Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Information Technology and Electrical Engineering
Department of Computer Science

Stine Lier

A Dual System View of AI Use in Organizations: An Empirical Study of Performance Effects

Master's thesis in Computer Science
Supervisor: Patrick Mikalef
Co-supervisor: Jessica Braojos Gomez

June 2023

NTNU
Norwegian University of Science and Technology

Stine Lier

A Dual System View of AI Use in Organizations: An Empirical Study of Performance Effects

Master's thesis in Computer Science
Supervisor: Patrick Mikalef
Co-supervisor: Jessica Braojos Gomez
June 2023

Norwegian University of Science and Technology
Faculty of Information Technology and Electrical Engineering
Department of Computer Science

NTNU
Norwegian University of
Science and Technology

Abstract

In recent years, there has been a noticeable shift in discussions surrounding artificial intelligence (AI), with a growing emphasis on exploring the practical implications of AI for private and public organizations, moving beyond solely technical aspects. AI promises to provide several benefits to firms, including increased business value. However, there is uncertainty about the effects of automation and augmentation by AI on organizational performance, how it can contribute to gaining a competitive advantage, and the underlying mechanisms involved. This thesis explores the field of AI augmentation and automation by employing a survey-based approach. Drawing upon existing literature on AI implementation in organizations, this thesis establishes definitions and scales for the measures for AI-enabled automation and AI-enabled augmentation. Then, a survey is conducted to examine the effects of AI automation and augmentation on strategic improvement, radical rejuvenation, and competitive performance. The survey data, consisting of responses from 154 high-level IT executives employed in American companies, are analyzed to test the proposed research model. The empirical findings support the proposed research model, demonstrating that firms can enhance their strategic improvement and radical rejuvenation by leveraging AI for automation and augmentation, ultimately improving their competitive performance.

Sammendrag

I løpet av de siste årene har det vært en merkbar endring i diskusjonene rundt kunstig intelligens (KI), med et økende fokus på å utforske de praktiske konsekvensene av KI for både private og offentlige organisasjoner, utover bare de tekniske aspektene. KI har lovet flere fordeler for bedrifter, inkludert økt forretningsverdi. Likevel er det usikkerhet knyttet til virkningene av automatisering og forsterkning gjennom KI for organisasjoner, hvordan det kan bidra til å gi de en konkurransefordel, og hvilke mekanismer som er involvert for å oppnå dette. Denne masteroppgaven utforsker feltet KI-automatisering og KI-forsterkning ved hjelp av en undersøkelsesbasert tilnærming. Først bygger masteroppgaven på tidligere forskning om bruken av KI i organisasjoner og lager, basert på den, definisjoner for KI-basert automatisering og KI-basert forsterkning. Deretter brukes en spørreundersøkelse for å undersøke effekten av automatisering og forsterkning ved hjelp av KI på strategisk forbedring, radikal fornyelse og konkurransedyktighet. Data fra spørreundersøkelsen hentes fra 154 IT-ledere på høyt nivå som jobber i amerikanske selskaper, og analyseres for å teste den foreslåtte forskningsmodellen. Resultatene av analysen støtter empirisk opp om den foreslåtte forskningsmodellen og viser at bedrifter kan forbedre sin strategiske forbedring og radikale fornyelse ved å utnytte KI for automatisering og forsterkning, og dermed øke sin konkurranseevne.

Preface

This master's thesis is written during Spring 2023 as the final work of achieving the Master of Science degree from the Norwegian University of Science and Technology (NTNU) in Trondheim, Norway. The research undertaken in this thesis builds upon previous work carried out in the TDT4501 Computer Science Specialization Project, which was completed during the fall of 2022. The research was conducted under the supervision of Associate Professor Patrick Mikalef and took place within the Information Systems and Software Engineering Group at the Department of Computer Science at NTNU.

I want to express my sincere gratitude to my supervisor, Patrick Mikalef, for his invaluable guidance and support throughout this research project. I am also grateful to my co-supervisor, Jessica Braojos Gomez, for her assistance in the data analysis and development of the research model, and her excellent feedback and support throughout the process of writing this thesis. Special thanks also go to my friends in the study room for the lunch breaks and moral support that brought laughter and respite during intense research moments, and to all my friends for the great memories these past five years that I will remember forever.

Stine Lier

Trondheim, 2023

Contents

Abstract i

Sammendrag ii

Preface iii

List of Figures ix

List of Tables xi

1. Introduction 1

1.1. Motivation . . . 1
1.2. Problem Statement . . . 1
1.2.1. Research Questions . . . 2
1.3. Research Method . . . 3
1.4. Contributions . . . 3
1.5. Thesis Structure . . . 4

2. Background Theory 5

2.1. Defining Core Concepts of AI . . . 5
2.1.1. Artificial Intelligence . . . 5
2.1.2. AI Capabilities . . . 6
2.2. AI Use . . . 7
2.2.1. Automation . . . 7
2.2.2. Augmentation . . . 8
2.3. Business Value of AI . . . 9
2.4. Exploration and Exploitation . . . 10

3. Research Model 11

3.1. Hypothesis 1 . . . 13

3.2. Hypothesis 2 14
3.3. Hypothesis 3 14
3.4. Hypothesis 4 15
3.5. Hypothesis 5 16
3.6. Hypothesis 6 17

4. Reseach Method **19**
4.1. Preparation 19
4.2. This Thesis 19
4.3. Survey Method 20
4.3.1. Data Collection 21
4.3.2. Construct Development 26
4.3.3. Construct Measurement 30
AI-enabled Automation 30
AI-enabled Augmentation 30
Strategic Improvement 30
Radical Rejuvenation 31
Competitive Performance 31
Control Variables on Competitive Performance 32
4.3.4. Prevention and the Test of Common Method Variance 32

5. Results **33**
5.1. Confirmatory Composite Analysis 34
5.2. Measurement Model Evaluation 34
5.3. Structural Model 38
5.3.1. Overall Fit of the Estimated Model 38
5.3.2. Evaluation of the Structural Model 39
5.3.3. Post Hoc Mediation Analysis 42

6. Discussion **43**
6.1. Discussing Research Questions 43
6.1.1. RQ1: What effect do AI automation and augmentation have on organizational performance? 43
6.1.2. RQ2: How are these effects realized, and through what mechanisms do they manifest? 44
6.2. Research Implications 45
6.3. Practical Implications 46

6.4. Societal Implications 47
6.5. Limitations and Future Research 47

7. Conclusion **49**

Bibliography **51**

Appendices **57**

A. Performance Measures **59**

B. Unmodified Measurement Model **61**

C. Inter-Construct Correlations **65**

List of Figures

3.1. Research Model 11

4.1. The Research Design and Process 20
4.2. Distribution of Represented Industries 22
4.3. Size-class of Organization 22
4.4. Hit Ratio of the Items 28
4.5. Average Clarity of Each Item 28

5.1. Estimated Relationship of Structural Model 38

List of Tables

2.1. Sample Definitions of Artificial Intelligence 6

3.1. Constructs and Definitions 12

4.1. Descriptive Statistics of the Sample and Respondents 24
4.2. Descriptive Statistics of AI Use in the Sample 25
4.3. Constructs and Measures of AI-enabled Automation and AI-enabled Augmentation 29

5.1. Goodness of Model Fit (saturated model) 34
5.2. Measurement Model Evaluation 37
5.3. Results of Hypothesis Testing 40
5.4. Structural Model Evaluation 41
5.5. Mediation Analysis 42

B.1. Unmodified Measurement Model 62
B.1. (continued) 63

C.1. Correlation Matrix 65

1. Introduction

1.1. Motivation

Artificial Intelligence (AI) is a wide-ranging set of technologies that use computers to model intelligent behavior with minimal human intervention (Wamba-Taguimdje, Fosso Wamba, Jean Robert & Tchatchouang, 2020). AI has become one of the most rapidly evolving technologies, and its applications have been seen in various industries, including healthcare, finance, and manufacturing (Stanford, 2023). The emergence of AI has led to the automation and augmentation of different organizational processes, leading to increased efficiency (Perez, 2023). Further, AI promises several advantages for enterprises in terms of added business value and competitive advantage (Enholm, Papagiannidis, Mikalef & Krogstie, 2021). For instance, utilizing AI for automation presents organizations with a new strategic opportunity to increase business value (Coombs, Hislop, Taneva & Barnard, 2020). Thus, before using AI applications, organizations have several key expectations, including that they would contribute to improving financial performance indicators like revenue, growth, and cost reduction (Alsheibani, Cheung, Messom & Alhosni, 2020). However, several enterprises investing in AI struggle to realize the value expected (Fountaine, McCarthy & Saleh, 2019), and the impact of AI adoption on organizational performance is still poorly understood in research. Therefore, this study aims to investigate the effect of AI automation and augmentation on organizational performance and how these effects are realized.

1.2. Problem Statement

The enhanced technical capabilities of AI systems have resulted in an increased rate of AI implementation across various industries, businesses, governments, and other organizations (Stanford, 2023). According to a McKinsey&Company report from 2022, the adoption of AI in organizations has seen significant growth in recent years, along with claims of cost decreases and revenue increases (McKinsey&Company, 2022b). However, after a rapid rise, AI adoption has leveled off since 2020 (Stanford, 2023), and the effects of AI automation and augmentation on organizational performance and the underlying mechanisms through which these effects manifest remain unclear. While there is excitement among business leaders about integrating AI into their organizations, concerns remain regarding its impact on productivity, wages, and the potential replacement of workers (Stanford, 2023). In Stanford's 2023 AI Index Report, one of the main challenges identified by business leaders in initiating AI-related projects is proving business value, accounting for 37% of the respondents (Stanford, 2023). Additionally, a Deloitte report on AI in enterprises from 2022 revealed that many organizations investing in AI are not achieving the value they anticipated, with a 29% increase in the share of respondents who identify as underachievers in 2022 compared to 2021 (Deloitte, 2022). Understanding the investment trends in AI and identifying the industries, regions, and fields that attract the most investor interest is crucial for comprehending the AI landscape (Stanford, 2023). To address these concerns and shed light on the effects and mechanisms of AI automation and augmentation on organizational performance, this research will investigate the relationship between AI adoption and organizational performance, aiming to provide valuable insights for decision-makers in academia and industry.

1.2.1. Research Questions

This research aims to explore the relationship between AI adoption and organizational performance. In particular, this thesis aims to investigate how AI automation and augmentation affect organizations' performance. More precisely, if and through what mechanisms organizations can attain a competitive advantage by deploying AI for automation and augmentation purposes. The following research questions express these problems:

Research question 1 *What effect do AI automation and augmentation have on organizational performance?*

Research question 2 *How are these effects realized, and through what mechanisms do they manifest?*

Answering these research questions is essential as they aim to comprehend the impact of AI technologies on organizations' performance. This is particularly relevant in today's rapidly evolving technological landscape, where AI is increasingly integrated into various business processes and industries. Answering research question one can help organizations make informed decisions regarding adopting AI applications. It can also provide insights into how AI can be leveraged to improve efficiency, productivity, and competitiveness in different industries. Thus, researchers and businesses can uncover the potential benefits and challenges associated with these technologies by investigating the effects of AI automation and augmentation on organizational performance.

Research question two extends the initial question by exploring the underlying mechanisms and processes through which the effects of AI automation and augmentation are observed in organizations. Answering this research question is crucial because it can help researchers and practitioners better understand the complex dynamics between AI technologies and organizational performance. It can uncover how AI impacts organizational performance, such as decision-making processes, employee productivity, customer satisfaction, and operational efficiency. By exploring the underlying mechanisms, valuable insights and recommendations can be provided for organizations to leverage AI technologies effectively. This knowledge can inform the development of strategies, policies, and practices that optimize the benefits and mitigate potential challenges associated with AI automation and augmentation in the context of organizational performance.

1.3. Research Method

This study will employ a survey-based research strategy to address the above research questions. This strategy will involve collecting data from high-level IT executives working in American companies and providing quantitative data for the analysis. First, based on existing literature on AI use in organizations, definitions of AI-enabled automation and AI-enabled augmentation, as well as scales for their measures, are developed. Then, a research model is proposed, where I hypothesize that AI automation and augmentation will positively affect strategic improvement and radical rejuvenation, ultimately enhancing competitive performance. Lastly, the data collected from the survey will be used to analyze the effects of AI use for automation and augmentation purposes on organizational performance and identify the mechanisms through which these effects are realized.

1.4. Contributions

This study will contribute to the growing literature on AI and its impact on organizations' performance. Additionally, this study will present the constructs of AI-enabled automation and AI-enabled augmentation in IS research, accompanied by scales for their measures.

The findings of this study will contribute to the understanding of the impact of AI on organizational performance, which will benefit organizations considering implementing AI to improve their performance. By answering the research questions, organizations may be assisted in effectively allocating resources during AI implementation, enabling efficient allocation of budget, personnel, and technological resources. Further, this research will also provide insights into the mechanisms through which AI automation and augmentation affect organizational performance, which can help optimize the implementation of AI in organizations. It may help organizations decide what AI technologies to invest in to improve operational performance, identify essential mechanisms through which this occurs, and allow them to self-assess their competitive performance maturity and identify areas for improvement. This is useful for organizations, as it may help them determine their capacity to implement AI successfully.

1.5. Thesis Structure

The structure of this thesis is as follows: Chapter 2 serves as a comprehensive introduction to the essential concepts of Artificial Intelligence (AI) within an organizational setting. In Chapter 3, a research model with empirically derived hypotheses concerning the effects of adopting AI for automation and augmentation is proposed. The methodology for the survey study, which is used to test the research model, is presented in Chapter 4. Chapter 5 presents the survey results, and findings from the survey study and the limitations of this research are discussed in Chapter 6. Lastly, Chapter 7 provides concluding remarks to this work.

