foresight in decision-making processes, this study employs a mixed-method approach that combines a quantitative experimental design with qualitative insights. The primary method is a deductive, ontological, quantitative experiment using vignettes to simulate realistic decision-making scenarios. This allows for systematic testing of the hypotheses, particularly the expectation that GenAI improves decision-makers' commitment, confidence, and perceived decision quality by assisting in filtering vast information sets and presenting alternative perspectives.

While the experimental design provides the accuracy necessary to identify statistically significant relationships between GenAI usage and decision-making outcomes, quantitative measures alone will not fully capture the nuanced cognitive and interpretative processes involved in how participants interact with GenAI. Thus, qualitative reflections from participants are also collected and analysed to complement the experimental findings. These qualitative insights enrich the understanding of not only whether but also how and why GenAI influences decision-making processes. This approach enables the study to address underlying mechanisms and subjective experiences that numbers alone cannot reveal. This chapter outlines a rationale for selecting this research design, explains its alignment with the study objectives, and details the procedures for data collection, analysis, and ethical considerations.

3.1 Research design

This study employs an ontological quantitative experimental design grounded in deductive theory to investigate the impact of GenAI on decision-making processes across various functional areas. Deductive theory-driven research involves testing hypotheses derived from existing theories or conceptual frameworks, providing a structured approach to understanding causal relationships between variables (Bryman & Bell, 2015). The primary dependent variable measured in this study is the level of commitment on a Likert scale. Confidence and quality of decision will also be measured. The experiment involves developing and presenting vignettes that simulate decision-making scenarios typical of different organisational functional areas. According to Atzmüller & Steiner (2010), a vignette study consists of the vignette experiment and a structured survey. Vignettes are short descriptions of a scenario and serve as a methodological tool for systematically manipulating variables while maintaining ecological validity, allowing researchers to test specific hypotheses derived from deductive theory.

During the development phase, vignettes are carefully crafted to authentically represent decision-making challenges encountered in the various functions of the surveyed organisation. The functional areas include marketing, customer operations, product development, technology, presales, and sales. In addition, a sampling strategy is crucial to ensure the validity and generalizability of study findings (Bryman & Bell, 2015). Participants are purposefully sampled based on their expertise or experience in strategic decision-making within functional contexts, aligning with deductive theory-driven research objectives. How the sampling was conducted will be elaborated later.

The experimental procedure involves randomly assigning participants to different conditions, including groups exposed to GenAI assistance, ChatGPT-4o, and control groups without GenAI intervention. Participants engage with the vignettes independently and provide responses reflecting their decision-making processes and outcomes through a questionnaire. The participants were prompted to use GenAI to answer the vignettes and were free to prompt however they wanted. Still, they were asked to insert their conversation for validation at the end of the survey. Data collection instruments include pre- and post-experiment surveys, capturing demographic information, decision-making preferences, and perceptions of GenAI assistance. Quantitative measures assess decision-making outcomes, facilitating statistical analysis using ANOVA to compare mean differences in decision-making across functional areas and experimental conditions, guided by deductive theory.

In addition to using quantitative methods in this study, allowing participants to reflect on their reasoning, experiences, and perceptions when using GenAI incorporates qualitative methods. While the quantitative component provides measurable evidence of GenAI's impact on commitment, confidence, and decision quality, capturing statistically significant trends and causal relationships, the qualitative component adds depth by uncovering the cognitive and interpretive processes behind participants' choices. This mixed-methods approach enables a more nuanced understanding of how GenAI interacts with human decision-making across diverse functional contexts. As Creswell and Plano Clark (2017) suggest, integrating quantitative and qualitative data in a complementary design enhances the validity and richness of the findings, particularly in exploratory research areas such as AI-augmented strategic foresight. This dual approach ensures that the study identifies *what* changes in decision outcomes and provides insight into *why* and *how* these changes occur, providing explanatory and interpretive value to test the hypotheses.

The research design integrates the principles of ontological quantitative experimentation and deductive theory-driven analysis to answer the research question. While existing research has explored the broader implications of AI in decision-making, the specific impact of GenAI on strategic decision-making within organisations remains under-explored. This study addresses this gap by using a vignette experiment to simulate real-world scenarios, providing insights into how GenAI might influence strategic foresight in decision-making, which is a topic that still must be fully understood. This methodological approach provides a structured framework for hypothesis testing and theoretical advancement, contributing to insightful interpretations and actionable insights.

3.2 Development of vignettes

The vignettes used in this study were developed based on the principles outlined by Arkes & Blumer (1985) and Meissner & Wulf (2017). They focus on creating realistic, engaging, and methodologically realistic scenarios that serve as proxies for real-world decision-making processes in organisational settings. To ensure ecological validity, the Director of Product Strategy from the participating company gave their guidance and opinion on the vignettes to make them as realistic as possible.

Arkes & Blumer (1985) emphasise ensuring that vignettes reflect actual decision environments to maintain ecological validity. Consistent with their guidelines, each vignette in this study is constructed to mirror the complexity and ambiguity typical of strategic decision-making scenarios. Given the limited empirical studies on the role of GenAI in strategic decision-making, these vignettes are designed to fill the gap by capturing complex decision-making processes in various organisational contexts. This study is among the first to systematically explore these scenarios, offering a structured approach to understanding GenAI's potential impact. By mimicking a scenario where the organisation aspires to enter a new market, this approach helps in simulating the cognitive and emotional pressures that decision-makers face, thereby examining the potential impact of GenAI more realistically.

Building on the framework by Arkes & Blumer (1985) and Meissner & Wulf (2017) provides additional insights into enhancing the efficacy of vignette-based research by incorporating elements that trigger specific cognitive and decision-making processes. Following their recommendations, each vignette includes detailed descriptions that prompt the participants to engage in a depth of analysis comparable to their professional settings. This includes providing background information, contextual variables, and potential consequences for each decision scenario.

The vignettes are designed to allow for a clear comparison between decisions made with and without the aid of GenAI. Two scenarios are created, first a company-specific that engages the participants in a real-world strategic decision-making process and second, an objective vignette to create a neutral and controlled scenario that applies broadly to any decision-maker without personal or organisational biases. The objective vignette is adapted from Arkes & Blumer's (1985) study on sunk costs and based on a study by Krakowski et al. (2025). In addition to the vignettes, in line with Atzmüller & Steiner's (2010) study, the vignettes are complemented with a questionnaire with questions to get quantitative data on commitment, confidence level and decision quality.

Preliminary feedback is sought from industry experts at the surveyed organisation to ensure the relevance and accuracy of the scenarios. Ecological validity is assured as each vignette has been carefully designed to mirror the surveyed organisation's authentic challenges. The development process followed established methodological guidelines (Arkes & Blumer, 1985; Meissner & Wulf, 2017) and is grounded in an iterative validation process with a person working with product strategy from the surveyed organisation. As part of this effort, I sat down with the Director of Product Strategy to collaboratively evaluate the accuracy and contextual relevance of a company-specific vignette related to strategic product planning. The Director provided feedback on the decision variables and the situational framing, ensuring that the scenario aligned with real strategic dilemmas encountered in their role. Similar feedback loops were sought across other functions to fine-tune the vignettes, ensuring they were theoretically robust, realistic, functionally grounded, and cognitively demanding. Therefore, this enhances the external and practical relevance of the study's findings.

3.3 Sampling strategy

This study's sampling strategy targets Company X employees directly involved in decision-making processes across various functional areas. The primary inclusion criteria are that the participant has current employment at Company X and has professional experience involving decision-making tasks, either at the operational, tactical, or strategic level. No additional exclusion criteria were applied beyond these basic parameters. Participation was entirely voluntary, and no incentives were offered to ensure that responses were based on genuine interest in the study topic.

The survey is distributed to 2100 employees through internal communication channels, including email and Slack, accompanied by an explanation of the study's objectives, confidentiality guarantees, and instructions for participation. In total, 102 employees completed the survey, resulting in a response rate of 19,6 per cent. This response rate raises potential concerns about non-response bias, particularly if those who chose not to participate systematically differ from those who did. To address potential non-response bias, descriptive comparisons are conducted between the available aggregated demographic data of the total employee population and the respondent sample. The diversity of roles and functional backgrounds among respondents suggests that the sample captures a reasonable cross-section of the organisations. However, it is acknowledged that more motivated or GenAI-curious employees may have been somewhat overrepresented. The key sampling details are summarised in Table 1.

Table 1: Sampling details of the survey

Aspect	**Description**
Target population	Employees at Company X
Inclusion criteria	Employment at Company X; experience in decision-making
Exclusion criteria	None beyond not meeting the inclusion criteria
Total invitations sent	2100
Total completed responses	102
Response rate	19,6 %
Sampling technique	Purposive, voluntary sampling
Methods of recruitment	Internal email, Slack channels
Non-response bias consideration	Addressed through functional diversity check among respondents

A purposive sampling technique is employed to ensure that the sample adequately represents a diversity of roles and experiences within the organisation, from junior team members to senior executives. This approach allows for a comprehensive analysis of how GenAI influences decision-making across different levels of expertise and responsibility (Bryman & Bell, 2015). By focusing on employees willing to participate, the study aims to gather insightful and motivated responses, enhancing the reliability and relevance of the findings.