2. Background Theory

This chapter aims to provide an overview of the application of Artificial Intelligence (AI) in organizations. First, the key concepts related to AI will be presented. Following this, the use of AI will be distinguished into automation and augmentation. Finally, the business value organizations may achieve by adapting AI for automation and augmentation will be presented, as well as how exploration and exploitation may help them reach the expected value.

2.1. Defining Core Concepts of AI

Despite the increasing attention and interest in Artificial Intelligence (AI) in recent years, the concept remains ambiguous. Since its inception as a scientific field in the 1950s, various definitions of AI have been proposed to distinguish it from other traditional information technologies. However, there is still a lack of a universally accepted definition of the term (Wang, 2019). This is because AI encompasses many technologies and sub-disciplines that are continuously evolving (Schmidt, Zimmermann, Moehring & Keller, 2020; Wamba-Taguimdje et al., 2020). Thus, it is crucial to clearly differentiate between the core concepts of AI: AI as a scientific discipline, AI utilization in an organizational setting, and the capabilities of AI. The following paragraphs will provide a distinction between these three concepts.

2.1.1. Artificial Intelligence

Artificial Intelligence (AI) is a term that has been the subject of numerous definitions in the literature. Five of them are presented in Table 2.1. From the definitions provided, there is agreement that AI refers to machines with capabilities that mimic human intelligence. However, there is currently a lack of a widely accepted definition of AI in the literature, which has resulted in difficulties in fully understanding the concept. To better comprehend AI, it is essential to understand the independent meanings of the terms "artificial" and "intelligence." Intelligence can be defined as the capacity for mental processes such as understanding, thinking, and learning (Lichentaler, 2019). On the other hand, the term "artificial" refers to something humans have created as a copy or reproduction of something natural (Mikalef & Gupta, 2021). Combining these two concepts makes it possible to understand AI as the creation of machines that can simulate human intelligence.

Table 2.1.: Sample Definitions of Artificial Intelligence

Author(s)	**Definition**
Lichentaler (2019)	Generally refers to computer systems that can perform tasks that usually would call for human intelligence.
Mishra and Pani (2020)	Attempts to understand and build a machine capable of doing intelligent tasks.
Mikalef and Gupta (2021)	The ability of a system to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals.
Zhu, Corbett and Chiu (2021)	Involves using digital technology to perform tasks that typically require human intelligence.
Sun, Yu and Wang (2022)	Refers to intelligence demonstrated by machines.

2.1.2. AI Capabilities

As Artificial Intelligence (AI) continues to evolve, it has become a crucial asset for organizations seeking a competitive advantage (Wamba-Taguimdje et al., 2020). However, leveraging the full potential of AI requires more than just acquiring technological resources. Organizations must also leverage other organizational resources, as technical resources alone can be easily replicated by competitors (Mikalef & Gupta, 2021). The concept of AI capability has been introduced to understand how this value is achieved, expanding the view of AI to encompass all organizational and technical resources necessary to realize its strategic potential fully (Enholm et al., 2021). It is important to note that harnessing the power of AI goes beyond mere technical skills and resources. It also involves an organization's overall strategy, culture, and structure. These elements play a crucial role in facilitating the efficient and effective adoption and utilization of AI solutions (Mikalef & Gupta, 2021). When organizations grasp their AI capabilities and embrace AI solutions, they can tap into the technology's potential to enhance their operations, gain new insights, and drive innovation. In simpler terms, AI capability is about how an organization selects, coordinates, and utilizes all its resources to create value (Mikalef & Gupta, 2021; Schmidt et al., 2020; Wamba-Taguimdje et al., 2020).

2.2. AI Use

Artificial Intelligence (AI) has gained widespread adoption across various industries, with the most advanced applications in fields such as IT operations, security, threat detection, and business process automation (IBM, 2022). In addition, organizations utilize NLP techniques to leverage AI in marketing, sales, and customer service. Though the specific tasks may vary across industries, many organizations have shown interest in or are already using AI, with the intention of automating various processes. Nearly half of the companies that have adopted AI-based automation have done so to improve IT efficiency while allowing for additional time and filling skill gaps for their employees (IBM, 2022). Furthermore, AI is being utilized along with human expertise to enhance decision-making processes and optimize actions. This concept is called "augmentation" (Schmidt et al., 2020). The following paragraphs will explain both automation and augmentation in greater detail.

2.2.1. Automation

Intelligent automation encompasses AI technologies that are intended to substitute human tasks. These technologies can determine rules and guidelines for what to do by creating protocols and choose what to do by selecting actions (Murray, Rhymer & Sirmon, 2021). Intelligent automation technologies can process vast amounts of data, continuously improve their performance through learning, and operate independently without human intervention. An example is an unstructured machine learning program, which can gather data, learn from it, formulate rules for action, and carry out those actions independently. This approach to automation involves creating repeatable procedures and instructions that either eliminate or significantly reduce the need for human intervention (Wamba-Taguimdje et al., 2020).

Intelligent automation provides organizations with numerous benefits, such as process optimization, resource liberation, and improved operational efficiency (IBM, 2021). One of the main benefits is the possibility of freeing employees from repetitive tasks, allowing them to concentrate on knowledge-intensive activities that bring more value to the firm and increase their productivity (Enholm et al., 2021). Furthermore, machines are more accurate and quicker at completing jobs than people, which boosts effectiveness and increases the speed of business processes (Babina, Fedyk, He & Hodson, 2022). Additionally, automating by using machines instead of people will eliminate or reduce errors made by employees, leading to improved quality of the results. Thus, automation may contribute financially through labor savings and budget reduction, cutting per-unit labor costs (Babina et al., 2022). While some people fear that automating tasks can lead to job loss, evidence from existing research shows that innovation through automation ultimately creates more jobs and greater earnings, suggesting that new jobs can compensate for those lost (Martens & Tolan, 2018).

2.2.2. Augmentation

AI technologies that augment human actions are designed to collaborate with human expertise to improve decision-making and optimize outcomes. In other words, augmentation focuses on AI serving as a supportive tool that enhances, rather than replaces, human involvement (Schmidt et al., 2020). These technologies process vast amounts of data, identify patterns, and provide predictive recommendations to solve specific problems. While they can establish protocols or rules, they do not have the power to make choices or select actions. For instance, a structured machine-learning algorithm can identify complex patterns and provide probabilistic recommendations for humans to adhere to. However, when an augmenting technology presents a recommendation that contradicts human expectations, it is up to humans to decide whether to perform the suggested action (Murray et al., 2021).

Forecasts are crucial in decision-making in all aspects of an organization's operations. With AI's ability to make better predictions, there is potential for businesses to discover new opportunities (Babina et al., 2022). Because of this, managers may rely on AI to offer decision support, providing insightful information from data to make better decisions (Borges, Laurindo, Spínola, Gonçalves & Mattos, 2020). Such insight can impact key performance indicators, allowing companies to decrease expenses, expand their range of products and/or services, and offer more personalized options to their customers (Mikalef & Gupta, 2021). In essence, the integration of AI with human expertise leverages the strengths of both to achieve better results (Murray et al., 2021).

2.3. Business Value of AI

Enterprises that use AI technologies are expected to improve their financial and accounting performance, such as increasing their revenues and cutting costs (Alsheibani et al., 2020; Martens & Tolan, 2018; Mikalef, Conboy & Krogstie, 2021; Sun et al., 2022). Several studies mention these effects. However, rather than emphasizing the economic impacts of AI, previous research has centered on the use of AI for economic purposes and financial services. No studies to date, as far as I am concerned, have directly examined the long-term economic effects of adopting AI, including returns on investments, potential cost savings, or revenue increases. Thus, it is unclear what economic metrics should be measured to evaluate the financial performance of organizations' investments in AI applications.

Furthermore, there is a growing discussion about the potential of AI to spark creativity in organizations. This idea's supporters claim that employees will have more time for creative activities by automating tedious manual tasks. Additionally, through augmented intelligence, AI can enhance human capabilities in creative fields like engineering, design, and the arts. This involves using specific AI techniques to leverage large data sets and provide professionals with suggestions that would be difficult to generate otherwise (Mikalef & Gupta, 2021).

In addition to fueling creativity in organizations, AI has the potential to enhance the quality of exciting products and services. Based on executive surveys conducted by Deloitte, this is the most general application of AI technology so far (Deloitte, 2018). AI can enhance the quality of products and services in several ways, one of which is personalization. By utilizing AI to evaluate customer data, businesses can provide each customer with a personalized experience that may lead them to believe the product or service is of higher quality and thus improve customer satisfaction. Various streaming services, such as Spotify, already utilize this practice, which provides customized song suggestions to its users (Spotify, 2022).

Besides enhancing existing products and services, businesses can benefit from AI by exploring opportunities to introduce a new product or service to the market (Mishra & Pani, 2020). As a predictive technology, AI holds the potential to impact product innovation in numerous ways. AI algorithms can quickly examine vast amounts of data and comprehend the connections within, resulting in decreased uncertainty and increased effectiveness in experimentation and learning. This may encourage more experimentation and the development of new products. In addition to providing opportunities for businesses to broaden their offerings, AI can play a crucial role in promoting firm growth by decreasing the cost of product innovation by speeding up the process (Babina et al., 2022). A recent example of how AI has accelerated the process of product innovation is the development and production of the COVID-19 vaccine Moderna. Moderna utilized AI algorithms that enabled the initial dose to be created in just 65 days, a process that would have taken several years without AI (Babina et al., 2022).

2.4. Exploration and Exploitation

Exploration refers to activities to create new knowledge, such as investigation, experimentation, and organized endeavors to produce more unpredictable innovations that go beyond the skills already established within an organization (Johnson, Laurell, Ots & Sandström, 2022). Conversely, exploitation involves enhancing existing resources and endeavoring to profit from found abilities (Johnson et al., 2022). While exploration, in terms of innovation, entails creating something new, exploitation encompasses refining something already existing. Decisions on how to focus R&D and use new technology (e.g., AI) for exploration or exploitation purposes are strategically crucial. They will influence short- and long-term earning capacity and how financial markets perceive firms (Johnson et al., 2022).

3. Research Model

The research model and hypotheses are constructed in this chapter, as illustrated in Figure 3.1. I argue that AI-enabled automation and AI-enabled augmentation in a company will enhance its strategic improvement and radical rejuvenation, improving the company's competitive performance. Table 3.1 contains definitions for the constructs outlined in the research model.

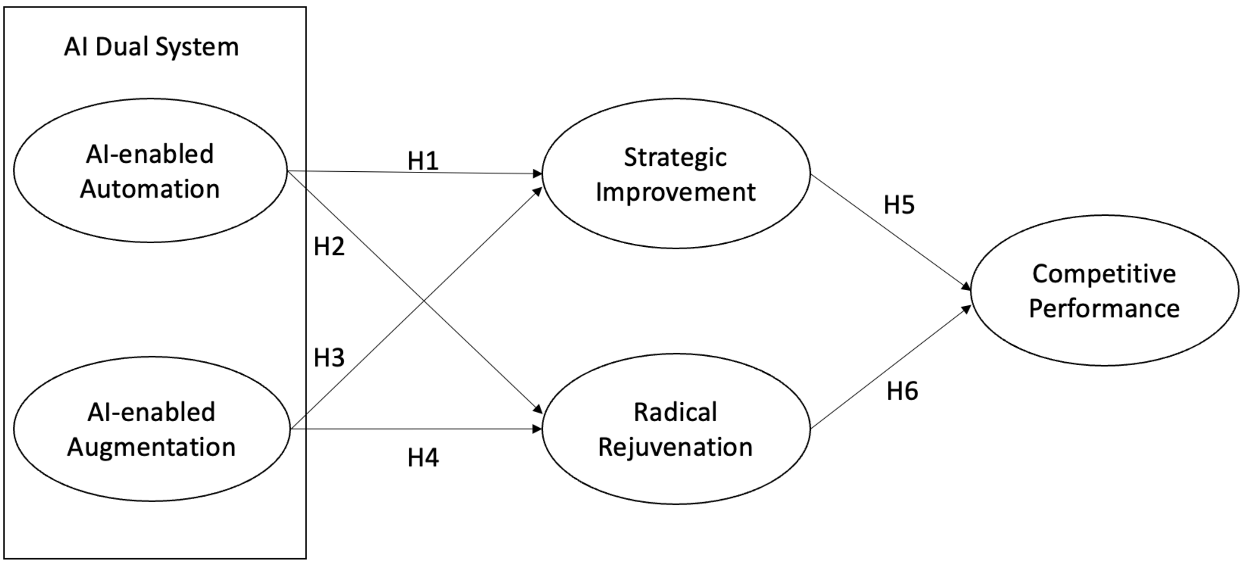

Figure 3.1.: Research Model

Table 3.1.: Constructs and Definitions

Construct	**Definition**	**Source(s)**
AI-enabled Automation	Refers to using artificial intelligence technologies to replace or substitute human actions. These technologies are capable of developing protocols that establish rules and guidelines for decision-making, as well as selecting actions based on those protocols.	Self-developed, based on Davenport and Ronanki (2018); Mikalef et al. (2023); Murray et al. (2021)
AI-enabled Augmentation	Refers to using artificial intelligence technologies to complement or assist human actions. These technologies can develop protocols that establish rules and guidelines for decision-making, but they do not have the ability to select actions independently.	Self-developed, based on Davenport and Ronanki (2018); Jain, Padmanabhan, Pavlou and Raghu (2021); Murray et al. (2021)
Strategic Improvement	Refers to a company's strategic approach to adapt to current environmental conditions by continually renewing its business model. This involves making incremental changes and enhancing the efficiency and productivity of internal practices. Strategic improvement represents a persistent and ongoing process of renewal that ensures the continuous enhancement of the existing business model.	Benner and Tushman (2003); Lubatkin, Simsek, Ling and Veiga (2006); Schroeder, Linderman, Liedtke and Choo (2008)
Radical Rejuvenation	Refers to a company's strategic approach to explore and respond to new environmental trends by fundamentally changing its business model. This involves creating disruptive innovation and seeking new and creative ways to adapt to the changing landscape.	Benner and Tushman (2003); Lubatkin et al. (2006); Schroeder et al. (2008)
Competitive Performance	Refers to the extent to which a company achieves its objectives relative to its primary competitors. It involves measuring a company's success in achieving its goals compared to other businesses operating in the same market or industry.	Rai and Tang (2010)

3.1. Hypothesis 1

AI-enabled automation refers to applying artificial intelligence technologies to either replace or complement human actions (Murray et al., 2021). This approach allows for continuous renewal and improvement of a firm's existing business model. Essentially, leveraging AI for automation can greatly assist businesses in optimizing their strategic planning and execution, leading to significant enhancements in their current processes. Some of the uses of intelligent automation include streamlining processes, freeing up resources, and increasing operational effectiveness (IBM, 2021). Incorporating AI into a company's operations, particularly for automating administrative tasks such as customer interaction, classification of emails, and accounting and financial management, enables the delegation of repetitive processes and routines to robots and bots. This may improve incremental changes and process adaptation of internal operations leading to efficiency (e.g., reducing time spent on administrative tasks). For instance, using AI to handle customer interaction can help the company improve its efficiency by reducing response time. One example is the credit card industry, which uses AI-powered chatbots to answer frequently asked questions, sell products, and resolve insurance claims through a voice or text interface more efficiently (Nuruzzaman & Hussain, 2018). Chatbots are thus filling a position that was formerly held by a human employee, which may result in improved internal processes.

Second, using AI for automation can provide real-time data and insights (e.g., client feedback) to improve offerings and strengthen existing customer relationships. For instance, Netflix uses recommendation algorithms that provide their members with personalized suggestions based on data and feedback about what content their members watch and enjoy (Netflix, 2022). This helps reduce the time and frustration of finding great content to watch, enhancing Netflix's relationship with its existing customers. It also supports the company in obtaining client feedback to improve customers' needs.

In summary, using AI to automate tasks may aid businesses in improving efficiency by delegating repetitive tasks to robots and bots. In addition, using real-time data allows companies to offer personalized recommendations to customers, improving customers' needs. Thus, I hypothesize that:

H1: *AI-enabled automation will have a positive effect on strategic improvement*

3.2. Hypothesis 2

Companies can use AI for automation to their advantage by looking for possibilities to launch a new product into the market (Mishra & Pani, 2020). As automation enables quick iterations of new products and services after understanding customers' desires through market research or other methods, businesses frequently employ it as part of their innovation strategy (McKinsey&Company, 2019). Besides, using AI to automate tasks may free up employees in routine tasks and data interpretation that are now automated. This can result in more time for the employees to innovate new products or services, explore breakthrough opportunities, or radically reinvent the business processes.

For example, Amazon extensively utilizes AI technologies and automation to drive innovation and launch new products. One notable example is the development of their voice-activated virtual assistant, Alexa. By leveraging AI and automation, Amazon was able to quickly iterate and improve the functionality of Alexa based on customer feedback and market research. Automation streamlined the process of collecting and analyzing customer data, allowing Amazon to develop and release new features and services for Alexa rapidly, such as integrating with smart home devices and expanding its capabilities (Curic, 2021). Following the preceding discussion, I hypothesize that:

H2: *AI-enabled automation will have a positive effect on radical rejuvenation*

3.3. Hypothesis 3

AI-enabled augmentation uses artificial intelligence technologies to complement and assist human actions, and may enable the ongoing process of renewal and enhancement of the firm's existing business model. Implementing AI for augmentation purposes offers executives numerous benefits, including avoiding biases in decision-making, extracting meaningful insights from vast amounts of data, and making strategic decisions more quickly (McKinsey&Company, 2023). Sentiment analysis using AI regularly uses client feedback to improve operations, allowing businesses to monitor brand and product sentiment in customer feedback. This helps employees better understand customer needs and make informed decisions (Microsoft, 2022). Sentiment analysis processes vast amounts of unstructured data quickly and offers insights to employees who can direct teams to improve the user experience and interact with specific customer segments through targeted initiatives (Microsoft, 2022). For instance, food giants such as Domino's, KFC, Pizza Hut, and McDonald's use sentiment analysis to analyze customer feedback and menu preferences (Nawaz et al., 2019). By understanding customer opinions from sentiment analysis, the employees can make informed decisions and improve operations, leading to better customer satisfaction.

AI can also assist in forecasting and prediction, improving managers' ability to schedule procurement, warehousing, and shipping, ensuring that customers can purchase desired products without delay. By forecasting sales levels in advance using AI algorithms, managers can better plan marketing strategies and refine offerings to keep customers satisfied and make decisions based on recommendations from the algorithms. For instance, to optimize production, distribution, and logistics processes, Coca-Cola leverages AI algorithms to analyze sales data and forecast customer demand, enabling employees to make informed decisions based on these insights (Forbes, 2017). According to McKinsey&Company, applying AI-driven forecasting can reduce waste and inefficiencies in the supply chain. AI-driven forecasting combined with human decision-makers may help fine-tune what businesses offer to satisfy their current customers. Besides, applying AI-driven forecasting to supply chain management can reduce errors by between 20 and 50%, improving existing processes (McKinsey&Company, 2022a).

Based on the preceding discussion, using AI for augmentation can benefit businesses in various ways. Sentiment analysis can use customer feedback to improve operations, leading to better customer satisfaction. AI can also assist in forecasting and prediction, reducing inefficiencies in the supply chain and improving existing processes. Overall, using AI combined with human expertise can aid in the ongoing renewal and enhancement of the firm's existing business model. Thus, I propose the following hypothesis:

H3: *AI-enabled augmentation will have a positive effect on strategic improvement*

3.4. Hypothesis 4

AI-enabled augmentation opens up possibilities for a more adaptive and innovative approach. By harnessing AI technologies, businesses can process vast amounts of data, uncover patterns, and receive predictive recommendations that assist humans in solving specific problems (Allam, 2016). The rapid analysis of massive data sets by AI algorithms, combined with their ability to learn from the data's underlying relationships, has the potential to reduce uncertainty in experimentation and enhance learning effectiveness. This, in turn, encourages further experimentation and the development of new products (Babina et al., 2022). For example, a well-structured machine-learning algorithm can identify complex patterns and offer stochastic-based recommendations for human implementation (Murray et al., 2021). Consequently, using AI for augmentation can transform decision-making processes, particularly in generating and validating new ideas. As a result, executives can leverage AI to their advantage by seeking out opportunities to explore groundbreaking possibilities, such as launching a new product in the market (Mishra & Pani, 2020).

Boston Scientific is one example of a company combining human knowledge and AI to change the firm's business model radically. The company is adapting to the pandemic-accelerated increase in telemedicine demand, which can potentially replace up to 80% of yearly in-person physician visits. They developed an augmented-reality-powered application to monitor medical device insertions (Johnson et al., 2022). Thus, the company is quickly shifting focus to prepare for this change by combining artificial intelligence and human knowledge to explore new opportunities and develop new skills for the future.

In summary, combining AI technologies and human knowledge may aid businesses in decision-making, encouraging experimentation and increasing learning effectiveness. This may result in breakthrough opportunities, new products or services, and new skills to shape the future. Thus, I propose the following hypothesis:

H4: *AI-enabled augmentation will have a positive effect on radical rejuvenation*

3.5. Hypothesis 5

Strategic improvement refers to a company's approach to adapting to current environmental conditions by continually renewing its business model. It represents a persistent and ongoing renewal process through exploitation that ensures the continuous enhancement of the existing business model (Benner & Tushman, 2003). Exploitation enables businesses to modify existing practices while improving resource efficiency and saving costs (March, 1991). This makes it possible for businesses to maintain their competitiveness and consistently satisfy customer demand by updating current products and services and applying current knowledge while boosting productivity, reducing failure, and continuously developing existing knowledge (Clauss et al., 2020). Research shows that exploitation is a performance driver. It enables businesses to create products consumers perceive as having a higher quality while charging less than their competitors due to increased cost-efficiency. Thus, a company can improve its competitive advantage by continuously refining its current practices. This gradual process of improvement, combined with long-term exploitation, leads to the accumulation of significant knowledge that is challenging for competitors to replicate (Clauss et al., 2020). Hence, I propose the following hypothesis:

H5: *Strategic improvement will have a positive effect on competitive performance*

3.6. Hypothesis 6

Radical rejuvenation refers to a company's strategic approach to exploring and responding to new environmental trends by fundamentally changing its business model (Lubatkin et al., 2006). Exploration is utilized to create disruptive innovation and seek new and creative ways to adapt to the changing landscape. It permits businesses to generate and acquire knowledge and information from any perspective of the organization's environment. Thus, it includes developing skills and looking for new information (Clauss et al., 2020). Firms can acquire new knowledge by collaborating and interacting with various people and businesses, leading to creativity and radical innovations (Montes, Benitez-Amado, Castillo & Braojos, 2018). For instance, creating radically new products or services that have not existed on the market before can give businesses a market advantage, which will impact their competitive performance. Besides, product innovation and product options extension are crucial growth drivers for organizations. They may boost sales and demand for currently available items, allow businesses to offer more products, and disrupt established firm structures (Clauss et al., 2020). Thus, exploration activities help identify failures and shortcomings in current firm practices and enable the firm to develop new competitive advantages (O'Cass, Heirati & Ngo, 2014).

Exploration is applied by firms that invest heavily in research and explore new technology areas. One example is Google, which expanded its offerings beyond being only a search engine, to include services such as image-recognition software, self-driving car technology, and broadband services. Google began as an online search company but has expanded quickly over the years to provide over 50 internet services and products. It manages more than 70% of global online search inquiries as of 2021, making it the market leader (Gray, 2021). Following the preceding discussion, I hypothesize that:

H6: *Radical rejuvenation will have a positive effect on competitive performance*

4. Reseach Method

Using an exploratory survey-based approach, this thesis explores the research questions outlined in Chapter 1.2. A large sample of data is required to find patterns in AI adoption and organizational performance. The chosen strategy provides quantitative data for the analysis and is therefore beneficial for this research. Figure 4.1 illustrates the thesis design, which will be further elaborated on in the following paragraphs.

4.1. Preparation

A systematic literature review (SLR), completed during the fall of 2022, was done in preparation for this thesis. The SLR was part of a specialization project that produced a report. The objective of the SLR was to identify the current status of knowledge concerning AI use cases in companies, the challenges organizations face when employing AI, and what value-generating mechanisms AI can enable. The review identified several areas for further research, including the impact of AI adoption on companies' competitiveness. The progress of this work prompted the development of the research questions examined in this study.

4.2. This Thesis

A thorough examination of the existing literature concerning the business value of AI was conducted. Based on this examination, tools for AI-enabled automation and AI-enabled augmentation were developed (Chapter 4.3.2). This involved creating a survey instrument to assess and quantify an organization's level of maturity in this area. Furthermore, a research model was suggested, which includes multiple hypotheses regarding the influence of AI-enabled automation and AI-enabled augmentation on organizations. Chapter 3 introduces the proposed research model. Next, the research model was tested through an empirical survey. The survey gathered quantitative data from 154 IT executives working in American-based companies. Chapter 4.3 provides additional information regarding the survey method. Lastly, the results from the survey study were analyzed. This process included partial least squares structural equation modeling (PLS-SEM), a method for structural equation modeling that allows the estimation of complex cause-effect relationships in path models with latent variables (Hair, Ringle & Sarstedt, 2011).

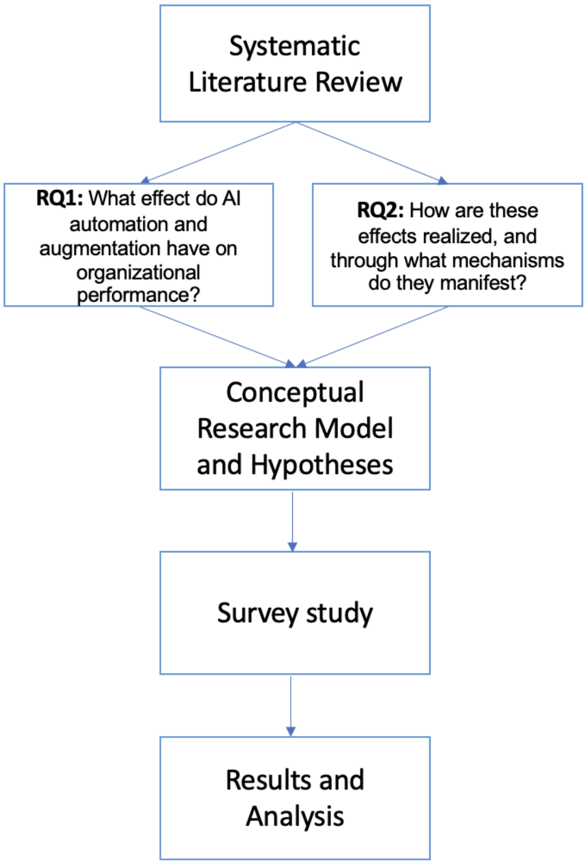

Figure 4.1.: The Research Design and Process

4.3. Survey Method

The survey method was chosen as a strategy to empirically test the research model presented in Chapter 3 and provides quantitative data for the analysis. The chosen strategy allows the same data types to be gathered from a large group and examined for trends that enable the findings to be generalized (Oates, 2006). The approach for collecting data was a questionnaire-based survey distributed to American companies. The following paragraphs will describe the procedure for gathering data for the survey and the construct measures employed.