3.4 Experimental procedure

The experimental procedure is designed with a few key steps to ensure the reliability of the study. The process begins with developing the vignettes, which have been outlined in the previous section. Once the vignettes have been created and validated by the expert at the target company, a survey is made using the online survey tool SoSciSurvey. Two surveys were created.

One meant for participants using ChatGPT-4o, and one meant for participants not using ChatGPT-4o to answer the questions. The survey was allocated randomly to participants through SoSciSurvey's random sampling generator. The survey includes questions measuring decision quality and a decision-maker's confidence in their decisions based on the presented vignettes (Appendix A).

Before distributing the survey to the target company, a preliminary test will be conducted with a selected test group. The test group comprises five employees at company X with whom I have daily contact. This test group will complete the survey, providing valuable feedback on its clarity, relevance, and overall design. Based on this feedback, any necessary adjustments will be made to refine the survey. Once the survey is finalised, it will be distributed to the company's employees via email and Slack. The survey will be open for completion from June 10th to August 1st, allowing enough time for participants to engage with the survey at their convenience. Participation is voluntary and anonymous, which is stressed at the start.

After the survey period concludes, the collected data will be analysed using Analysis of Variance (ANOVA). This method will identify decision quality and confidence differences across various scenarios and participant groups. The findings from this analysis will provide insights into how GenAI can enhance strategic decision-making processes within the company. By following this structured procedure, the study aims to produce reliable and actionable insights into the impact of GenAI on decision-making in an organisational context.

3.5 Data collection instruments

This study's primary data collection instrument is a survey developed and administered using SoSciSurvey. The survey is designed to capture detailed responses from participants regarding their decision-making processes in various strategic scenarios. Each scenario is presented through carefully crafted vignettes that simulate real-world decision-making contexts relevant to different functions within a SaaS company.

The survey comprises both quantitative and qualitative elements. Quantitative data will be gathered through Likert-scale questions, measuring the participants' decision quality and confidence levels after engaging with each vignette. These questions provide a numerical basis for comparing decision-making effectiveness across different scenarios and participant groups. Qualitative data will be collected through open-ended questions, allowing participants to elaborate on their decision-making process, the role of GenAI in their decisions, and any perceived advantages or challenges. This qualitative feedback will offer deeper insights into the contextual factors influencing decision-making and the practical implications of AI augmentation.

Demographic questions will be included to collect background information on the participants, ensuring that the analysis can account for variations in experience, role, age, gender, and handedness. In addition, a personality test will be done (Appendix C) to see if there is a relationship between a personality type and commitment and confidence in a decision. Together, these instruments will provide a comprehensive dataset for analysing the impact of GenAI on strategic decision-making in an organisational context.

3.6 Data analysis plan

The data analysis plan for this study involves a systematic approach to examining the responses collected from the survey. The primary objective is to assess GenAI's impact on strategic decision-making within an organisation. The analysis will be conducted in several stages, using quantitative and qualitative methods to understand the data comprehensively.

Quantitative data analysis will begin with descriptive statistics to summarise the basic features of the dataset, including mean, median, and standard deviation for each of the Likert-scale questions. This initial analysis will provide an overview of participants' decision quality and confidence levels across different scenarios. To identify significant differences in decision quality and confidence, ANOVA will be used. ANOVA is chosen for its ability to compare multiple groups simultaneously and determine whether any observed differences are statistically significant. Post-hoc tests will be conducted if ANOVA results indicate significant differences, allowing for a detailed examination of specific group comparisons.

Given that this study employs an experimental vignette-based design with categorical independent variables (GenAI-assisted vs. non-assisted decision-making) and seeks to compare group means rather than model predictive relationships, ANOVA is the most appropriate statistical method compared to other alternatives such as regression analysis. While regression is typically used to predict dependent variables based on continuous or multiple predictors, the primary aim of this study is not to predict outcomes. Rather, the purpose is to test for statistically significant differences between experimental conditions on decision-related outcomes. ANOVA allows for strong hypothesis testing by identifying statistically significant differences in decision-making commitment levels across functional areas and experimental conditions. The use of ANOVA aligns with standard practices in experimental research (Bryman & Bell, 2015) and ensures a structured approach to assessing the impact of GenAI on strategic decision-making processes.

Potential confounding variables, such as participants' functional area, seniority level, familiarity with AI technologies, or prior experiences with strategic decision-making, could influence the outcomes independently of the experimental manipulation. To address these potential confounds, the experimental design employed random assignment to treatment and control groups. Randomisation helps ensure that any pre-existing differences between participants are distributed evenly across conditions, thereby supporting internal validity. In addition, the use of a mixed-method design is necessary and innovative for addressing the research question. The dual approach aligns with best practices in emerging fields like human-AI interaction, where purely numerical models risk missing the subjective and social dimensions of technology adoption. It also represents an innovative step by combining behavioural experiments with participant-centred reflections. Thus contributing uniquely to the literature on GenAI and strategic foresight.

Qualitative data analysis will involve coding and thematic analysis of the open-ended responses. Thematic analysis will help identify recurring patterns and themes related to participants' experiences with GenAI in decision-making. This qualitative insight will complement the quantitative findings by providing context and depth to the numerical data. The process followed Braun and Clarke (2006) widely accepted six-phase framework, including familiarisation with the data, initial coding, searching for themes, reviewing themes, defining and naming themes, and producing the final report. Coding procedures were conducted manually to allow close engagement with the text. An open coding strategy was first employed, where segments of text were examined line-by-line to identify initial codes that captured key ideas, perceptions, or reactions to GenAI use in decision-making. Axial coding was then used to explore relationships between codes, clustering them into higher-order categories and noting patterns of similarity or contrast. Finally, selective coding refined these broader categories into overarching themes that directly addressed the research objectives, such as perceptions of GenAI's role in enhancing information synthesis, concerns about over-reliance on GenAI outputs, and reflections on decision confidence and quality.

To ensure reliability and validity, several measures were undertaken. Coding procedures were conducted iteratively, with initial coding results revisited after a delay to test for consistency in interpretation. Particular attention was also paid to negative cases, i.e., instances where participant responses contradicted the dominant theme. These were carefully analysed and incorporated into the thematic discussion to ensure that findings reflected the diversity and complexity of participants' experiences. The combined quantitative and qualitative analyses will explain how GenAI influences strategic decision-making, highlighting knowledge workers' benefits and challenges in a SaaS company. This comprehensive analysis will inform the study's conclusions and recommendations for leveraging AI to enhance decision-making processes.

3.7 Ethical considerations

This study's methodological approach adheres to strict ethical standards to ensure all participants' integrity and ethical treatment. Informed consent will be obtained from all participants before they are involved in the survey, ensuring they are fully aware of the study's purpose and procedures and their right to withdraw without penalty. Given the study's focus on GenAI-assisted decision-making, additional ethical considerations were addressed regarding the use of OpenAI's GPT-4o model. Awareness of potential training data biases inherent was critical, as such biases could subtly influence the content or framing of GenAI-generated outputs. To mitigate the risk, participants were instructed to stay critical of GenAI-generated information. By recognising both participant autonomy and the technological limitations of GenAI tools, the study seeks to uphold a high ethical standard in both human and machine-related dimensions of the research.

Confidentiality and anonymity of the participants will be maintained throughout the study. Data will be collected and stored securely, with personal identifiers removed to protect participants' privacy. Only aggregated data will be reported in the findings to ensure individual responses cannot be traced back to any participant. The study will also ensure that GenAI's use in decision-making scenarios does not accidentally reinforce biases or ethical dilemmas, as the design and implementation of vignettes will be carefully reviewed to avoid potential ethical issues. The study aims to uphold the highest ethical standards in research by addressing these considerations.

3.9 Conclusion

This study adopts a deductive, quantitative experimental design to explore how GenAI can be used to enhance strategic foresight. Using a multi-method vignette-based approach, participants who were sampled for their expertise in decision-making were randomly assigned to GenAI-assisted and non-assisted conditions. They completed decision-making tasks and a survey administered through SoSciSurvey, capturing Likert-scale and open-ended responses. Commitment levels served as the primary dependent variable. Quantitative analysis involved descriptive statistics and ANOVA to assess group differences, while qualitative responses were analysed thematically. Ethical considerations, including informed consent, confidentiality, and bias mitigation, were addressed. Although limited by industry specificity and self-reported measures, the study aims to clarify how GenAI can augment strategic decision-making processes.

4. Empirical findings & analysis

This section will dive into the study's findings and analyse the results from the mixed-methods vignette experiment. The study investigates how having GenAI as a tool to assist in a strategic decision-making process enhances the strategic foresight of the decision-making by facilitating information-seeking and analysis. This research study uses quantitative and qualitative data to overview GenAI's role and influence in strategic decision-making. The section will begin with presenting the descriptive statistics of the study’s sample, then move on to the quantitative results on resource allocation, level of commitment and confidence, and perception of decision quality.

Finally, the quantitative results will be analysed, providing a more nuanced understanding of the quantitative results.