4.3.1. Data Collection

A survey in the form of an electronic questionnaire was distributed to U.S.-based companies to evaluate the research model. The Tortoise Global AI Index assesses various metrics, such as the extent of investment, innovation, and implementation of artificial intelligence, and provides rankings for 62 countries worldwide based on their AI development capacity. According to the index, the United States is the foremost nation regarding AI development capabilities, indicating its preparedness for digital transformation (Mousavizadeh, Mehta & Darrah, 2021).

Data was collected for about four weeks, specifically in March and April 2023. A panel service provider (Alchemer[1]) was contacted to collect data via the questionnaire. When the data collection period ended, a dataset was obtained from the panel service. It consisted of 154 complete responses to be analyzed further.

A wide range of industries is represented in the data set (Table 4.1), with technology accounting for the most significant share of replies (39%), followed by manufacturing (12.3%), ICT and telecommunications (8.4%), and financial services (7.8%). Various industries provided the remaining responses (Figure 4.2), including education, transportation, media, and marketing. Most survey respondents worked for large companies, with 79.2% of the organizations having more than 250 employees (Figure 4.3). Furthermore, Table 4.1 highlights that most respondents held managerial or higher-level positions and that most companies have several years of experience using AI, with 49.3% having three or more years of experience.

[1] https://www.alchemer.com/

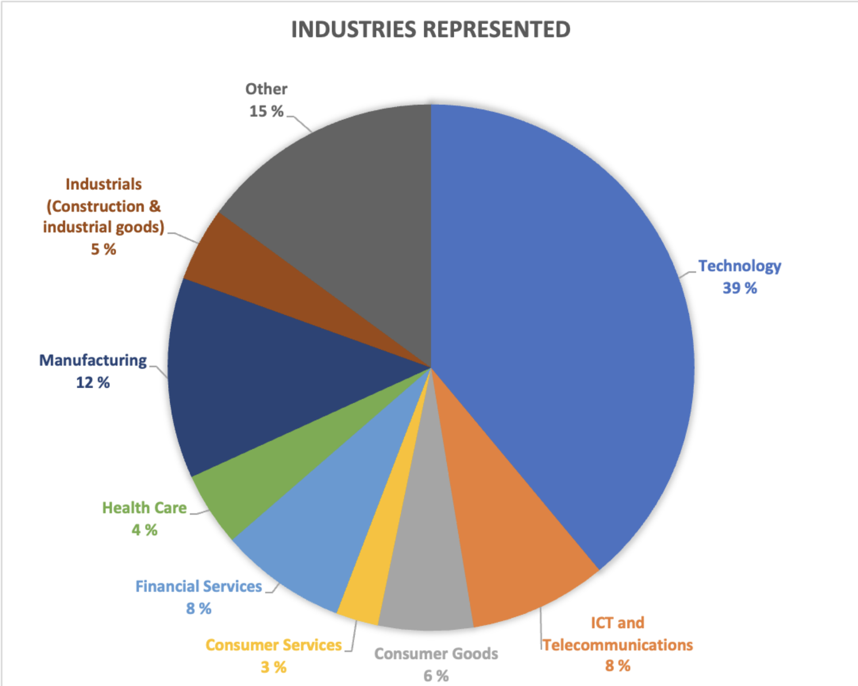

Figure 4.2.: Distribution of Represented Industries

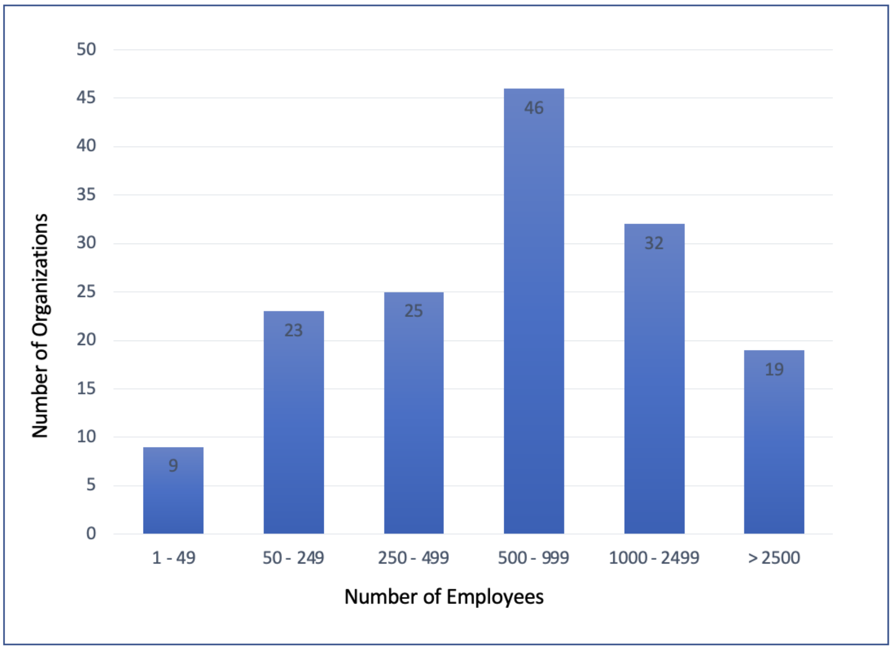

Figure 4.3.: Size-class of Organization (Number of Employees)

Table 4.2 indicates that several companies are utilizing AI for multiple applications, and they are also using various AI technologies. Machine learning is the most frequently used AI technology (70.1%), followed by speech analysis (55.8%), planning, scheduling, and optimization techniques (52.6%), expert systems (51.9%), and natural language processing (50.0%). Further, the most common AI application is chatbots (74.7%), followed by cybersecurity (67.5%), virtual agents (virtual agents 59.7%), and intelligence supply chain management (51.9%).

Table 4.1.: Descriptive Statistics of the Sample and Respondents

Factors	**Sample (N=154)**	**Proportion (%)**
Industry		
Technology	60	39.0 %
ICT and Telecommunications	13	8.4 %
Financial Services	12	7.8 %
Consumer Goods	9	5.8 %
Consumer Services	4	2.6 %
Health Care	7	4.5 %
Industrials (Construction and Industrial goods)	7	4.5 %
Manufacturing	19	12.3 %
Other (Education, Media, Marketing etc.)	23	14.9 %
Firm Size (Number of Employees)		
1-49	9	5.8 %
50-249	23	14.9 %
250-499	25	16.2 %
500-999	46	29.9 %
1000-2499	32	20.8 %
2500+	19	12.3 %
Total AI Experience of Company (Years)		
<1 year	6	3.9 %
1 year	13	8.4 %
2 years	59	38.3 %
3 years	43	27.9 %
4+ years	33	21.4%
Respondent's Position		
CIO/CTO	28	18.2 %
Head of IT Department	17	11.0 %
IT Project Manager	22	14.3 %
IT Director	35	22.7 %
CEO	15	9.7 %
Operations Manager	6	3.9 %
Data Analyst / Data Scientist	5	3.2 %
Other (Business Manager, Project Manager, Consultant etc.)	26	16.9 %

Table 4.2.: Descriptive Statistics of AI Use in the Sample (Top Answers)

AI Use	**Sample (N=154)**	**Proportion (%)**
AI Applications		
Chatbots	115	74.7 %
Cybersecurity	104	67.5 %
Virtual Agents	92	59.7 %
Intelligence Supply Chain Management	80	51.9 %
AI for Decision Management	79	51.3 %
Real-Time Translation	76	49.4 %
Robotic Process Automation	68	44.2 %
AI Technologies		
Machine Learning	108	70.1 %
Speech Analytics	86	55.8 %
Planning, Scheduling and Optimization	81	52.6 %
Expert Systems	80	51.9 %
Natural Language Processing (NLP)	77	50.0 %
Robotics	66	42.9 %
Machine Vision	56	36.4 %
Recurrent Neural Networks	46	29.9 %
Feed-Forward Networks	42	27.3 %
Convolutional Neural Networks	36	23.4 %
Reinforcement Learning	24	15.6 %

4.3.2. Construct Development

As mentioned in Chapter 4.2, the measures for the constructs "AI-enabled automation" and "AI-enabled augmentation" was developed in this thesis. The measures were developed collaboratively by my supervisor, co-supervisor, and myself. The following steps explain the process and are based on the ten steps in the construct development approach from MacKenzie, Podsakoff and Podsakoff (2011).

Step 1: Construct Conceptualization and Definition

The first step included revising the existing literature on the business value of AI. Based on the revision, the constructs "Strategic Improvement", "Radical Rejuvenation", and "Competitive Performance" were adapted from prior studies. On the other hand, the constructs "AI-enabled Automation" and "AI-enabled Augmentation" were formally defined, with the definitions presented in Table 3.1.

Step 2: Generate Items to Represent the Construct

Next, the items utilized to represent the constructs "AI-enabled Automation" and "AI-enabled Augmentation" were generated by reviewing the literature on AI use for automation and augmentation purposes. The item list constitutes the constructs' measurement models and is presented in Appendix B.

Step 3: Assess the Content Validity of the Items

Subsequently, the content validity of the items was evaluated by administering a Q-sort test to a group of 12 individuals, who were asked to identify the construct associated with each item and assess the clarity of the items. Notably, the participants in the Q-sort test were computer science students who were familiar with and understood the term "Artificial Intelligence". Following the Q-sort test, each item's hit ratio and average clarity were computed by the test individuals, and these metrics are illustrated in Figure 4.4 and Figure 4.5, respectively.

Step 4: Formally Specify the Measurement Model

Lastly, based on the result from the Q-sort test, the measurement model (Appendix B) was modified. The items with a hit ratio of less than 8 out of 12, and average clarity of less than 8 out of 10, were removed from the measurement model. After assessing the hit ratio, items nr. 2, 7, 8, 9, 10, 16, and 18 were eliminated. Then, based on the average clarity results, items 1, 12, 14, 15, 21, 25, 26, and 27 were discarded. In addition, items 22 and 23 were rephrased to enhance their clarity. Ultimately, items 4 and 24 were deemed inferior compared to the remaining items based on the group's consensus, and consequently, these two items were excluded from the model. The remaining statements formed the set of items used to measure the constructs and are presented in the formally specified measurement model (Table 4.3).

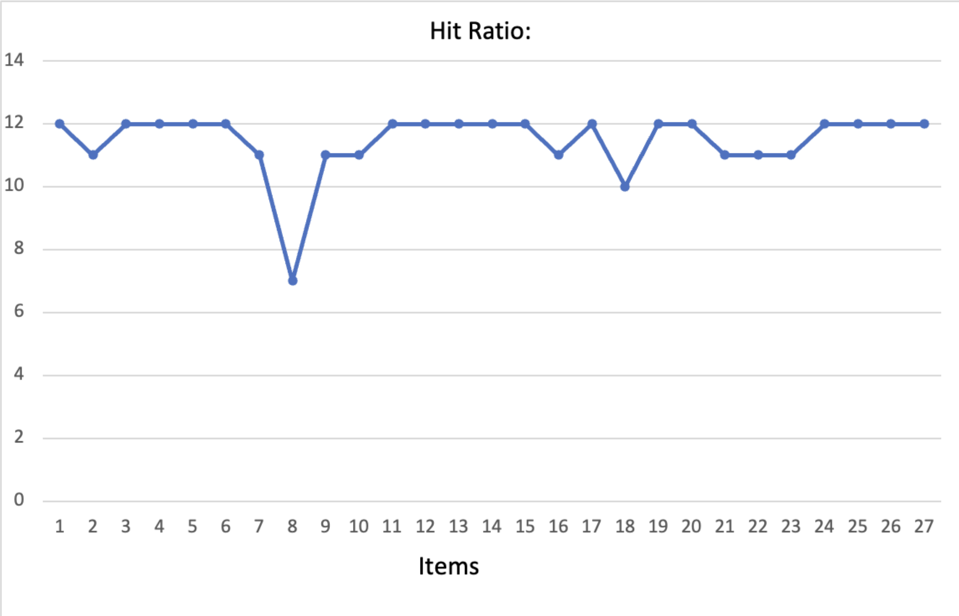

Figure 4.4.: Hit Ratio of the Items

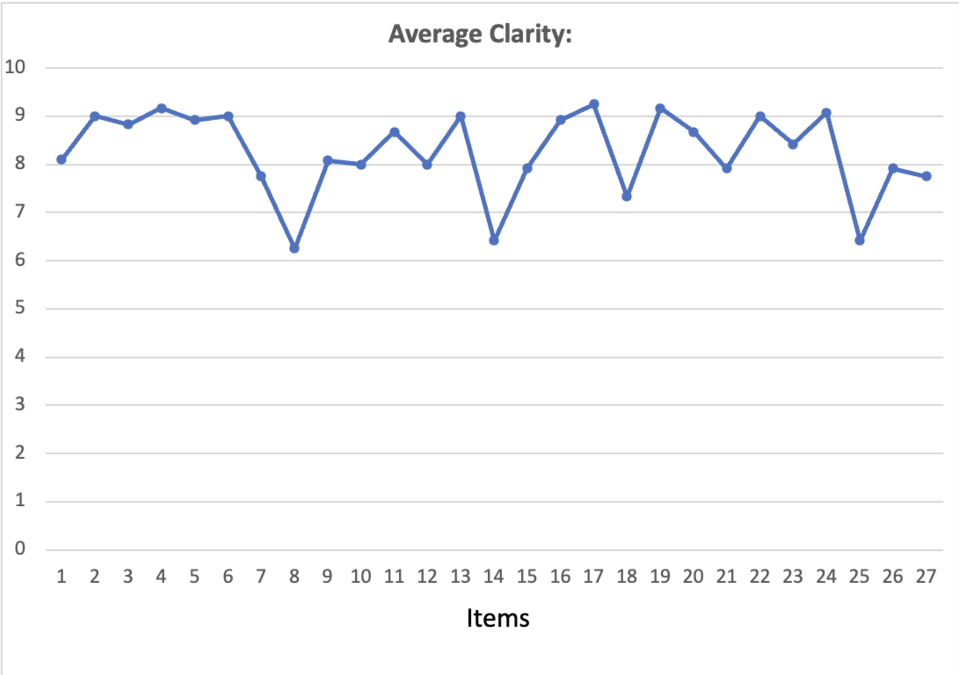

Figure 4.5.: Average Clarity of Each Item

Table 4.3.: Constructs and Measures of AI-enabled Automation and AI-enabled Augmentation

Construct	Items
AI-enabled Automation	AUTO1: The use of AI has enabled us to free up employees in tasks that are now automated.
	AUTO2: The use of AI has allowed us to automate financial activities.
	AUTO3: The use of AI has helped us automate structured and administrative tasks (e.g., transferring data, and updating records).
	AUTO4: In our organization, AI continuously learns and automatizes how to seek data and optimize analyses.
	AUTO5: In our organization, AI automatizes and autonomously formulates recommendations to execute them ultimately.
AI-enabled Augmentation	AUGM1: The use of AI has enabled us to support workers in decision-making.
	AUGM2: In our organization workers can determine whether to select the recommendations given by the AI technologies.
	AUGM3: The use of AI has enabled us to collaborate with machines to do things that neither (i.e., machines nor humans) could do well on their own.
	AUGM4: The use of AI has enabled us to augment humans' and machines' strengths and compensate for weaknesses.
	AUGM5: The use of AI has enabled us to combine human and machine knowledge.

4.3.3. Construct Measurement

It is necessary to have a precise method of measuring each construct to assess the correlations between them quantitatively. Appendix A contains the measures for the constructs *strategic improvement*, *radical rejuvenation*, and *competitive performance*, which were adapted from prior studies. These scales have already undergone empirical testing. On the other side, this thesis has developed the measures for AI-enabled automation and AI-enabled augmentation (Chapter 4.3.2).

AI-enabled Automation

AI-enabled automation is conceptualized as a composite construct. The construct is developed in this research and based on the research from Murray et al. (2021), Mikalef et al. (2023), and Davenport and Ronanki (2018). The items utilized to evaluate the construct were created in this thesis (Chapter 4.3.2) and are listed in Table 4.3. The survey participants were asked to evaluate how AI has replaced manual efforts with automated processes, and a 7-point Likert scale was utilized to obtain their responses (1: Strongly disagree, 7: Strongly agree).

AI-enabled Augmentation

AI-enabled augmentation was developed as a construct in this thesis and is based on research from Murray et al. (2021), Jain et al. (2021), and Davenport and Ronanki (2018). The items used to assess the construct for AI-enabled augmentation were created in this thesis and are provided in Table 4.3. Like AI-enabled automation, this construct is also a composite construct. The items employed to measure the level of AI-enabled augmentation address the use of AI to facilitate collaboration between human employees and machines to achieve better outcomes. A Likert scale was employed and ranged from 1 (completely disagree) to 7 (completely agree).

Strategic Improvement

Strategic improvement refers to a firm's strategic approach to adapt to current environmental conditions by continually renewing its business model (Benner & Tushman, 2003; Lubatkin et al., 2006; March, 1991; Schroeder et al., 2008), and was measured as a composite construct. The items utilized to measure the strategic improvement of companies were adapted from a study by Lubatkin et al. (2006), which was also supported by empirical evidence. The survey participants were inquired about their efforts to improve their operations and products/services. A 7-point Likert scale was utilized to evaluate their responses, with a score of 1 indicating complete disagreement and a score of 7 indicating entire agreement. The items used to measure strategic improvement are given in Appendix A.

Radical Rejuvenation

Radical rejuvenation refers to a company's strategic orientation to explore and respond to emerging environmental trends by radically changing its business model, producing disruptive innovation, and discovering novel and inventive means to adapt to the new (Benner & Tushman, 2003; Lubatkin et al., 2006; March, 1991; Schroeder et al., 2008). The items employed to measure the level of radical rejuvenation include, among others, looking for creative ways to satisfy customer needs, radically reinventing the organization's processes, exploring breakthrough opportunities, and creating radically new products/services that have not existed on the market before. The items can be found in Appendix A, adapted from previous research (Lubatkin et al., 2006; Seepana, Paulraj & Smart, 2022) and verified through empirical evidence. Radical rejuvenation was measured as a composite construct. A 7-point Likert scale was employed and ranged from 1 (completely disagree) to 7 (completely agree).

Competitive Performance

Competitive performance refers to the degree to which a business performs better than its main competitors (Rai & Tang, 2010). The construct is adapted from the multidimensional construct *Organizational Performance* from Mithas, Ramasubbu and Sambamurthy (2011) and Wu, Straub and Liang (2015), and was measured as a composite second-order construct. The survey participants were requested to evaluate their performance compared to their major competitors in various areas, such as financial performance, customer satisfaction, delivery cycle time, and environmental performance (Appendix A). A 7-point Likert scale was utilized to obtain their responses (1: Strongly disagree, 7: Strongly agree).

Control Variables on Competitive Performance

Differences in competitive performance can be attributed to differences in the portfolio of resources by the firm size, industry, and total IT investment. Firm size, industry, and IT investment were thus applied as control variables, as they may directly affect competitive performance.

4.3.4. Prevention and the Test of Common Method Variance

Composite measures are unlikely to suffer from common method variance bias (Rönkkö & Ylitalo, 2011). However, potential common method variance was tested and prevented. Initially, there was a focus on mitigating the occurrence of common method bias in the research's design. To accomplish this, the survey administration maintained confidentiality and anonymity. Second, the correlation matrix was checked to prevent high correlation among key variables ($r > 0.90$) (Braojos, Benitez, Llorens & Ruiz, 2020). The correlation matrix is presented in Appendix C, proving the highest correlation to be 0.816. Next, the variance inflation factor (VIF) values at the construct level were examined, as VIF values exceeding 3.3 at this level can indicate the presence of potential common method variance (Kock & Lynn, 2012). To assess the VIF values, a comprehensive collinearity test was conducted. The obtained values for all constructs included in the model ranged from 1.588 to 2.648 (Table 5.2). These findings imply that it is unlikely for the research model to be affected by common method variance bias (Kock & Lynn, 2012).

5. Results

This chapter will present the results from the survey study introduced in Chapters 3 and 4. The proposed research model (Chapter 3) was empirically tested by performing a partial least squares-based structural equation modeling (PLS-SEM). PLS is capable of evaluating the precise overall fit of a model, and it belongs to the category of variance-based structural equation modeling (SEM) techniques as a complete estimator. Given that this research is exploratory and aims to construct a theory rather than do theory confirmation, PLS-SEM is an appropriate method to apply (Hair et al., 2011). In addition, PLS is well-suited for evaluating composite models, like the one proposed in this research (Henseler et al., 2014; Henseler, Hubona & Ray, 2016). Also, PLS is particularly recommended when working with models that consist of multidimensional constructs, such as this study's competitive performance construct (Hair, Sarstedt, Ringle & Mena, 2012). Lastly, PLS is an appropriate choice when utilizing newly developed scales, which is the situation in this study regarding AI-enabled Automation and AI-enabled Augmentation (Tiwana & Konsynski, 2010).

Advanced Analysis for Composites (ADANCO [1]) software was utilized to estimate the measurement and structural models. This variance-based SEM software has the capability to model various types of constructs, including composites, common factors, and single-indicator constructs. Moreover, it enables both causal and predictive modeling (Rueda, Benitez & Braojos, 2017). A bootstrapping algorithm with 10 000 sub-samples was employed to determine the significance of weights and loadings for each item and the significance of path coefficients. The structural model offers the relationships between the constructs, whereas the measurement model presents the relationships between the constructs and their indicators (Sarstedt, Ringle & Hair, 2017). The following paragraphs present the evaluation of the measurement and structural models.

[1] http://www.composite-modeling.com/

5.1. Confirmatory Composite Analysis

All constructs of the research model were defined as composite. To estimate the research model, the weighting schemes of regression weights (mode B) were used. Mode B was utilized for all composites because their indicators were not correlated. To assess the suitability of the measurement structure, a confirmatory composite analysis that involved comparing the model-implied correlation matrix and the empirical correlation matrix was conducted (Benitez, Henseler, Castillo & Schuberth, 2020; Henseler et al., 2014). This analysis provided an evaluation of the overall model fit of the measurement structure. The standardized root mean squared residual (SRMR), unweighted least squares discrepancy (dULS), and geodesic discrepancy (dG) were used to estimate the fit of the saturated model (Henseler et al., 2014, 2016). SRMR indicates the degree of mismatch between the model-implied correlation matrix and the empirical correlation matrix. A value of SRMR below 0.800 indicates a good overall fit. dULS and dG are exact measures of overall model fit, and lower values of these measures indicate better model fit (Braojos et al., 2020). An acceptable fit between the model and the data is indicated by dULS and dG values below the 99%-quantile of the bootstrap discrepancy (Benitez et al., 2020). The confirmatory composite analysis results are shown in Table 5.1, which, with a 1% probability, supports the structure of the measures.

Table 5.1.: Goodness of Model Fit (saturated model)

	Value	**HI95**	**HI99**	**Conclusion**
SRMR	0,061	0,063	0,069	Supported
dULS	2,493	2,602	3,176	Supported
dG	1,125	1,370	1,656	Supported

5.2. Measurement Model Evaluation

Before evaluating the structural model, it is necessary to evaluate the measurement model, which explains the relationships between the observed data and the latent variables (Hair, Risher, Sarstedt & Ringle, 2019). Since competitive performance is a second-order construct, a two-step approach (Chin, 2010) was adopted to estimate the research model. In the first step, the latent variable scores for the dimensions of competitive performance were obtained by freely correlating the first-order constructs with the dimensions of the second-order constructs (e.g., operational performance, financial performance, and customer performance). In the second step, the research model was estimated using the latent variable scores to measure competitive performance (Chin, 2010).

Validation of the composite constructs involved assessing content validity, checking for multicollinearity, and examining the significance of weights and loadings (Cenfetelli & Geneviève, 2009). Initially, content validity was ensured by employing previously validated scales wherever feasible (Lubatkin et al., 2006; Mithas et al., 2011; Seepana et al., 2022; Wu et al., 2015). Additionally, new scales for AI-enabled automation and AI-enabled augmentation were created by using the preliminary conceptual foundations put forward in prior research (Davenport & Ronanki, 2018; Jain et al., 2021; Mikalef et al., 2023; Murray et al., 2021). Also, the significance of weights, loadings, and multicollinearity at both first- and second-order levels were evaluated.

The variance inflation factor (VIF) values were examined to ensure the absence of multicollinearity. VIF values lower than 3.3 are generally recommended for constructs estimated in mode B (Diamantopoulos & Siguaw, 2006). As shown in Table 5.2, all VIF values are below the recommended threshold of 3.3. Next, the significance of weights and loadings was verified. All loadings were significant at the 0.001 level. The significance of the weights was assessed through bootstrapping, and the analysis showed that the majority of weights were found to be significant. This analysis indicates favorable measurement properties. The measurement model evaluation is displayed in Table 5.2, and the evaluation of the structural model will now proceed.

Table 5.2.: Measurement Model Evaluation

Construct/indicator	Mean	S.D.	VIF	Weight	Loading
AI-enabled Augmentation (Composite Mode B)					
AUGM1	5,760	1,433	2,159	0,269*	0,833***
AUGM2	5,721	1,291	1,734	0,135	0,718***
AUGM3	5,597	1,407	1,941	0,280**	0,808***
AUGM4	5,773	1,197	1,727	0,362***	0,827***
AUGM5	5,877	1,212	1,666	0,207	0,739***
AI-enabled Automation (Composite Mode B)					
AUTO1	5,766	1,366	1,634	0,348**	0,805***
AUTO2	5,623	1,415	1,838	0,237**	0,777***
AUTO3	5,812	1,307	2,419	0,182	0,810***
AUTO4	5,844	1,232	1,683	0,335***	0,805***
AUTO5	5,851	1,230	2,275	0,150	0,790***
Radical Rejuvenation (Composite Mode B)					
RadRej1	5,708	1,495	2,169	0,214*	0,781***
RadRej2	5,766	1,298	1,605	0,230*	0,682***
RadRej3	5,675	1,323	1,957	0,105	0,740***
RadRej4	5,831	1,209	1,768	0,143	0,722***
RadRej5	5,929	1,103	1,851	0,291***	0,776***
RadRej6	5,649	1,331	1,588	0,347**	0,776***
Strategic Improvement (Composite Mode B)					
SI1	5,825	1,324	2,117	0,378***	0,866***
SI2	5,922	1,152	1,791	0,246**	0,777***
SI3	5,864	1,339	1,705	0,251**	0,770***
SI4	5,961	1,090	1,830	0,228*	0,776***
SI5	5,870	1,235	1,883	0,148*	0,748***
CompPerf (Composite Mode B)					
FP	0,000	1,000	2,502	0,483***	0,926***
CustPer	0,000	1,000	2,648	0,248*	0,873***
OP	0,000	1,000	2,243	0,379**	0,885***
Industry (Control variable)					
IndDummy1	0,390	0,489	1,574	0,992*	0,508
IndDummy2	0,123	0,330	1,315	0,805*	0,394
IndDummy3	0,058	0,235	1,165	-0,068	-0,421
IndDummy4	0,026	0,160	1,077	0,132	-0,093
IndDummy5	0,071	0,258	1,197	0,440*	0,085
IndDummy6	0,084	0,279	1,229	0,584*	0,213
SizeDummy (Control variable)					
SizeDummy1	0,058	0,235	1,388	0,639*	0,623*
SizeDummy2	0,149	0,358	1,880	0,656	0,678
SizeDummy3	0,162	0,370	1,940	0,019	-0,075
SizeDummy4	0,299	0,459	2,399	-0,261	-0,518
SizeDummy5	0,208	0,407	2,126	-0,097	-0,237
ITInvest (Control variable)					
ITInvest	3,961	0,914	1,000	1,000	1,000

Note: †p < 0.10, *p < 0.05, **p < 0.01, ***p < 0.001, two-tailed test.