4.1 Descriptive data results

Understanding participants' demographic and professional backgrounds is important for contextualising the impact of GenAI on strategic decision-making. The existing literature lacks a comprehensive exploration of how factors such as the functional roles or educational backgrounds might influence the integration of GenAI in strategic decision-making, a gap this study aims to address. These statistics provide a foundational understanding of the sample composition and its relevance to the research context, which is exploring how GenAI can be used in a strategic decision-making context.

The demographic characteristics of the sample provide important context for interpreting the study's findings. The predominance of participants from Technology and Presales Analytics (Appendix F) suggests a sample well-versed in working with digital tools and data-driven processes, potentially leading to greater openness toward adopting GenAI-assisted decision-making. However, this technical familiarity may also have contributed to higher baseline confidence in handling complex information independently, potentially reducing the observable incremental impact of GenAI on decision confidence and commitment levels. The relatively young age profile (Appendix H) and high educational attainment of the participants may have fostered a generally positive disposition towards new technologies, consistent with moderate trust in IT scores (Appendix I). While international composition (Appendix E) of the sample adds richness to the findings, it may also introduce variability in cognitive styles, risk perceptions, and decision-making norms across cultural backgrounds, which could have further influenced the degree of reliance on GenAI-generated insights. Overall, these factors suggest that while the sample was well-positioned to engage with GenAI tools, pre-existing confidence and tech-familiarity may have moderated the measurable effects on decision outcomes.

4.2 Quantitative results

This section analyses in-depth the financial allocations, commitment levels, and confidence levels of participants during the five rounds of the study, contrasting decisions influenced by those guided by GenAI and those not guided by GenAI. In addition, the participants were provided with an objective vignette based on Arkes and Blumer's study from 1985, modified by Krakowski et al. (2025). While some studies have highlighted the potential of AI to enhance decision-making efficiency, there is a significant gap in understanding how GenAI specifically affects decision quality and commitment in high-stakes environments. This analysis fills that gap by providing empirical data on these critical factors. The central hypothesis suggests that GenAI would enhance strategic decision-making by simplifying information-seeking and data analysis, leading to more committed, confident, and financially substantial decision-making. The results were analysed using ANOVA to evaluate the impact of advice type on resource allocation, commitment, and confidence levels.

4.2.1 Resource allocation

The study investigated how participants allocated financial resources across five decision-making rounds, either using GenAI or not. The participants were first presented with a company-specific vignette (Appendix A) and randomly assigned to use GenAI or not. The company-specific vignette asked the participants to allocate USD within a specific span. This is depicted in Table 2.

Table 2: Resources allocated by aid type during the company-specific vignette

Resources by advice type	Aid Type	Mean (100K USD)	Mean / max	Available (100K USD)
Round 1	None	3,806	76,12 %	2,5-5,0
	GenAI	4,057	81,13 %	2,5-5,0
	Total	3,936	78,73 %	2,5-5,0
Round 2	None	2,408	60,20 %	1,0-4,0
	GenAI	2,406	60,14 %	1,0-4,0
	Total	2,407	60,17 %	1,0-4,0
Round 3	None	1,622	54,08 %	0,5-3,0

	GenAI	1,896	63,21 %	0,5-3,0
	Total	1,765	58,82 %	0,5-3,0
Round 4	None	2,724	60,54 %	1,5-4,5
	GenAI	2,972	66,04 %	1,5-4,5
	Total	2,853	63,40 %	1,5-4,5
Round 5	None	3,061	61,22 %	1,0-5,0
	GenAI	3,047	60,94 %	1,0-5,0
	Total	3,054	61,08 %	1,0-5,0

Across all five rounds, participants using GenAI consistently allocated slightly more financial resources than those in the control group, especially in rounds 1, 3, and 4 (Table 2). The most notable difference appeared in round 3, where GenAI users allocated over 9 percentage points more than their non-GenAI counterparts. In rounds 2 and 5, allocation levels between the two groups were nearly identical. Overall, these patterns suggest a modest but recurring preference for Gen-AI-supported decision-making, likely due to its perceived strengths in synthesising complex information and reducing uncertainty.

Based on the standardised scenario, the financial allocations followed a similar pattern as seen in Table 3.

Table 3: Resources allocated by aid type during the standardised vignette

	Aid Type	Mean (mUSD)	Mean / max	Available (mUSD)
Round 1	None	7,100	71,00 %	5 - 10
	GenAI	7,150	71,50 %	5 - 10

	Total	7,130	71,30 %	5 - 10
Round 2	None	3,900	65,00 %	3 - 6
	GenAI	4,180	69,67 %	3 - 6
	Total	4,030	67,17 %	3 - 6
Round 3	None	2,600	52,00 %	2 - 5
	GenAI	3,020	60,40 %	2 - 5
	Total	2,850	57,00 %	2 - 5
Round 4	None	4,700	67,14 %	4 - 7
	GenAI	5,040	72,00 %	4 - 7
	Total	4,900	70,00 %	4 - 7
Round 5	None	1,500	37,50 %	1 -4
	GenAI	1,950	48,75 %	1 -4
	Total	1,770	44,25 %	1 -4

Across all rounds, participants using GenAI consistently allocated more resources than those without GenAI assistance. The largest difference was in rounds 3 and 5. The gap was especially visible in round 5, where GenAI users allocated over 11 percentage points more than non-GenAI users. While both groups showed a general decline in allocations over time, those supported by GenAI maintained higher commitment levels throughout, suggesting that GenAI may help sustain engagement in decision-making under uncertainty.

During the standardised vignette, the participants could abandon the project instead of allocating more funding. Of the 102 participants, 23 (22,54 per cent) abandoned the project. After round 2, 9 participants abandoned the project, six chose to abandon the project after round 3, 5 decided to abandon the project after round 4, and 3 chose to abandon the project after round 5. This shows that some participants abandon the project when the outlook is weak. The data from the standardised vignette shows a stronger preference for GenAI advice, particularly in rounds involving higher stakes or complexity, suggesting that participants might view GenAI as more reliable or objective in such contexts.

4.2.2 Commitment levels by aid type

During the company-specific vignette, commitment levels were assessed after each round to measure participants' dedication to the decisions made (Appendix A). The choice was made on a Likert scale from 1 to 7, as seen in Table 4.

Table 4: Commitment levels by aid type

	Aid	Mean	Mean / max
Round 1	None	4,939	70,56 %
	GenAI	5,038	71,97 %
	Total	4,990	71,29 %
Round 2	None	4,286	61,23 %
	GenAI	4,434	63,34 %
	Total	4,363	62,33 %
Round 3	None	4,388	62,69 %
	GenAI	4,679	66,84 %
	Total	4,539	64,84 %
Round 4	None	4,571	65,30 %

	GenAI	4,792	68,46 %
	Total	4,686	66,94 %
Round 5	None	4,694	67,06 %
	GenAI	4,849	69,27 %
	Total	4,775	68,21 %

These results suggest that participants felt more committed to decisions when guided by GenAI, possibly due to a perception of GenAI's impartiality and data-driven analysis.

4.2.3 Confidence levels by advice type

In addition to the level of commitment, the participants' confidence in the decision was asked after each round (Appendix A). Confidence levels, also measured on a scale from 1 to 7, reflected participants' certainty in decisions based on the advice received. The data is displayed in Table 5.

Table 5: Confidence levels by aid type

	Aid Type	Mean	Mean / Max
Round 1	None	4,434	63,35 %
	GenAI	5,106	72,95 %
	Total	5,061	72,30 %
Round 2	None	3,695	52,79 %
	GenAI	4,255	60,79 %
	Total	4,217	60,25 %

Round 3	None	4,158	59,39 %
	GenAI	4,340	62,01 %
	Total	4,250	60,71 %
Round 4	None	4,290	61,29 %
	GenAI	4,404	62,92 %
	Total	4,348	62,11 %
Round 5	None	4,247	60,67 %
	GenAI	4,489	64,13 %
	Total	4,370	62,42 %

Higher confidence levels with GenAI advice across most rounds suggest that participants viewed GenAI as a more reliable source of information, providing comprehensive and objective insights that bolster confidence in decision-making.

4.2.4 Quality of decision

The quality of decisions made was assessed at the end of the five rounds in the company-specific vignette, focusing on the perceived thoroughness and effectiveness of the decisions, measured on a scale from 1 to 7. This is seen in Table 6.

Table 6: Perceived decision quality

Type of Aid	Perceived Quality	Quality/max	Range
None	4,02	57,46 %	1-7
GenAI	4,00	57,14 %	1-7
Total	3,50	50,00 %	1-7

These findings indicate that while participants using and not using GenAI are valued similarly in decision quality, the slight edge given to not using GenAI suggests that participants still value human intuition and experience in final decision-making evaluations.

4.2.5 Statistical analysis: ANOVA

An ANOVA was conducted to evaluate the impact of advice type (not using vs. using GenAI) on financial allocations, commitment levels, and confidence levels. This study hypothesises that GenAI would enhance decision-making effectiveness by facilitating faster data analysis and presenting alternative perspectives, thereby increasing decision confidence and commitment.

The ANOVA results in Table 7 reveal an F-value of 0,614 and a p-value of 0,435, indicating no statistically significant difference in financial allocations based on the type of advice. Similarly, the commitment and confidence levels did not show significant variation attributable to the advice source. These findings suggest that, contrary to the hypothesis, GenAI did not significantly influence participants' financial decisions, commitment, or confidence levels.

Table 7: ANOVA results

Commitment by GenAI usage	Df	Sum Sq	Mean Sq	F value	Pr(>F)
GenAI users vs. non-GenAI users	1	37	36,68	0,614	0,435

4.2.6 Summary of quantitative findings

Even though the results show slight upward trends in decision confidence and commitment among GenAI-assisted participants, these differences did not reach statistical significance. This suggests that the hypothesis might have overestimated GenAI's immediate cognitive impact on strategic decision-making. Organisational learning and decision theory emphasise that confidence and commitment are not driven solely by information access but also by trust, experimental judgement, and sensemaking. All factors which evolve over longer periods and richer social contexts (Argote & Miron-Spektor, 2011; Fredrickson, 1984). Methodological factors further explain the outcome. The sample size of 102, while diverse, may have lacked the statistical power needed to detect small effects. Also, the vignette design, despite efforts to ensure ecological validity, may not have created sufficient decision pressure to elicit behavioral differences.

Nonetheless, the slight improvements in GenAI-supported groups indicate that GenAI can positively influence users' sense of preparedness by broadening information breadth and offering reassurance. However, without strong perceived stakes, enforced usage structures, or deeper trust in GenAI's outputs, these benefits remained marginal. In line with Doshi et al. (2024), the implications of the findings is that GenAI can enhance strategic foresight but cannot substitute human judgement.

4.3 Qualitative findings

Open-ended questions were asked at the end of the survey to focus on the participant's experiences and perceptions during the strategic decision-making process. This, to complement the qualitative data and test the hypotheses further. Depending on if the participant answered the survey with or without GenAI (Appendix A) the questions were formulated differently. This section presents the qualitative data and aims to identify key themes that emerged from the participants' responses, providing insights into their thoughts on strategic decision-making, information sources, and the role of GenAI in these processes.

4.3.1 Factors influencing commitment

A common theme highlighted by most participants was the *economic context*, reflecting the participants' consideration of economic conditions in their strategic decision-making. Many respondents, independent of whether or not they were using GenAI, highlighted the economic downturn as a significant factor influencing their commitment to entering the Japanese market. One participant who answered the non-GenAI survey noted that:

"I was fairly sure that a downturn would not be all bad from our point of view [..]"

This indicates a belief in the potential opportunities even during economic challenges, which can be reflected in a higher commitment level to the decision. Other respondents echoed this bias:

“[…]getting a foot in the door with the market would be fruitful in the long-term when the economic situation stabilises.”

“Short-term economic downturns do not pose a big enough risk to the future long-term strategic plan.”

This shows that the participants believe the downturn is an opportunity for long-term gains, demonstrating a focus on strategic foresight rather than immediate market conditions.

The theme of *strategic consideration* was also seen often. Participants frequently mentioned the need to align decisions with long-term company strategies, including competitor analysis and the importance of securing a foothold in new markets. For instance, one participant stated:

“The company had already committed to the market with heavy investments […]”

This underscores the role of prior commitments in shaping their decisions. This theme highlights the weight given to existing strategies and the expected benefits of maintaining market presence, even in challenging economic times.

4.3.2 Perception of decision quality

Participants expressed varied levels of confidence in the quality of their decisions, forming the theme of *Decision quality and confidence*. While some felt confident, citing structured analysis and clear decision-making frameworks, others expressed doubts due to the experience of not having enough information about the situation. This was more notable among the respondents who answered the survey independently without GenAI.

“I felt unsure the whole time because I had information only about the sunk costs and costs of the next increment, not about estimates about the business potential and total costs - or about other investment opportunities.”

“The quality was not the best, since the subject was outside my area of expertise and it would require proper allocation of time to make well informed decisions”

“I felt I didn't have the required information to make good decisions”

However, some in the non-GenAI group felt that their decision quality was good and that they confidently supported it.

“Quite good. I am happy with the outcome”

“I think they were good. The outcome will tell”

For those respondents who used GenAI to answer the questions, they did not recognise that the tool significantly increased the quality of the decision but that it helped provide perspective and analyse the situation.

“It gave clear recommendations with solid few bullet point reasonings for multiple options.”

“GenAI improved my strategic decision-making by providing clear analysis and ensuring consistency in decisions.”

“[GenAI] gave summaries of pros, cons, risks, and possibilities, and reminded about information in previous steps.”

This shows that there is an appreciation towards GenAI and that it can be a helpful tool in clarifying a complex scenario. However, there were also concerns about GenAI, which impacted the decision quality of the respondents. A common thought was the need for a "human in the loop," ensuring that GenAI tools complement rather than replace human decision-making capabilities. One respondent summarised this view:

"Good tool but one should not completely rely on it."

This shows that the respondents recognise GenAI's existing limitations and consider them when using the tools in this way.

4.3.3 Summary of qualitative findings

The thematic analysis reveals that while participants recognise the potential of GenAI tools to enhance strategic decision-making, they prefer to rely on traditional methods, such as intuition and internal data. The themes of economic context and strategic considerations underscore the importance of aligning decisions with long-term goals, even in uncertain conditions. Meanwhile, mixed perceptions of GenAI highlight the need for careful technology integration in decision-making processes, balancing its strengths with the irreplaceable value of human insight and judgment.

These findings suggest that while GenAI and other advanced tools offer valuable support, the human element remains crucial, particularly in complex and high-stakes decision-making scenarios. This balance between human and GenAI contributions is not simply a division of labor but represents an evolving relationship of cognitive complementarity. Since GenAI excels at expanding the breadth of information whilst humans retain a comparative advantage in depth of judgement, the findings from the data develop into practical implications for organisations. These will be developed further in Chapter 5. As strategic decision-making increasingly resembles a dual-processing system, where GenAI supports divergent thinking and humans apply convergent thinking to final choices, a practical model can provide the guidance organisations need to use the findings from this data. The following section will dive deeper into both the quantitative and qualitative finding to synthesise a fuller understanding of GenAI’s evolving role in strategic decision-making.

4.4 Interpretation of findings

In this section, the quantitative and qualitative findings from the study will be analysed in line with the research question and hypothesis. The primary focus of this thesis is to understand how GenAI can enhance the strategic foresight of decision-making processes by simplifying information-seeking and analysis, thus increasing commitment and confidence in strategic decision-making. Previous studies have focused on technological advancements and their implications for knowledge workers and organisations. Thus, this study aims to contribute to the existing literature by exploring whether GenAI can act as a value-increasing tool in decision-making to improve strategic foresight.

Understanding the perception of GenAI among knowledge workers is crucial for organisations increasingly relying on GenAI to maintain a competitive edge in decision-making processes. Without understanding the approach the company should have, they risk implementing GenAI in ways that may not fully capitalise on its potential or, worse, could lead to suboptimal decision outcomes. Thus, the research question seeks to explore the potential for organisations to leverage GenAI to enhance strategic decision-making. At the same time, the hypothesis assumes that GenAI aids in filtering data and answering prompts, thus supporting more committed and confident decision-making. The resources allocated, commitment, and confidence levels will be analysed in this context.

4.4.1 Quantitative data interpretation

The quantitative data revealed that participants generally allocated more resources when using GenAI, particularly in the standardised vignette. This trend suggests that GenAI supports enhanced participants' confidence, likely due to its ability to synthesise large datasets and offer comprehensive analyses. For instance, in the company-specific vignette, GenAI users consistently allocated more resources, peaking at 81,13 per cent in Round 1, supporting the hypotheses. However, despite these positive trends, the differences were not statistically significant, indicating that while GenAI can support complex decision-making, it does not fundamentally alter decision outcomes without deeper integration and trust.

Commitment levels were also slightly higher for GenAI users across most rounds, peaking at 69,27 per cent in round 5, supporting the hypothesis that GenAI could reduce uncertainty and strengthen decision commitment. Confidence followed a similar pattern, with GenAI users reporting higher levels, particularly in Round 1 (72,95 per cent vs. 63,35 per cent for non-GenAI users). These findings suggest that GenAI contributed to a greater sense of assurance, yet the lack of statistical significance highlights the enduring role of human intuition, experience, and organisational context in strategic decisions.

Decision quality ratings were nearly identical between GenAI and non-GenAI users, with a slight preference for human intuition (57,46 per cent vs. 57,14 per cent). This challenges the hypothesis's stronger version that while GenAI supports better information processing, it does not substitute the nuanced judgment required for strategic decision-making. Overall, the findings affirm that GenAI can enhance elements of decision-making, such as perceived confidence and commitment, but that human expertise remains indispensable for achieving high-quality outcomes.

4.4.2 Qualitative data interpretation

While the quantitative data showed no statistically significant improvements in strategic foresight with GenAI assistance, the qualitative data provide critical nuance, offering insights into why these statistical effects may have remained modest and under what conditions GenAI's potential could be amplified. Many participants appreciated GenAI's ability to deliver clear, concise analyses and summarise complex information, aligning with the observed slight increases in confidence and commitment. However, participants repeatedly underscored the limits of these gains. They challenged the hypothesis and emphasised that GenAI alone does not replace the need for human intuition and strategic experience. This perspective suggests that the quantitative measures may have captured only surface-level effects without reaching deeper layers of judgment required for strategic foresight.