5.3. Structural Model

The PLS analysis produced a structural model depicted in Figure 5.1, displaying the standardized path coefficients (β) and the coefficient of determination (R^2). The path coefficients represent the strength of the relationship between two constructs (Sarstedt et al., 2017), with a value close to (+/-) 1 indicating a strong (positive/negative) correlation. The coefficient of determination measures the explained variance of the endogenous variables and indicates the model's explanatory power (Hair et al., 2019), with higher values indicating greater predictive accuracy (Hair, Hult, Ringle & Sarstedt, 2017). To ensure the statistical significance of the PLS analysis findings, a bootstrap analysis was conducted to determine the t-statistics. The analysis included two models: 1) a base model comprising only the hypothesized relationships, and 2) a mediation model incorporating the direct impact of AI-enabled automation and AI-enabled augmentation on competitive performance to the base model. Table 5.4 and the following paragraphs present the results of the structural model analysis.

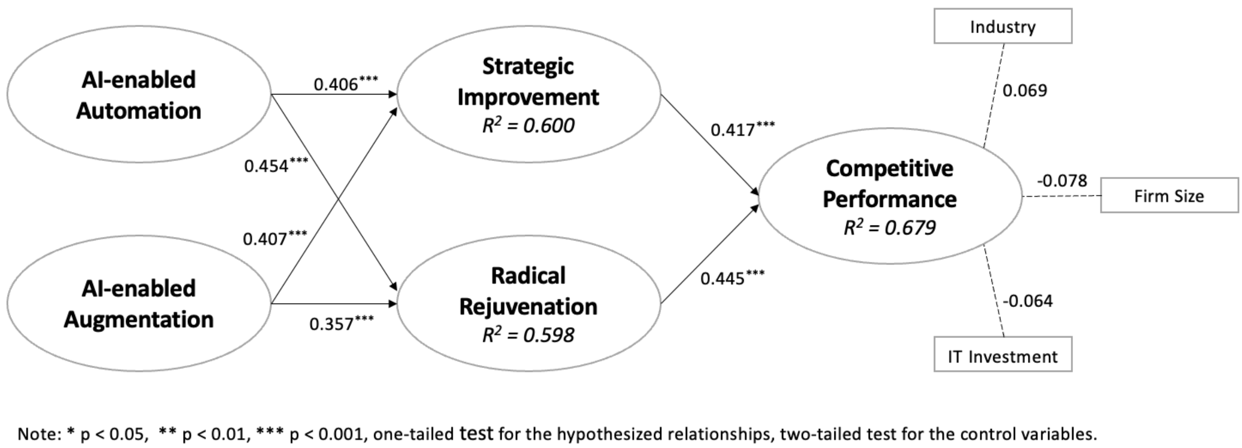

Figure 5.1.: Estimated Relationship of Structural Model

5.3.1. Overall Fit of the Estimated Model

Similar to the confirmatory composite analysis, the goodness of fit for the structural model (i.e., the estimated model) was assessed by evaluating SRMR, dULS, and dG

(Benitez et al., 2020). The base model, which does not consider the direct effects of the mediation analysis, has an SRMR value of 0.0680, and its discrepancy values are below the 99%-quantile of the bootstrap discrepancies. Based on these results, it can be concluded that the base model should not be rejected at the alpha level of 0.01. In general, the proposed research model exhibits a good fit with the structural model, which suggests that the research model has the capacity to be a robust theory for elucidating the relationship between AI-enabled automation, AI-enabled augmentation, and a firm's strategic improvement, radical rejuvenation, and competitive performance. The structural model's evaluation can then proceed.

5.3.2. Evaluation of the Structural Model

All six hypotheses are supported in the base model, as presented in Table 5.3. Employing AI-enabled automation is found to impact the strategic improvement of a firm (β=0.406, t=4.403, p<0.001), as well as the radical rejuvenation of a firm (β=0.454, t=4.783, p<0.001). The same applies to AI-enabled augmentation, which is positively associated with strategic improvement (β=0.407, t=4.509, p<0.001) and radical rejuvenation (β=0.357, t=3.624, p<0.001). Further, strategic improvement is found to positively affect competitive performance (β=0.417, t=3.693, p<0.001). In addition, it is indicated that strategic improvement positively impacts competitive performance (β=0.445, t=3.873, p<0.001). The effect of industry, firm size, and level of IT investment on competitive performance was insignificant. Nevertheless, incorporating these control variables enhances the empirical analysis by reconfirming whether the impacts of AI-enabled automation, AI-enabled augmentation, strategic improvement, and radical rejuvenation on competitive performance remain consistent even after considering these control variables.

Table 5.4 shows that the coefficients of determination (R^2 values), which indicate the model's explanatory power, range from 0.598 to 0.679, suggesting good explanatory power for the endogenous variables. Further, the adjusted R^2 values range from 0.593 to 0.669. The effect size values (f^2) indicate how much each additional relationship contributes to the model, and range from 0.106 to 0.206, indicating weak-medium to strong effect sizes in the research model (Benitez et al., 2020).

Table 5.3.: Results of Hypothesis Testing

Hypothesis	**Effect**	**t-value**	**Conclusion**
H1: AI-enabled automation → Strategic improvement	0.406	4.403***	Supported
H2: AI-enabled automation → Radical rejuvenation	0.454	4.783***	Supported
H3: AI-enabled augmentation → Strategic improvement	0.407	4.509***	Supported
H4: AI-enabled augmentation → Radical rejuvenation	0.357	3.624***	Supported
H5: Strategic improvement → Competitive performance	0.417	3.693***	Supported
H6: Radical rejuvenation → Competitive performance	0.445	3.873***	Supported

Note: †$p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Table 5.4.: Structural Model Evaluation

Beta Coefficient	**Mediation Model**		**Base Model**	
AUTO → SI (H1)	0.405*** (4.489) [0.224, 0.575]		0.406*** (4.404) [0.219, 0.582]	
AUTO → RadRe (H2)	0.455*** (4.860) [0.274, 0.644]		0.454*** (4.781) [0.270, 0.647]	
AUTO → CompPerf	0.069 (0.563) [-0.163, 0.311]			
AUGM → SI (H3)	0.408*** (4.624) [0.231, 0.577]		0.407*** (4.508) [0.228, 0.581]	
AUGM → RadRe (H4)	0.358*** (3.724) [0.182, 0.560]		0.357*** (3.624) [0.176, 0.564]	
AUGM → CompPerf	0.088 (0.793) [-0.103, 0.330]			
SI → CompPerf (H5)	0.369* (2.499) [0.045, 0.604]		0.417*** (3.694) [0.185, 0.624]	
RadRe → CompPerf (H6)	0.391** (3.176) [0.157, 0.633]		0.445*** (3.873) [0.225, 0.665]	
Control Variables				
ITInvest → CompPerf	-0.103 (-1.710) [-0.211, 0.025]		-0.064 (-1.033) [-0.179, 0.063]	
FirmSize → CompPerf	-0.062 (-0.748) [-0.187, 0.154]		-0.078 (-0.919) [-0.197, 0.153]	
Industry → CompPerf	0.067 (0.822) [-0.147, 0.193]		0.069 (0.813) [-0.154, 0.198]	
	R^2	**Adjusted R^2**	**R^2**	**Adjusted R^2**
SI	0.598	0.593	0.600	0.594
RadRe	0.600	0.595	0.598	0.593
CompPerf	0.686	0.671	0.5679	0.669
	Effect Size f^2		**Effect Size f^2**	
AUTO → SI (H1)	0.138		0.137	
AUTO → RadRe (H2)	0.176		0.171	
AUTO → CompPerf	0.004			
AUGM → SI (H3)	0.140		0.138	
AUGM → RadRe (H4)	0.109		0.106	
AUGM → CompPerf	0.006			
SI → CompPerf (H5)	0.126		0.180	
RadRe → CompPerf (H6)	0.142		0.206	
ITInvest → CompPerf	0.020		0.008	
FirmSize → CompPerf	0.010		0.016	
Industry → CompPerf	0.013		0.013	

Note: †$p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

5.3.3. Post Hoc Mediation Analysis

A post hoc mediation analysis was conducted to examine the mediating role of AI-enabled automation and AI-enabled augmentation in the proposed research model. The analysis involved studying the indirect effects of adding links from AI-enabled automation and AI-enabled augmentation to competitive performance. Table 5.5 shows the results, which indicate that the indirect effects are significant (AUTO: 0.328, $p_{\text{one-tailed}} < 0.001$), (AUGM: 0.291, $p_{\text{one-tailed}} < 0.001$), and support all the hypothesized relationships in the mediation model, while the direct effects are insignificant. These findings strengthen the results of the test of hypotheses. The results suggest that competitive performance is only indirectly mediated by AI-enabled automation and AI-enabled augmentation, which affect competitive performance through strategic improvement and radical rejuvenation.

Table 5.5.: Mediation Analysis

Relationship	**Direct effect**	**Indirect effect**	**Total effect**
AUTO → CompPerf	0.069 (0.563) [-0.163, 0.311]	0.328*** (3.758) [0.154, 0.491]	0.396*** (3.824) [0.168, 0.576]
AUGM → CompPerf	0.088 (0.793) [-0.103, 0.330]	0.291*** (3.715) [0.132, 0.436]	0.378*** (3.639) [0.182, 0.591

Note: †p < 0.10, *p < 0.05, **p < 0.01, ***p < 0.001, one-tailed test for the indirect and total effect, two-tailed test for the direct effect.

6. Discussion

This chapter aims to examine the thesis results in relation to the research questions. First, the research questions will be discussed. Then, the implications for research, practice, and society will be explored. Finally, potential limitations and suggestions for future research will be addressed.

6.1. Discussing Research Questions

The research questions outlined in Chapter 1.2 will be examined in this section, taking into consideration the insights gained from the survey study presented in Chapters 3, 4, and 5.

6.1.1. RQ1: What effect do AI automation and augmentation have on organizational performance?

AI is becoming increasingly vital for organizations seeking a competitive advantage. Organizations are anticipated to improve their financial performance by implementing AI, such as increasing revenue and lowering costs (Alsheibani et al., 2020). However, despite numerous attempts, many still struggle to unlock their potential fully (Fountaine et al., 2019). Understanding how AI generates business value and the expected outcomes remains insufficient. Additionally, uncertainties persist regarding the specific impact of AI on organizational performance, particularly in the context of automation and augmentation.

In this thesis, I have examined the deployment of AI for automating and augmenting business processes in American companies. The survey method provides valuable insight into firms' AI use and their realized business value. Findings have revealed that AI automation and augmentation positively affect organizational performance, leading to more innovation and improvement of existing business models. As a result, businesses that implement AI for automation and augmentation gain a competitive advantage.

In addition, the survey instrument highlights that AI automation and augmentation improve respondents' perception of financial performance, which was measured by indicators such as return on investment (ROI), profits as a percentage of sales, profit growth rate, and market share increase. Also, it positively affects their perception of customer performance, such as customers' perception of the company's quality of products and services, enhanced customer satisfaction, and firm image. Furthermore, the survey demonstrates that automating and augmenting business processes by the utilization of AI leads to better operational performance in the respondents' opinions, including a decrease in product or service delivery cycle time, reduction in production cycle time, the timeline of customer service, reduced operating costs, and provision of better product and service quality. Hence, it is clear that AI automation and augmentation significantly positively affect firms' organizational performance.

6.1.2. RQ2: How are these effects realized, and through what mechanisms do they manifest?

Even though organizations are anticipated to improve their financial performance by implementing AI, such as increasing revenue, growth, and lowering costs (Eriksson, Bigi & Bonera, 2016), it is unclear through which mechanisms this occurs. Prior studies have identified short-term operational trends of AI adoption, such as financial losses caused by large costs incurred by some organizations due to technology adoption (Chakravorty, Dulaney & Franza, 2020). However, how the positive effects are realized and through what mechanisms they occur has not been clear.

This thesis employed a survey-based strategy to investigate the relationships between AI-enabled automation, AI-enabled augmentation, strategic improvement, radical rejuvenation, and competitive performance. The research model proposed that implementing AI for automation and augmentation would positively affect both strategic improvement and radical rejuvenation within a firm, ultimately enhancing competitive performance. Data was collected through a questionnaire-based survey completed by 154 senior IT executives in American companies. The collected data was then analyzed using PLS-SEM analysis. The structural model analysis confirmed the significance of all paths, supporting all proposed hypotheses.