Participants also highlighted the enduring role of economic context and strategic alignment in their decision-making. Even when supported by GenAI, decisions were framed around broader organisational strategies and external market conditions, suggesting that GenAI is most effective as a complementary tool rather than a strategic driver. Trust emerged as a major barrier to full GenAI adoption, with concerns over data accuracy, algorithmic bias, and transparency. Trust emerged as a pivotal theme shaping participants' perceptions of GenAI. Concerns over data accuracy, algorithmic bias, and opaque reasoning processes limited participants' willingness to fully integrate GenAI insights into their decisions. This offers an important interpretive lens on the quantitative null results. Even when GenAI provided potentially useful recommendations, participants' reluctance to fully trust or rely on these suggestions may have dampened behavioural shifts. This shows how trust is a mechanism mediating the impact of GenAI on decision outcomes.

GenAI may reduce informational complexity, but its contribution to foresight depends on investments in transparency, explainability, and human-AI coordination. This finding shows how the qualitative findings extend the quantitative findings, as without these investments, GenAI's influence remains bounded. Its integration risks reinforcing superficial efficiencies rather than enabling deeper, forward-looking judgment. These qualitative findings both reinforce and challenge the quantitative results. They support the hypothesis showing that GenAI has a meaningful role in enhancing information processing, but challenge the hypothesis as these gains do not translate automatically to improved strategic foresight. The qualitative findings suggest that the transformative potential of GenAI requires a more systemic approach that integrates organisational trust-building and human critical engagement.

4.5 Conclusion

This study explored how GenAI could enhance strategic foresight by facilitating information-seeking and analysis in decision-making processes. By systematically addressing an under-researched area, it provides new insights into the opportunities and limitations of GenAI augmentation for organisations aiming to maintain a competitive edge. Through a combination of quantitative and qualitative data, the study evaluated whether GenAI meaningfully alters decision outcomes or primarily serves as cognitive support.

The sample of 102 participants, predominantly aged 26-35 and highly educated, was representative of technology-driven, international organisations. Quantitative analysis revealed that GenAI users generally allocated more resources, showed slightly higher commitment and confidence levels, and reported similar decision quality compared to non-GenAI users. However, none of these differences reached statistical significance, suggesting that while GenAI enhanced perceived decision support, its immediate impact on strategic behaviour was modest and undertaken under experimental conditions. Thus, while the findings align with the hypothesis directionally, they refine it by showing that GenAI acts as a supportive tool rather than fundamentally transforming decision-making processes.

These results reflect earlier theoretical tensions. GenAI can expand analytic breadth, but human judgment remains crucial for contextual interpretation (Argote & Miron-Spektor, 2011; Fredrickson, 1984). While some scholars (Doshi et al., 2024; Kaggwa et al., 2024) highlight GenAI's benefits, concerns about transparency and trust persist (Glikson & Woolley, 2020). This study challenges excessive caution, showing that when GenAI is thoughtfully integrated into workflows, it can effectively augment human expertise. Qualitative insights further confirmed that while participants value GenAI's information synthesis, they emphasised the continued importance of economic context, strategic alignment, and human oversight.

The study demonstrates that GenAI has the potential to enhance strategic decision-making by increasing confidence, commitment, and information breadth, but its effects are context-dependent and require critical human engagement. However, even though participants reported higher perceived clarity and efficiency when using GenAI it did not transfer to stronger commitment or foresight in the quantitative results. This complexity suggests that GenAI's influence on decision-making is not uniform but contingent on organisational context and individual attitudes. These key findings will be further discussed in the next section, focusing on the practical and theoretical implications and future research directions.

5. Discussion

Having presented the findings of the conducted vignette experiment to explore how GenAI can enhance a strategic decision-making process, the following section will discuss the findings in light of the research presented in Chapter 2. Firstly, the theoretical implications of the findings will be discussed, followed by the practical implications for organisations and recommendations on how an organisation can consider using GenAI in their decision-making processes. Additionally, the limitations of this study will be presented, and suggestions for future research will be provided.

5.1 Theoretical implications of the findings

The findings from Chapter 4 provide theoretical implications when contextualised within the existing literature on GenAI and strategic decision-making, as reviewed in Chapter 2. This section integrates the empirical insights with established theoretical frameworks, particularly organisational learning, decision theory, and human-AI collaboration, to clarify how the study advances theory. The findings challenge overly deterministic models of GenAI impact, offer a new conceptual distinction between information augmentation and strategic agency, and highlight trust as a mediating mechanism in GenAI-supported decision-making.

The findings of this study align with and extend organisational learning and decision theory frameworks (Argote & Miron-Spektor, 2011; Duan et al., 2019). GenAI acts as a cognitive extension, facilitating faster information processing, broader scenario exploration, and iterative knowledge refinement. By supplementing human strategic reasoning, GenAI addresses the pre-identified theoretical gap concerning GenAI's interaction with human judgment under uncertainty. While previous studies (Doshi et al., 2024, Chaturvedi et al., 2024) emphasised GenAI's role in streamlining decision processes, this study shows that GenAI also supports real-time adaptation, helping decision-makers reinterpret emerging information and recalibrate choices dynamically. This adds an important layer to Duan et al.'s (2019) work, extending their framework from static process support to dynamic sensemaking under uncertainty. This is a new theoretical distinction that positions GenAI as both a process optimiser and a cognitive collaborator.

The assumption in some economic models of AI (Agrawal et al., 2019; Kleinberg et al., 2017) that improved predictive accuracy will translate into superior decision outcomes is challenged by the findings. Although GenAI enhanced participants' access to information and alternative perspectives, the absence of statistically significant effects in the quantitative analysis reveals that human judgment, intuition, and contextual interpretation remain indispensable in high-stakes strategic decisions. This challenges overly optimistic automation narratives and supports a bounded augmentation model in which GenAI strengthens human agency. Therefore, this study refines existing theory by explicitly separating what GenAI provides from what humans control.

GenAI’s ability to accelerate decision-making by providing comprehensive data analysis, scenario-based forecasting, and varying perspectives on strategic options, as seen in the findings, aligns with Doshi et al. (2024) study. They argue that aggregated GenAI-generated assessments closely resemble expert human evaluations, reinforcing the role of GenAI as a complement to human cognition rather than a replacement. Furthermore, Kaggwa et al. (2024) emphasise that GenAI-enhanced decision-making fosters knowledge creation, supporting the argument that GenAI drives organisational learning rather than mere analytical tools. This study builds upon their work by demonstrating that GenAI enhances knowledge synthesis and facilitates real-time adaptation in decision-making processes.

A key theoretical contribution of this study is its exploration of GenAI’s role in strategic decision-making under uncertainty. As Fredrickson (1984) and Van den Steen (2017) noted, strategic decisions require balancing systematic analysis with adaptive thinking. This study finds that GenAI aids decision-makers by providing probabilistic assessments, pattern recognition, and alternative scenario evaluations, aligning with Agrawal et al. (2019) and Kleinberg et al. (2017), who argue that AI reduces the cost of accurate predictions. However, the findings refine these arguments by showing that while GenAI improves predictive accuracy and efficiency, it does not fundamentally change the strategic decision-making process. The lack of statistically significant differences in ANOVA results highlights that human intuition remains indispensable in complex, high-stakes contexts. Contrary to claims that GenAI will replace many current jobs (McKinsey & Company, 2023), this study supports Chaturvedi et al.'s (2024) view that GenAI serves best as a support tool, enhancing rather than replacing human judgment. Thus, GenAI should be understood as a cognitive aid that strengthens strategic foresight without displacing human expertise.

This study gives insight into bias mitigation and decision quality, which adds to the current literature on the topic. The literature has consistently raised concerns about AI-induced biases, transparency issues, and algorithmic fairness (Silva & Kenney, 2018; Courtland, 2018). The qualitative findings from this study reinforce these concerns, revealing that while GenAI improves decision consistency and data accessibility, scepticism remains regarding GenAI-driven biases and the over-reliance on machine-generated insights. This aligns with

Annany and Crawford (2016), who emphasise that algorithmic transparency remains a challenge, particularly when AI systems operate as black-box models, i.e., the input and output are understood but not how the output has been generated. Doshi et al. (2024) propose that integrating human oversight into GenAI-generated decisions can mitigate biases, a perspective further supported by Chaturvedi et al. (2024), who argue that a hybrid GenAI-human decision-making model ensures fairness and reduces systemic biases. These findings add nuance to the polarised literature, highlighting the importance of human oversight and organisational safeguards to realise GenAI's bias-reduction potential. It also introduces the idea that explainability protocols are not just technical add-ons but essential social enablers of trustworthy AI use.

Another critical area of theoretical contribution concerns the trust dynamic between humans and GenAI in strategic decision-making. Prior research has suggested that successful GenAI integration into decision-making processes requires trust and user acceptance (Glikson & Woolley, 2020; Hoff & Bashir, 2014). The qualitative data from this study reveal that even when GenAI provides accurate, well-structured outputs, participants' scepticism around data reliability, bias, and transparency can dampen its practical impact. This advances the theory by proposing that trust in GenAI is not static but dynamically co-evolves with user experience, organisational practices, and perceived system explainability.

As discussed in Chapter 2, organisational learning involves the continuous refinement of knowledge and decision-making capabilities (Argote & Miron-Spektor, 2011). The findings suggest that GenAI significantly enhances this process by facilitating faster knowledge acquisition, improving decision accuracy, and enabling organisations to respond to uncertainties with data-driven insights. This aligns with Babina et al. (2024), who argue that AI-driven decision-making fosters a culture of continuous learning and adaptation. Nevertheless, this study extends its hypothesis by illustrating that while GenAI accelerates information processing, it does not replace human judgment. Decision-makers rely on their expertise even when AI provides structured recommendations, reinforcing the importance of a human's intuition and experience in strategic decision-making.

This study challenges deterministic models, introduces a conceptual distinction between augmentation and agency, and highlights trust as a central mechanism. Therefore, it advances theoretical debates on GenAI, decision-making, and human-technology interaction. The findings extend existing theories by demonstrating that while GenAI improves decision-making capacity, it does not automatically improve outcomes. Theoretically, this study contributes to existing research by extending organisational learning theory (Argote & Miron-Spektor, 2011) by showing that GenAI accelerates knowledge refinement only within human-led evaluative frameworks. It challenges overly optimistic models of GenAI-driven decision-making (Agrawal et al., 2019) by confirming that cognitive augmentation does not replace human intuition under uncertainty. Lastly, it refines decision theory by proposing that GenAI expand information exploration but that strategic commitment remains fundamentally human-driven. The study bridges the gap between technological capability and human strategic agency. The next section will elaborate on the practical implications for organisations.

5.2 Practical implications of the findings

The findings of this study lead to several practical implications for organisations, which must be considered if they want to stay strong in an ever-changing market. The hypotheses are confirmed, saying that GenAI can enhance a decision-maker's ability to process information, explore alternatives, and anticipate future scenarios. However, only when GenAI is integrated thoughtfully alongside human judgement. To realise GenAI's potential, organisations must invest in GenAI literacy, transparency mechanisms, and iterative human-GenAI collaboration loops.

Building GenAI literacy is essential, as the study's findings showed that participants were more confident and engaged in their decisions when they understood how to critically assess GenAI outputs. They highlighted the importance of equipping employees with the skills to work effectively alongside GenAI. Thus, organisations must treat GenAI literacy not as a technical add-on but as a core decision-making skill. This means going beyond tool training. At a basic level, all employees should understand how GenAI systems work, i.e., how they generate responses, their reliance on patterns, and where they excel or struggle. For strategic decision-makers, deeper learning is required, including how they should challenge GenAI insights, judge relevance, and spot embedded biases. GenAI-specific training modules should be integrated into leadership programs and decision-making workflows. Simulations that contrast GenAI-augmented and human-only decisions can build both confidence and scepticism, ensuring employees know when to trust the tool and when not to. Building GenAI literacy requires time, funding, and a willingness to slow down decision-making while capabilities are being developed. This may appear counterproductive in fast-moving environments. Therefore, organisations should adopt a tiered training model. All employees should have access to foundational GenAI literacy, while those in strategic decision-making roles should have access to more advanced modules. In this way, GenAI literacy is tailored to the needs of each organisational level. It provides basic understanding for general staff while equipping strategic decision-makers with advanced skills in critical assessment, ethical evaluation, and scenario analysis relevant to their roles.

Trust in GenAI must be earned. The findings showed that scepticism arises when users do not understand how GenAI generated a recommendation. To address this, GenAI tools used in strategy work should disclose the logic and sources behind their recommendations. Review checkpoints should be built into workflows, requiring users to assess or challenge GenAI outputs. Design features such as explainability, dashboards, or confidence indicators can empower users, promote reflection, and avoid blind acceptance of GenAI-generated insights. Yet, designing GenAI systems that explain their outputs can create information overload or reduce user experience quality. By embedding progressive disclosure principles into GenAI interfaces, for example, offering basic, high-level justification by default with the option to drill down for source data, allows decision-makers to engage at the level appropriate for the task's complexity and their own familiarity. This allows for trust to be built over time and also supports GenAI literacy in the longer term.

GenAI works best when it is a part of an iterative loop. The findings showed that when human decision-makers continuously engage with, evaluate, and refine GenAI outputs rather than relying on one-off recommendations they feel more confident and committed to the decision. Decision processes should be structured to allow for multiple cycles of GenAI-supported analysis, human reflection, and re-analysis. For example, early-stage GenAI outputs can be used to expand the option space, which humans then narrow through critical evaluation. New GenAI queries can then be run based on refined criteria. This feedback-rich approach keeps humans in control while leveraging GenAI's analytical breadth. It also helps surface and test assumptions, contributing to organisational learning. However, in high-pressure settings, this iterative loop may be perceived as inefficient. To mitigate this from happening, adaptive workflows should be adopted that scale iteration based on decision criticality. For example, in low-risk decision-making settings, GenAI can offer quick suggestions with limited human iteration, whilst in high-risk decision-making settings, GenAI is part of a multistage review. Over time, as trust and experience with GenAI grows, organisations can fine-tune the level of iteration required.

Organisations must treat GenAI implementation as an organisational change initiative. This study's hypothesis, which stated that GenAI would enhance the decision-maker's ability to process information, explore alternatives, and anticipate future scenarios more effectively, was confirmed as the findings highlight that GenAI functions most effectively as an extension of human judgment, offering enhanced data analysis and scenario exploration while preserving the critical role of human interpretation and final decision-making. Thus, organisations must create safe spaces for experimentation and mistakes where employees are encouraged to test the limits of GenAI to see in what way they can best embed it in their decision-making process. The key is to manage the trade-offs of perceived inefficiency and information overload that might arise continuously, adapting as technologies, workflows, and organisational need to evolve.

5.3 Limitations of the study

While this study offers valuable insights into the role of GenAI in strategic decision-making, several limitations must be acknowledged. These limitations provide important context for interpreting the findings and help outline specific opportunities for future research, particularly as GenAI technologies continue to evolve rapidly.

The study's sample was drawn from a single B2B technology organisation, limiting the generalisability of the findings across industries. Decision-making dynamics in healthcare, finance, manufacturing, or the public sector may differ significantly due to distinct regulatory environments and organisational cultures. Moreover, participants' high education and technical proficiency likely made them more receptive to GenAI, potentially skewing results. Future research should diversify samples across industries, technological maturity levels, and geographies to better understand how sectoral differences moderate GenAI's influence on decision-making.

The study's reliance on voluntary participation and a single organisational context introduces potential sampling and self-selection biases. Participants interested in AI or strategic decision-making may have been more inclined to participate, potentially overrepresenting more tech-savvy or optimistic perspectives. Future studies should seek randomised sampling or compare adopters and non-adopters to explore broader attitudinal differences toward GenAI. Also, the vignette-based experimental design, while useful for standardisation, cannot fully replicate real-world decision pressures, long-term stakes, or social dynamics inherent in strategic decision-making. The reliance on self-reported measures such as confidence, commitment, and decision quality further introduces subjectivity.

At the time of data collection, GenAI technologies such as GPT-4 were advanced but still maturing. As GenAI tools become more context-aware, autonomous, and trustworthy, their role in decision-making processes is likely to shift. Future research should explore how evolving GenAI capabilities alter human-AI collaboration models, particularly whether GenAI moves from a cognitive support tool toward a more autonomous strategic advisor. Additionally, trust in GenAI emerged as a critical but only partially explored theme. While the study captured moderate trust levels and signs of scepticism, it did not fully investigate how trust develops over time, nor how trust interacts with algorithm aversion, transparency mechanisms, and iterative human-AI collaboration. Future longitudinal research should examine how repeated use, organisational policies, and system explainability influence the trajectory of GenAI trust.

Ethical implications, including AI bias, data transparency, and unintended reinforcement of inequalities, were acknowledged but not explored systematically. As GenAI systems become more embedded in decision-making, ethical governance frameworks will be crucial. Future studies should aim to develop practical models for responsible GenAI deployment in strategic contexts. Finally, this study focused on short-term perceptions and outcomes. Strategic decisions often have delayed, long-term consequences not captured in this research. Longitudinal studies tracking the downstream impacts of AI-augmented decisions over time will be critical to understanding the true organisational value and potential risks of GenAI integration.

5.4 Future research

The findings and limitations of this study highlight several critical areas for future research into GenAI's role in strategic decision-making. As organisations increasingly integrate GenAI into workflows, a more nuanced understanding is essential to guide its effective development. Future research should explore GenAI-assisted decision-making across diverse sectors, such as healthcare and manufacturing, where regulatory complexity, risk levels, and strategic context differ. Thus, research questions could include exploring *How does industry-specific context moderate the effect of GenAI on strategic foresight?* and *How does organisational size or technological maturity affect GenAI adoption and impact?*

The vignette-based experimental design, while offering controlled conditions, does not fully replicate real-world decision pressures. Future studies should use field experiments, diary studies or ethnographic approaches to observe GenAI as used in actual strategic decisions. This study captured not only short-term outcomes. Strategic decision impacts often unfold over years. Longitudinal research should track GenAI augmented decisions across time to answer *How does GenAI affect long-term organisational performance indicators such as innovation, competitive advantage, and strategic agility?* Also, trust in GenAI emerged as a critical determinant but was only partially addressed. Future research should systematically investigate how transparency mechanisms, such as source attribution, build or destroy trust and how organisational culture, prior exposure, and training influence GenAI adoption and scepticism over time.