The results obtained from the PLS-SEM analysis demonstrate that deploying AI for automation and augmentation purposes significantly positively influences strategic improvement and radical rejuvenation within organizations. These findings suggest that organizations can enhance their ability to continuously improve existing business models, foster disruptive innovation and adapt to a changing landscape by leveraging automation and augmentation technologies. Additionally, the analysis reveals that the impact of AI automation and augmentation on strategic improvement is equal. However, regarding radical rejuvenation, automation has a more substantial effect than augmentation. This result implies that implementing AI for automation is more significant in facilitating radical rejuvenation within organizations than using AI for augmentation.

The study revealed that strategic improvement and radical rejuvenation positively contribute to competitive performance. However, radical rejuvenation demonstrates a slightly more significant impact. These findings indicate that deploying AI for automation and augmentation can enhance organizations' competitive performance by leveraging the mediating effects of both strategic improvement and radical rejuvenation.

6.2. Research Implications

The IS discipline benefits from two significant contributions from this research. Initially, this research presents the constructs of AI-enabled automation and AI-enabled augmentation in IS research, accompanied by measurement scales for their evaluation. Previously, no validated measures were established for the AI-enabled automation and augmentation constructs. To evaluate a company's competitive performance, this study has introduced these constructs to the IS research and their relevance to the business value of AI discussion. Following the guidelines of MacKenzie et al. (2011) and utilizing the identified principles, AI-enabled automation and AI-enabled augmentation instruments were developed. The measurements for these constructs were created using existing literature on the use of AI for automation and augmentation purposes in organizational settings. The survey study demonstrated the reliability and validity of the constructs. Thus, I have in this study provided calibrated measures that can be utilized by future IS scholars.

Second, I have in this study demonstrated the potential impact of deploying AI for automation and augmentation purposes on organizations. Specifically, I have evaluated how the use of AI for automation and augmentation affects competitive performance, mediated through strategic improvement and radical rejuvenation of an organization. Prior research has focused on using AI for economic purposes and the short-term financial benefits of adopting AI, rather than the long-term performance gains. Also, as far as I know, previous empirical studies have not connected the conceptualization of AI automation and augmentation with performance indicators. Through this research, I have provided empirical evidence that implementing AI for automation and augmentation can lead to significant benefits such as improved strategic improvement, radical rejuvenation, and competitive performance. These findings suggest that utilizing AI for automation and augmentation can be crucial for organizations seeking a competitive advantage as it enhances competitive performance.

6.3. Practical Implications

Organizations are expected to improve, among other things, their financial performance by employing AI in their processes. However, several enterprises investing in AI struggle to realize the anticipated business value (Fountaine et al., 2019). The outcomes of this thesis have significant implications for practical implementation, revealing how the strategic utilization of AI for automation and augmentation extends beyond mere efficiency enhancement in business processes. It also proves to be a catalyst for elevating customer satisfaction, financial performance, and operational efficiency, thereby granting organizations a distinct competitive advantage.

Moreover, the survey instrument developed in this thesis offers a valuable initial framework for organizations aiming to integrate AI for automation and augmentation purposes. This instrument may serve as a guide for organizations employing AI technologies, as it contains essential mechanisms to consider. Organizations can begin their evaluation process by using the items provided to determine which mechanisms are relevant to their specific context. Also, by utilizing this framework, organizations can self-assess their maturity level regarding competitive performance. This assessment may reveal areas where processes and mechanisms must be implemented or improved to reach a satisfactory standard. Furthermore, this research can assist organizations in effectively allocating resources when implementing AI for automation and augmentation. For instance, organizations can allocate their budget, personnel, and technological resources more effectively by understanding the mechanisms and areas of focus outlined in the survey instrument.

6.4. Societal Implications

In addition to practical and research implications, the implications of this thesis offer significant societal implications. In this thesis, I have demonstrated the potential for enterprises that employ AI for automation and augmentation to derive business value and gain a competitive performance. This outcome can encourage businesses to devote time and money to invest in and implement AI since they will realize the benefits, ultimately leading to societal benefits. For instance, by implementing AI for automation, enterprises can create new opportunities and empower employees by automating repetitive tasks. This can foster an environment that encourages continuous learning, contributing to society's human capital.

Furthermore, encouraging organizations to implement AI to augment decision-making can improve their strategic planning, customer satisfaction, and the overall quality of goods and services. Ultimately, it will increase global competitiveness, promoting societal prosperity and economic growth.

Lastly, as mentioned earlier, organizations can contribute to technological advancement and innovation by employing AI technologies, driving progress in the field. This can lead to the developing of more sophisticated AI algorithms, improved systems, and innovative applications with significant societal impacts. For example, AI-powered automation can assist the healthcare industry in diagnosis, treatment planning, and drug discovery, improving patient outcomes (Bajwa, Munir, Nori & Williams, 2021).

6.5. Limitations and Future Research

Like any research, this study has limitations. First, other significant factors might influence competitive performance through the implementation of AI, which was not considered in this research. Also, since AI technologies are still developing, and there is still much to learn about their impact on society, discoveries may arise that change how the technology is applied and utilized.

Second, the survey respondents worked in companies based solely in the United States of America. Compared to other countries, the US is at the forefront of implementing AI in businesses (Stanford, 2023), and companies from diverse countries may respond differently. Therefore, the findings of this research may need to be more generalizable to other countries or regions. Additionally, respondents from a single country may exhibit biases that can influence their responses, impacting the overall validity and reliability of the research. Future research should gather data from multiple countries to obtain more broadly applicable findings.

Third, using single respondents in the survey may lead to bias in the outcomes, which can impact the overall dependability and validity of the research. In an effort to address this, the survey targeted technology managers as the respondents. Nonetheless, there is still a chance of bias. Data should be gathered from multiple respondents within the same companies to overcome this constraint in future research.

Finally, the survey respondents represented diverse industries, including technology, finance, healthcare, and manufacturing. These industries may exhibit differences that can impact the results. For instance, respondents from distinct industries may possess different backgrounds, experiences, and expertise. This heterogeneity can result in variability in responses and interpretations, making comparing and analyzing the data difficult. Additionally, respondents from diverse industries may display other biases that can influence their answers. For example, respondents from the healthcare industry may have varying perceptions and opinions about AI use compared to respondents from the finance industry. The survey should be distributed exclusively within a particular sector to overcome this challenge in future research.

7. Conclusion

In this thesis, the field of AI utilization and organizational performance has been examined. Valuable insights about how AI automation and augmentation affect organizations' performance are provided through the survey-based strategy. In addition, insights into how organizations can attain a competitive advantage by deploying AI for automation and augmentation are presented. Furthermore, this thesis suggests that deploying AI for automation and augmentation will impact competitive performance through the mediating roles of enhanced strategic improvement and radical rejuvenation.

This research employed a survey-based strategy to explore the field of the business value of AI. The maturity of enterprises' use of AI was assessed using a survey-based questionnaire, which provided quantitative data for the analysis. In addition, a research model hypothesizing about the effects of deploying AI for automation and augmentation was created. PLS-SEM was used to analyze survey data from 154 high-level IT executives from American companies. The survey instrument was empirically tested and showed that organizations using AI for process automation and augmentation might see performance gains by enhancing their strategic improvement and radical rejuvenation, ultimately leading to a competitive advantage.

The results of this thesis have significant implications for research, practice, and society. It provides a valuable addition to the existing literature on AI by demonstrating the performance effects of deploying AI for automation and augmentation. Moreover, the study offers calibrated measures for the constructs of AI-enabled automation and AI-enabled augmentation that can be utilized by future IS scholars. The survey instrument developed in this thesis provides a valuable initial framework for organizations aiming to integrate AI for automation and augmentation. It serves as a guide to making them better equipped to deploy AI for these purposes. Furthermore, society can benefit from this research by noticing the positive effects of implementing AI, which enables enterprises to create new opportunities and empower their employees by automating repetitive tasks, fostering a learning-oriented environment that contributes to society's human capital.

Bibliography

Allam, S. (2016). The impact of artificial intelligence on innovation- an exploratory analysis. *International Journal of Creative Research Thoughts (IJCRT)*, *4(4)*.

Alsheibani, S. A., Cheung, Y., Messom, D. C. & Alhosni, M. (2020). Winning ai strategy: Six-steps to create value from artificial intelligence. *Americas Conference on Information Systems (AMCIS) 2020 Proceedings*.

Babina, T., Fedyk, A., He, A. X. & Hodson, J. (2022). Artificial intelligence, firm growth, and product innovation. *Firm Growth, and Industry Concentration*.

Bajwa, J., Munir, U., Nori, A. & Williams, B. (2021). Artificial intelligence in healthcare: transforming the practice of medicine. *Future Healthcare Journal*, *8 (2)*.

Benitez, J., Henseler, J., Castillo, A. & Schuberth, F. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory is research. *Information and Management*, *57 (2)*, 1-16.

Benner, M. & Tushman, M. (2003). Exploitation, exploration, and process management: The productivity dilemma revisited. *The Academy of Management Review*, *28*, 238-256.

Borges, A. F., Laurindo, F. J., Spínola, M. M., Gonçalves, R. F. & Mattos, C. A. (2020). The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. *Americas Conference on Information Systems (AMCIS) 2020 Proceedings*.

Braojos, J., Benitez, J., Llorens, J. & Ruiz, L. (2020). Impact of it integration on the firm's knowledge absorption and desorption. *Information and Management*, *57 (7)*.

Cenfetelli, R. T. & Geneviève, B. (2009). Interpretation of formative measurement in information systems research. *MIS Quarterly*, *33 (4)*, 689-707.

Chakravorty, S. S., Dulaney, R. E. & Franza, R. M. (2020). Erp implementation failures: a case study and analysis. *The TQM Journal*, 795-814.

Chin, W. W. (2010). *How to write up and report pls analyses.* Berlin, Germany: Springer.

Clauss, T., Kraus, S., Kallinger, F. L., Bicanc, P. M., Bremd, A. & Kailer, N. (2020). Organizational ambidexterity and competitive advantage: The role of strategic agility in the exploration-exploitation paradox. *Journal of Innovation & Knowledge*, *6*, 203-213.

Coombs, C., Hislop, D., Taneva, S. K. & Barnard, S. (2020). The strategic impacts of intelligent automation for knowledge and service work: An interdisciplinary review. *The Journal of Strategic Information Systems*, *29(4)*.

Curic, N. (2021). *Amazon announces alexa custom assistant.* Retrieved from https://developer.amazon.com/en-US/blogs/alexa/alexa-auto/2021/01/Amazon-Announces-Alexa-Custom-Assistant

Davenport, T. H. & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*.

Deloitte. (2018). *State of ai in the enterprise,.* Retrieved from https://www2.deloitte.com/content/dam/insights/us/articles/4780_State-of-AI-in-the-enterprise/DI_State-of-AI-in-the-enterprise-2nd-ed.pdf

Deloitte. (2022). *Fueling the ai transformation: Four key actions powering widespread value from ai, right now.* Retrieved from https://www2.deloitte.com/content/dam/Deloitte/us/Documents/deloitte-analytics/us-ai-institute-state-of-ai-fifth-edition.pdf

Diamantopoulos, A. & Siguaw, J. A. (2006). Formative versus reflective indicators in organizational measure development: A comparison and empirical illustration. *British Journal Management*, *17 (4)*, 263-282.

Enholm, I. M., Papagiannidis, E., Mikalef, P. & Krogstie, J. (2021). Artificial intelligence and business value: a literature review. *Information Systems Frontiers*.

Eriksson, T., Bigi, A. & Bonera, M. (2016). Think with me, or think for me? on the future role of artificial intelligence in marketing strategy formulation. *International Journal of Business Information Systems*, 462-476.

Forbes. (2017). *The amazing ways coca cola uses artificial intelligence and big data to drive success.* Retrieved from https://www.forbes.com/sites/bernardmarr/2017/09/18/the-amazing-ways-coca-cola-uses-artificial-intelligence-ai-and-big-data-to-drive-success/

Fountaine, T., McCarthy, B. & Saleh, T. (2019). Building the ai-powered organization. *Harvard Business Review*, 62-73.

Gray, C. (2021). *How google became the world's most popular search engine.* Retrieved from https://technologymagazine.com/digital-transformation/how-google-became-worlds-most-popular-search-engine

Hair, J. F., Hult, G. T. M., Ringle, C. M. & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (pls-sem) second edition.* SAGE Publications.

Hair, J. F., Ringle, C. M. & Sarstedt, M. (2011). Pls-sem: Indeed a silver bullet. *Journal of Marketing Theory and Practice,*, *19(2)*, 139-152.

Hair, J. F., Risher, J. F., Sarstedt, M. & Ringle, C. M. (2019). When to use and how to report the results of pls-sem. *European Business Review*, *31(1)*, 2-24.

Hair, J. F., Sarstedt, M., Ringle, C. M. & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science*, *40 (3)*, 414–433.

Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. W., ... Calantone, R. J. (2014). Common beliefs and reality about pls: Comments on rönkkö and evermann (2013). *Organizational Research Methods*, *17 (2)*, 182-209.

Henseler, J., Hubona, G. & Ray, P. A. (2016). Using pls path modeling in new technology research: updated guidelines. *Industrial Management and Data Systems*, *116 (1)*, 1-23.