As GenAI capabilities advance, future studies should examine how increasingly autonomous GenAI systems reshape the boundary between human and machine judgment. Research must assess when AI outputs should be directly implemented versus critically filtered by human oversight. Additionally, studies should investigate how GenAI systems can be improved to incorporate contextual, cultural, and ethical factors into recommendations. Future work should aim to develop robust measurement models to facilitate comparability across studies and build cumulative knowledge. Addressing these areas will be essential to understanding not only whether GenAI enhances strategic decision-making, but also under what conditions, over what time horizons, and with what human-AI relationship models.

6. Conclusion

This thesis aimed to answer: *How can an organisation leverage generative AI to enhance strategic foresight of decision-making processes?* Through a mixed-method vignette study involving knowledge workers in a real organisational context, the study found that GenAI holds valuable potential to enhance strategic foresight, but only under specific conditions. Its benefits depend on how it is integrated into decision-making, the organisation's GenAI literacy levels, and the trust decision-makers place in GenAI.

The quantitative results showed that GenAI users reported slightly higher perceived confidence, commitment, and decision quality. However, the lack of statistically significant differences between the GenAI and control groups suggests that GenAI's role is complementary rather than transformative. These findings challenge assumptions that GenAI independently drives better strategic decisions. Instead, GenAI is most effective within hybrid decision-making frameworks, supporting but not replacing human judgment. Qualitative insights reinforced this. Participants valued GenAI's data synthesis capabilities but remained sceptical about its contextual and ethical awareness. Thus, strategic foresight emerges not from GenAI alone but from the integration of GenAI efficiency with human expertise.

This study had multiple theoretical implications. It extends organisational learning theory (Argote & Miron-Spektor, 2011) by showing that GenAI accelerates knowledge acquisition and supports iterative sensemaking, while also confirming that experiential and tacit knowledge remain crucial. It refines decision theory under uncertainty (Fredrickson, 1984; Van den Steen, 2017) by showing that while GenAI reduces perceived uncertainty through scenario forecasting, human intuition remains indispensable when stakes are high. Also, it builds on GenAI-human collaboration research (Doshi et al., 2024; Glikson & Woolley, 2020) by arguing that organisations must cultivate GenAI literacy, transparency, and iterative human-AI interactions to realise GenAI's strategic potential. Future researchers can build on this work by exploring how these organisational enables interact over time to sustain trust and performance in

GenAI-augmented strategic environments. These theoretical contributions challenge overly optimistic models of automation and enrich theoretical models by showing that GenAI's benefits materialise only through carefully designed hybrid decision-making systems.

The practical implications of this study were multiple. Organisations should treat GenAI as a decision-support partner, not a replacement. They should build workflows that position GenAI as a collaborator that augments but does not replace human expertise. Investments in GenAI literacy across the organisation is crucial to equip employees with scenario-based training to improve their ability to interact critically and effectively with GenAI tools. Transparency mechanisms must be embedded to ensure that GenAI outputs are explainable and auditable. There must be established clear checkpoints where human judgment moderates, interprets, and finalises GenAI-supported recommendations. Lastly, management must encourage a culture of human-AI co-creation. They must encourage teams to experiment with GenAI iterative cycles, integrating its outputs into collective sensemaking and strategic discussions.

Beyond the organisational level, these findings raise important ethical and societal considerations. GenAI adoption amplifies concerns about bias, transparency, and accountability. Therefore, organisations must prioritise ethical deployment frameworks that mitigate risks of over-reliance, discrimination, or deskilling of human judgement. Future research should explore several avenues. Longitudinal impacts should be explored, such as how GenAI-supported decisions perform over time, and what their unintended consequences are. Cross-sectional dynamics of how industry norms, regulatory environments, and cultural factors shape GenAI integration and trust. Measurement development, including what validated tools can reliably assess GenAI's contributions to strategic foresight and decision quality. Lastly, organisational culture as a moderator, for example, how do variations in organisational values, leadership styles, and openness to experimentation affect GenAI's impact.

In a world marked by complexity and uncertainty, strategic foresight is no longer a luxury but a necessity. This study answers the research question and confirms the hypothesis to some extent, concluding that organisations can enhance strategic foresight not by outsourcing decision-making to GenAI, but by embedding it within structured, ethical, and critically adaptive decision-making frameworks. These frameworks should focus on human judgment, transparency, and organisational learning. In doing so, organisations are not simply adopting a tool, but they are helping redefine the future of decision-making in the age of GenAI.

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8. Appendices

8.1 Appendix A. Company-specific vignette

Company-specific

Company X is planning to enter the Japanese market. Japan's grocery retail industry is known for its high efficiency, sophisticated supply chain management, and rapid adoption of technology, making it an attractive target for the solution. Japan's grocery retail sector is highly competitive and diversified, featuring a mix of large supermarket chains, regional players, and small local stores.

You are a part of top management at Company X and have planned this expansion for some time. Over the past year, you have invested $2 million in researching the Japanese market, with a focus on adapting the software to meet local regulations and consumer preferences.

Round 1:
Recently, Japan has introduced stringent data protection laws, and there has been an unexpected economic slowdown. These developments threaten to undermine the market entry strategy you have been working on. The initial investment cannot be recovered if the project is abandoned now. You do a market analysis and discover that at least an additional $250,000 is needed to continue the current plan but preferably up to $500,000.

How much between 250,000 and 500,000 do you allocate to the expansion?

Questions

- On a scale of 1 to 7, how committed are you to continuing the expansion into the Japanese market despite the economic slowdown? (1 = not committed, 7= extremely committed)

Round 2:
Two months have passed. You have succeeded in booking customer meetings and awakening an interest among Japanese retailers in the solution offering. However, the predictions of the economic downturn are more severe than expected, and the Japanese government is tightening its regulations on foreign investment. Will you now allocate an additional $400,000 to further enhance the current plan, adjusting for a deeper understanding of the downturn or allocate $100,000 to manage an orderly exit from the market, minimising losses?

- How did the predictions of the economic downturn affect your perception of the quality of your initial decision? (1 = Not at all, 7 = A great deal)

- How would you describe your risk tolerance in deciding whether to allocate an additional $400,000 or $100,000? (1 = Very low, 7 = Very high)

    · On a scale of 1 to 7, how committed are you to continuing the expansion into the Japanese market despite the economic slowdown? (1 = not committed, 7= extremely committed)

    · How confident are you in the quality of your decision to allocate the amount you chose? (1= not confident at all, 7=extremely confident)

Round 3:
The previous choice you made keeps you up at night so you make a new market analysis. You discover that Competitor A and Competitor B have also been contacting your prospects and giving them presentations on their offering. This discovery lights a new fire in you, so you discuss it with the rest of top management and consider allocating $350,000 to revise the strategy to match competitors. However, some in top management are not convinced and recommend allocating $0 to finalise the decision to exit the market, conserving funds. What do you decide?

    · On a scale of 1 to 7, how committed are you to continuing the expansion into the Japanese market despite the economic slowdown? (1 = not committed, 7= extremely committed)

    · How confident are you in the quality of your decision to allocate the amount you chose? (1= not confident at all, 7=extremely confident)

- How much did the discovery of competitors' actions influence your commitment to the market? (1 = Not at all, 7 = A great deal)

- How did the competitive pressure from Competitor A and Competitor B affect your risk-taking behaviour? (1 = Not at all, 7 = A great deal)

Round 4:

A colleague has gotten information on a possible cost-reducing technology and potential partnership opportunities that could facilitate market entry. The downturn in the Japanese market does not seem so gloomy after all. You are left with two options: allocating $450,000 to integrate new technology and solidify partnerships or allocating $150,000 to maintain minimal engagement while assessing the reliability and benefits of potential partnerships. Which option do you choose?

· On a scale of 1 to 7, how committed are you to continuing the expansion into the Japanese market despite the economic slowdown? (1 = not committed, 7= extremely committed)

· How confident are you in the quality of your decision to allocate the amount you chose? (1= not confident at all, 7=extremely confident)

· How did the potential cost-reducing technology and partnership opportunities influence your risk-taking approach? (1 = Not at all, 7 = A great deal)

- Would you consider the decision to invest $450,000 as a high-risk or low-risk move? (1 = Very low-risk, 7 = Very high-risk)

Round 5:

A year has passed, and together with the top management, you have done a comprehensive market analysis and risk assessment to provide a final look at potential outcomes based on all strategies considered. The final decision is to enter the market, but there is a disagreement among the top management on how much to invest in. You can now decide to allocate $500,000 to fully commit to the market entry or $100,000 to have funds left for other strategic initiatives. Between this span, how much do you decide to finally allocate?

- On a scale of 1 to 7, how committed are you to continuing the expansion into the Japanese market despite the economic slowdown? (1 = not committed, 7= extremely committed)

- How confident are you in the quality of your decision to allocate the amount you chose? (1= not confident at all, 7=extremely confident)

- To what extent does the level of final investment reflect your commitment? (1 = Not at all, 7 = Completely)

- How would you evaluate the overall quality of the strategic decisions made throughout this scenario? (1 = Very poor, 7 = Excellent)

Questions to ask at the start

- Big 5 personality test
    - Gender, age, nationality, position at company/function, education, handedness
- My typical approach is to trust new information technologies until they prove to me that I should not trust them (1=do not trust at all, 7=fully trust)
- I usually trust information technology until it gives me a reason not to (1=not at all correct, 7=very correct)
- I generally give the information technology the benefit of the doubt when I first use it (1=not at all true, 7=very true)
- Are you a person who is generally fully prepared to take risks (1=does not apply to me, 7=does apply to me)
- How competitive do you consider yourself to be? (1=not at all, 7=very)

Questions to ask at the end:

- What factors most influenced your level of commitment to entering the Japanese market throughout the different rounds?
- How do you feel about the quality of the decisions you made during this scenario?
- What sources of information and tools did you rely on most heavily during this decision-making process?

For participants using GenAI:

- How did AI tools influence your decision-making process?
- Were there any moments when you doubted the insights provided by AI?
- In what ways did AI improve your strategic decision-making?
- What are your overall thoughts on using AI for strategic decision-making in real-world scenarios?

8.2 Appendix B. Objective-scenario: Radar plane

In the following task, you will assume the role of Vice President of Operations for a mid-sized high-technology manufacturing firm. You will be presented with vignettes describing an investment decision related to a radar plane. Please use the slider to indicate how much money you would like to authorise.

Round 1:
You are VP of Operations for a mid-sized high-technology company. You have 10M dollars and three (3) years to complete a research project that will develop a radar-scrambling device that would render a chip undetectable by a conventional radar, in effect, a radar blank ship. Prior to the beginning of the project, Steve, the project engineer, informs you that he does not think that all 10M dollars will be needed to successfully complete the project, but he will need at least 5M dollars. Between 5M and 10M dollars, how much money would you like to invest in the project?

Round 2:

Two years after the project started, Steve retired from the company. Jackie is the new project manager. You meet with Jackie to get an update on the project. Jackie informs you that Steve used the money you initially invested to purchase expensive materials that are of poor quality. As a result, all the computer components in the plane keep short-circuiting. Jackie says she is certain she can remedy the mistake but that she will need an additional 3M to 6M dollars in funding. You must now either abandon the project or authorise more funding. If abandoning, move on to the next question. Do you abandon the project or authorise more funding?

Round 3:

Three months after you provided the additional funding for Jackie to replace the faulty parts that Steve had purchased, you asked Jackie for an update on the project. You are pleased to hear that the parts are now working properly. Jackie also informs you that she believes the project will be finished on schedule. However, she informs you that the radar-scrambling device also scrambles other electronic devices, such as the pilot's communication system. She informs you that the problem can be fixed with a new software system for the radar-scrambler but that she needs an additional 2-5M dollars in funding. You must now abandon the project or allocate more funding. If abandoning, move on to the next question. Do you abandon the project or authorise more funding?

Round 4:

After another three (3) months have passed, you visit the engineering department to view the radar-scrambling plane. You are pleased to learn that the additional funding has solved the problems. Jackie informs them that the plane is ready for a test flight. You are excited to see how the plane works and hop on a test drive. During the test ride, everything works perfectly. None of the radar systems are detecting the plane. After 30 minutes from take-off, the plane is landing. Once you have landed, you ask the pilot why you landed so shortly after take-off. He informs you that the new radar-scrambling device is heavier and thus burns more fuel. The pilot suggests that the fuel systems must be upgraded to allow for longer flights, but that will cost an additional 4M to 7M dollars. You must now abandon the project or provide more funding. If abandoning, move on to the next question. Do you abandon the project or authorise more funding?

Round 5:

Three months later, you notice that another firm has started marketing a similar product that takes up less space and is easier to operate than your design. Jackie informs you that the project is 90% complete. She informs you that she is pleased with all the progress that has been made despite the issues along the way. Jackie informs you that though the new tanks allow them to fly longer, they are more expensive than expected. She needs an additional 1M to 4M dollars in funding to pay for the remainder of the project. You must now abandon the project or provide funding. If abandoning, move on to the next question. Between 1M and 4M dollars,how much do you allocate?

8.3 Appendix C. Big-5 Personality Test, 10-minute version from Rammstedt & John (2007)

Instruction: How well do the following statements describe your personality?

I see myself as someone who …	Disagree strongly	Disagree a little	Neither agree nor disagree	Agree a little	Agree strongly
… is reserved	(1)	(2)	(3)	(4)	(5)
… is generally trusting	(1)	(2)	(3)	(4)	(5)
… tends to be lazy	(1)	(2)	(3)	(4)	(5)
… is relaxed, handles stress well	(1)	(2)	(3)	(4)	(5)
… has few artistic interests	(1)	(2)	(3)	(4)	(5)
… is outgoing, sociable	(1)	(2)	(3)	(4)	(5)
… tends to find fault with others	(1)	(2)	(3)	(4)	(5)
… does a thorough job	(1)	(2)	(3)	(4)	(5)
… gets nervous easily	(1)	(2)	(3)	(4)	(5)
… has an active imagination	(1)	(2)	(3)	(4)	(5)

8.4 Appendix D. Gender distribution

Gender	Count	Mean/102
Male	63	61,76 %
Female	37	36,27 %
Prefer not to say	2	1,96 %

8.5 Appendix E. Nationalities represented

Nationality	Count	Mean/102
Finland	42	41,18 %
Other, please specify	19	18,63 %
Sweden	11	10,78 %
Russia	5	4,90 %
UK	5	4,90 %
Germany	4	3,92 %
France	4	3,92 %
US	4	3,92 %
Mexico	1	0,98 %
Australia	1	0,98 %
Italy	1	0,98 %
Greece	1	0,98 %
Spain	1	0,98 %
China	1	0,98 %
Portugal	1	0,98 %
Switzerland	1	0,98 %

8.6 Appendix F. Functional roles

Function	Count	Mean/102

Technology	36	35,29 %
Presales Analytics	19	18,63 %
Customer Operations	17	16,67 %
Product	9	8,82 %
Sales	6	5,88 %
People	5	4,90 %
Finance, legal, and IT	5	4,90 %
Marketing & Communications	2	1,96 %

8.7 Appendix G. Educational backgrounds

Level of Degree	Count	Mean/102
Master’s	53	51,96 %
Bachelor’s	41	40,20 %
Secondary school up to 18-years-old	4	3,92 %
PhD	3	2,94 %

8.8 Appendix H. Age distribution

Age	Count	Mean/102
20-25	12	11,76 %
26-30	27	26,47 %
31-35	29	28,43 %
36-40	16	15,69 %
41-45	9	8,82 %
46-50	9	8,82 %

8.9 Appendix I. Trust in IT and risk-taking

Variable	**Mean**	**SD**	**Range**
My typical approach is to trust new information technologies until they prove to me that I should not trust them	4,225	1,680588	1-7
I usually trust information technology until it gives me a reason not to	4,4125	1,751383	1-7
I generally provide information technology with the benefit of the doubt when I first use it	4,55	1,540292	1-7
Risk Taking & Competitiveness			
Variable	**Mean**	**SD**	**Range**
I am a person who is fully prepared to take risks.	4,607143	1,480169	1-7
I am a highly competitive person.	4,458824	1,837856	1-7

8.10 Appendix J. Personality traits

Trait	Mean	Mean / 5
Openness	3,53	70,69 %
Conscientiousness	3,37	67,45 %
Extraversion	3,31	66,18 %
Agreeableness	3,25	65,10 %
Neuroticism	3,10	61,96 %

9. AI-disclosure

I would like to acknowledge the use of the following digital tools during the preparation of this work. For language editing and improvement, I relied on the AI tool Grammarly (https://www.grammarly.com/). The reference management was handled using Zotero (https://www.zotero.org/). In the process of writing this thesis, ChatGPT-4o was used as an assistive tool. It was used in clarifying academic concepts encountered in the literature and comparing thesis content with grading criteria to gain insight into areas that could be strengthened. The use of ChatGPT-4o contributed to the quality of the thesis by enhancing comprehension of difficult academic material, enabling clearer articulation of theoretical concepts, and improving overall coherence. Also, it supported iterative reflection on how well the thesis addressed grading standards. It is important to mention that none of the content was generated by using GenAI output.

There were some risks of incorporating ChatGPT-4o in this way. Since GenAI-generated content may not always reflect the latest research the information could have been outdated. Therefore, I cross-checked against the original sources and with my supervisor. Also, to avoid overreliance on GenAI phrasing or ideas. Using ChatGPT-4o provided valuable insights into the potential of using GenAI as a support for academic work by facilitating deeper understanding of complex theories. It also underscored the importance of critical engagement with GenAI outputs, reinforcing that GenAI should be used as a complement, not substitute, for independent academic reasoning.