IBM. (2021). *Intelligent automation.* Retrieved from https://www.ibm.com/cloud/learn/intelligent-automation

IBM. (2022). *Ibm global ai adoption index 2022.* Retrieved from https://www.ibm.com/downloads/cas/GVAGA3JP

Jain, H., Padmanabhan, B., Pavlou, P. A. & Raghu, T. S. (2021). Editorial for the special section on humans, algorithms, and augmented intelligence: The future of work, organizations, and society. *Information Systems Research*, *32 (3)*.

Johnson, P. C., Laurell, C., Ots, M. & Sandström, C. (2022). Digital innovation and the effects of artificial intelligence on firms' research and development – automation or augmentation, exploration or exploitation? *Technological Forecasting and Social Change*, *179*.

Kock, N. & Lynn, G. S. (2012). Lateral collinearity and misleading results in variance-based sem: An illustration and recommendations. *Journal of The Association for Information Systems*, *13(7)*.

Lichentaler, U. (2019). An intelligence-based view of firm performance: Profiting from artificial intelligence. *Journal of Innovation Management*, *7*, 7-20.

Lubatkin, M., Simsek, Z., Ling, Y. & Veiga, J. (2006, 01). Ambidexterity and performance in small- to medium-sized firms: The pivotal role of tmt behavioral integration. *Journal of Management*, *32*, 1-17.

MacKenzie, S. B., Podsakoff, P. M. & Podsakoff, N. P. (2011). Construct measurement and validation procedures in mis and behavioral research: Integrating new and existing techniques. *MIS Quarterly*.

March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science*, *2(1)*, 71-87.

Martens, B. & Tolan, S. (2018). Will this time be different? a review of the literature on the impact of artificial intelligence on employment, incomes and growth. *JRC Digital Economy Working Paper*.

McKinsey&Company. (2019). *Driving impact at scale from automation and ai.* Retrieved from https://www.mckinsey.com/~/media/McKinsey/Business%20Functions/McKinsey%20Digital/Our%20Insights/Driving%20impact%20at%20scale%20from%20automation%20and%20AI/Driving-impact-at-scale-from-automation-and-AI.ashx

McKinsey&Company. (2022a). *Ai-driven operations forecasting in data-light environments.* Retrieved from https://www.mckinsey.com/capabilities/operations/our-insights/ai-driven-operations-forecasting-in-data-light-environments

McKinsey&Company. (2022b). *The state of ai in 2022—and a half decade in review.* Retrieved from https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2022-and-a-half-decade-in-review

McKinsey&Company. (2023). *Artificial intelligence in strategy.* Retrieved from https://www.mckinsey.com/capabilities/strategy-and-corporate-finance/our-insights/artificial-intelligence-in-strategy

Microsoft. (2022). *What is sentiment analysis?* Retrieved from https://dynamics.microsoft.com/en-us/ai/customer-insights/what-is-sentiment-analysis/

Mikalef, P., Conboy, K. & Krogstie, J. (2021). Artificial intelligence as an enabler of b2b marketing: A dynamic capabilities micro-foundations approach. *Industrial Marketing Management*, *98*, 80-92.

Mikalef, P. & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information Management*, *58*.

Mikalef, P., Lemmer, K., Schaefer, C., Ylinen, M., Fjørtoft, S. O., Torvatn, H. Y., ... Niehaves, B. (2023). Examining how ai capabilities can foster organizational performance in public organizations. *Government Information Quarterly*, *40(2)*.

Mishra, A. N. & Pani, A. K. (2020). Business value appropriation roadmap for artificial intelligence. *VINE Journal of Information and Knowledge Management Systems*.

Mithas, S., Ramasubbu, N. & Sambamurthy, V. (2011). How information management capability influences firm performance. *MIS Quarterly*, *35(1)*, 237-256.

Montes, F., Benitez-Amado, J., Castillo, A. & Braojos, J. (2018). It-enabled knowledge ambidexterity and innovation performance in small us firms: The moderator role of social media capability. *Information Management*, *55*, 131-143.

Mousavizadeh, A., Mehta, B. & Darrah, K. (2021). *Ai boom time.* Retrieved from https://www.tortoisemedia.com/2021/12/02/ai-boom-time/

Murray, A., Rhymer, J. & Sirmon, D. (2021). Humans and technology: Forms of conjoined agency in organizations. *Academy of Management Review*, *46(3)*, 552-571.

Nawaz, H., Al, T., Al-Laith, A., Ahmad, I., Tharanidharan, S. & Nazar, S. (2019). Sentimental analysis of social media to find out customer opinion. *International Conference on Intelligent Technologies and Applications*, 110-115.

Netflix. (2022). *Recommendations.* Retrieved from https://research.netflix.com/research-area/recommendations/

Nuruzzaman, M. & Hussain, O. K. (2018). A survey on chatbot implementation in customer service industry through deep neural networks. *IEEE 15th International Conference on e-Business Engineering (ICEBE).*

Oates, B. J. (2006). *Researching information systems and computing.* SAGE Publications.

O'Cass, A., Heirati, N. & Ngo, L. V. (2014). Achieving new product success via the synchronization of exploration and exploitation across multiple levels and functional areas. *Industrial Marketing Management*, *43(5)*, 862-872.

Perez, J. (2023). *How automation drives business growth and efficiency.* Retrieved from https://hbr.org/sponsored/2023/04/how-automation-drives-business-growth-and-efficiency

Rai, A. & Tang, X. (2010). Leveraging it capabilities and competitive process capabilities for the management of interorganizational relationship portfolios. *Information Systems Research*, *3*, 516-542.

Rueda, L., Benitez, J. & Braojos, J. (2017). From traditional education technologies to student satisfaction in management education: A theory of the role of social media applications. *Information and Management*, *54(8)*, 1059-1071.

Rönkkö, M. & Ylitalo, Y. (2011). Pls marker variable approach to diagnosing and controlling for method variance. *Proceedings of the 32nd International Conference on Information Systems*, 1-16.

Sarstedt, M., Ringle, C. M. & Hair, J. F. (2017). Partial least squares structural equation modeling. *Handbook of Market Research*, 1-40.

Schmidt, R., Zimmermann, A., Moehring, M. & Keller, B. (2020). Value creation in connectionist artificial intelligence - a research agenda. *International Journal of Information Management*.

Schroeder, R., Linderman, K., Liedtke, C. & Choo, A. (2008, 07). Six sigma: Definition and underlying theory. *Journal of Operations Management - J OPER MANAG*, *26*, 536-554.

Seepana, C., Paulraj, A. & Smart, P. (2022). Relational resources for innovation ambidexterity within coopetitive relationships: the contingent role of managerial ambidexterity. *International Journal of Operations & Production Management*, *42*.

Spotify. (2022). *About recommendations.* Retrieved from https://about-recommendations.spotify.com/

Stanford, U. (2023). *The ai index report: Measuring trends in artificial intelligence.* Retrieved from https://aiindex.stanford.edu/report/#individual-chapters

Sun, Y., Yu, H. & Wang, H. (2022). Impact of value co-creation in the artificial intelligence innovation ecosystem on competitive advantage and innovation intelligibility. *Systems Research and Behavioral Science*, *39*, 474-488.

Tiwana, A. & Konsynski, B. (2010). Complementarities between organizational it architecture and governance structure. *Information Systems Research*, *21 (2)*, 288-304.

Wamba-Taguimdje, S.-L., Fosso Wamba, S., Jean Robert, K. K. & Tchatchouang, C. E. (2020). Influence of artificial intelligence (ai) on firm performance: The business value of ai-based transformation projects. *Business Process Management Journal*.

Wang, P. (2019). On defining artificial intelligence. *Journal of Artificial General Intelligence*, *10(2)*, 1-37.

Wu, S. P.-J., Straub, D. W. & Liang, T.-P. (2015). How information technology governance mechanisms and strategic alignment influence organizational performance: Insights from a matched survey of business and it managers. *MIS Quarterly*, *39(2)*, 497-518.

Zhu, Y.-Q., Corbett, J. & Chiu, Y.-T. (2021). Understanding employees' responses to artificial intelligence. *Organizational Dynamics*, *50*.

Appendices

A. Performance Measures

Strategic Improvement (Lubatkin et al., 2006)

Assess your firm's orientation during the last year (from 1 - strongly disagree to 7 - strongly agree).

- SI1: Our firm regularly uses client feedback to improve operations.
- SI2: Our firm looks for an ongoing improvement of our existing processes.
- SI3: Our firm looks for a continuous incremental improvement of products/services.
- SI4: Our firm frequently fine-tunes what it offers to keep its current customers satisfied.
- SI5: Our firm penetrates more deeply into its existing customer base.

Radical Rejuvenation (Lubatkin et al., 2006)

Assess your firm's orientation during the last year (from 1 - strongly disagree to 7 - strongly agree).

- RJ1: Our firm looks for a novel mindset and new skills to shape the future.
- RJ2: Our firm looks for exploring breakthrough opportunities.
- RJ33: Our firm looks for radically reinventing the organization processes.
- RJ4: Our firm looks for creating radically new products/services that have not existed on the market before.
- RJ5: Our firm looks for creative ways to satisfy its customers' needs.
- RJ6: Our firm aggressively ventures into new market segments.

Organizational Performance (Mithas et al., 2011; Wu et al., 2015)

Compared with your key competitors, please indicate how much you agree or disagree (from 1 strongly disagree, to 7 strongly agree) with the following statements regarding the degree to which you perform better than them on

Financial Performance (Mikalef et al., 2021):

- FP1: return on investment (ROI).
- FP2: profits as percentage of sales.
- FP3: profit growth rates.
- FP4: increasing our market share.

Customer Performance (Mikalef et al., 2021):

- CP1: customers perception of our company's quality of products and services.
- CP2: increasing customer satisfaction.
- CP3: firm image.

Operational performance (Mikalef et al., 2021):

- OP1: decreasing product or service delivery cycle time.
- OP2: decreasing production cycle time.
- OP3: timeline of customer service.
- OP4: reducing operating costs.
- OP5: providing better product and service quality.

B. Unmodified Measurement Model

Table B.1.: Unmodified Measurement Model

Construct	Measure
AI-enabled AUGMENTation	1. The use of AI has enabled us to integrate human and machine work to identify complex patters and end up with creative solutions
AI-enabled AUTOMation	2. The use of AI has enabled us to automate back office administrative tasks
AI-enabled AUGMENTation	3. The use of AI has enabled us to augment humans and machines strengths and compensate for weaknesses
AI-enabled AUGMENTation	4. In our organizations workers make decisions based on recomendations from AI technologies
AI-enabled AUGMENTation	5. The use of AI has enabled us to collaborate with machines to do things that neither (i.e., machines nor humans) could do well on their own
AI-enabled AUTOMation	6. The use of AI has allowed us to automate financial activities
AI-enabled AUGMENTation	7. The use of AI has enabled us to detect patterns in large amount of data, helping workers to better address actions
AI-enabled AUTOMation	8. The use of AI has optimized our information systems itself (e.g., optimizing processes, machine learning)
AI-enabled AUGMENTation	9. The use of AI has enabled us to identify customer preferences supporting workers to give better customer solutions
AI-enabled AUTOMation	10. The use of AI has helped us automate complex human processes of our employees
AI-enabled AUTOMation	11. The use of AI has helped us automate structured tasks (e.g., transferring of data, updating records)
AI-enabled AUGMENTation	12. The use of AI has enabled us to see the big-picture when making decisions
AI-enabled AUGMENTation	13. In our organization workers can determine whether to select the recommendations given by the AI technologies
AI-enabled AUGMENTation	14. In our organization workers are skilled in programming and designing conditions under which AI will be applied
AI-enabled AUGMENTation	15. The use of AI has enabled us to start from a given hypothesis assisting workers to analyze its feasibility
AI-enabled AUGMENTation	16. The use of AI has enabled us to augmentate front office tasks
AI-enabled AUGMENTation	17. The use of AI has enabled us to support workers in decision-making
AI-enabled AUGMENTation	18. In our organization, workers monitor and modify AI functioning and outputs when it diverges from their expectations

*Table continues on the next page

Table B.1.: (continued)

AI-enabled AUTOMation	19. The use of AI has enabled us to free up employees in tasks that are now automated
AI-enabled AUGMENTation	20. The use of AI has enabled us to combine human and machine knowledge
AI-enabled AUTOMation	21. The use of AI has helped us to identify customer preferences and give personalized service without human intervention
AI-enabled AUTOMation	22. In our organization AI continuously learn how to optimize analyses and autonomously make choices of what to do
AI-enabled AUTOMation	23. In our organization AI independently seeks data, formulates recommendations and ultimately executes them
AI-enabled AUGMENTation	24. The use of AI provides workers with recommendations for what to do
AI-enabled AUGMENTation	25. In our organizations workers sinthesize and give a commonsense to AI insights
AI-enabled AUGMENTation	26. The use of AI has enabled computers and humans work together to enhance one another
AI-enabled AUGMENTation	27. The use of AI has enabled us to combine computers and humans intelligence to develop superior systems

C. Inter-Construct Correlations

Table C.1.: Correlation Matrix

Construct	1	2	3	4	5	6	7	8
1. AI-enabled Automation	1,000							
2. AI-enabled Augmentation	0,816	1,000						
3. Strategic Improvement	0,738	0,738	1,000					
4. Radical Rejuvenation	0,745	0,727	0,807	1,000				
5. Competitive Performance	0,676	0,669	0,773	0,780	1,000			
6. Industry	0,224	0,244	0,197	0,202	0,248	1,000		
7. Firm Size	-0,270	-0,343	-0,211	-0,222	-0,265	-0,297	1,000	
8. IT Investment	0,572	0,612	0,521	0,517	0,424	0,243	-0,316	1,000

NTNU

Norwegian University of
Science and Technology