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Drivers and Barriers to AI tool adoption in Technical vs. Non-Technical Departments

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Sammanfattning:

Examensarbete Titel: Drivkrafter och Barriärer för AI-Verktygs Adoption i Tekniska Kontra Icke-Tekniska Avdelningar

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Ämne/Kurs: FEKH38, Examensarbete i Business and Data Analytics, 15 ECTS

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Nyckelord: UTAUT, PLS-SEM, AI verktyg, Prestationsförväntan, Underlättande förhållande

Forskningsfråga: Vilka är de olika drivkrafterna och hindren som påverkar individuell användning av AI-verktyg, och hur skiljer sig dessa mellan individer som arbetar i tekniska respektive icke-tekniska avdelningar?

Syftet: Studien syftar till att undersöka de faktorer som hindrar eller driver användningen av AI inom tekniska och icke-tekniska organisationer.

Metod: Data samlades in från 95 individer som arbetar inom studiepopulationen via en enkät. Enkäten var utformade för att mäta variabler som *Prestationsförväntanan*, *Ansträngningsförväntan*, *Socialt Inflytande* och *Underlättande förhållanden*. Den insamlade datan analyserades med en PLS-SEM-modell.

Teoretiska perspektiv: Studien utgick från UTAUT (Unified Theory of Acceptance and Use of Technology) och *Ecological Framework of Management Decision-Making.*

Resultat: *Prestationsförväntan* och *Underlättande Förhållande* har en statistiskt signifikant effekt på ökande *Användning* hos individer. Effekten av *Prestationsförväntan* på *Faktisk Användning* är statistiskt signifikant starkare för individer på tekniska avdelningar jämfört med icke-tekniska avdelningar.

Slutsats: *Prestationförväntan* och *Underlättande förhållande* uppvisade en statistiskt signifikant positiv påverkan på *Faktisk Användning*. Vidare var påverkan av *Prestationförväntan* på *Faktisk Användning* statistiskt signifikant starkare för individer som arbetar på tekniska avdelningar än icke-tekniska avdelningar.

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Abstract:

Thesis Title: Drivers and Barriers to AI tool adoption in Technical vs. Non-Technical Departments

Seminar Date: 16/1 - 2025

Subject/Course: FEKH38, Thesis in Business and Data Analytics, 15 ECTS

Authors: David Möttus, Timothy Stjernfeldt, Attila Kasza

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Key Words: UTAUT, PLS-SEM, AI tools, Performance Expectancy, Facilitating Conditions

Research question: What are the different drivers and barriers that impact the individual adoption of AI tools and how do these differ between individuals who work in technical and non-technical organizational departments?

Purpose: The research aims to explore the factors which hinder or drive AI tool adoption across technical and non technical organizations.

Method: Data was collected from 95 individuals working across the study population via a survey study. The survey was designed to measure variables such as *Performance Expectancy, Effort Expectancy, Social Influence* and *Facilitating Conditions*. The collected data was analyzed with a PLS-SEM model.

Theoretical perspectives: The study was based on a modified theoretical framework based on the UTAUT model with elements from the *Ecological Framework of Management Decision-Making.*

Result: *Performance Expectancy* and *Facilitating Conditions* have a statistically significant effect in increasing *Use Behaviour* among individuals. The effect of *Performance Expectancy* on *Use Behaviour* is statistically significantly stronger for individuals in technical departments compared to non technical.

Conclusion: The predictors *Performance Expectancy* and *Facilitating Conditions*, in the UTAUT model, have a statistically significant positive impact on *Use Behaviour*. The effects of *Performance Expectancy* on *Use Behaviour* is statistically significantly stronger for individuals working in technical departments.

Word Count: 19340

Preface:

We would like to express our sincere gratitude towards all of the respondents who partook in the study, all of the contact people who distributed the survey, as well as the respective organizations which allowed for the respondents' participation. We would also like to thank our supervisor, Niklas Lars Hallberg, for providing us with valuable input, feedback, and guidance.

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1. Introduction

1.1 Background

Artificial Intelligence (AI) has evolved from niche technology to a widely accessible tool that enables productivity gains for individuals and organizations. AI Adoption rates on an organizational level have surged, with 37% of organizations using AI, a 270% increase in four years (Singh, 2019). Investment in generative AI is expected to double within a year (KPMG, 2023). The expectations surrounding AI are high, with some sources likening data and data analysis tools to "the new oil" due to the way that it can facilitate organizational growth through the support of different organizational functions (Sun et al. 2018). The utilization of AI is expected to largely improve efficiency within organizations and will likely be a key source of future competitive advantage.In fact, 80% of the respondents to a survey carried out by KPMG answered that they believe that generative AI will disrupt their entire industry (KPMG, 2023).

AI is reshaping modern organizations by enhancing decision-making and streamlining tasks. AI offers unprecedented opportunities to improve efficiency by enabling, among others, autonomous analytics, which allows for the creation of models that learn and evolve from data with minimal human intervention (Gressel et al. 2021, pp. 50-51). AI has the power to identify causal relationships in complex data sets, simplifying big data analysis. This technology empowers organizations to adopt data-driven decision-making more effectively (Gressel et al. 2021, pp. 49-54). Successfully adopting AI is therefore of significant importance for organizations.

The adoption of AI not only provides efficiency gains due to the impacts it can have when adopted on an organizational level, but can also increase the efficiency and productivity of individual professionals. The development of AI powered tools enables individuals to increase their efficiency in their daily tasks. The existence of a plethora of different types of AI including *Natural Language Processing (NLP), Generative AI, Large Language Models (LLM),* and more, implies that there is an AI tool suitable for almost every type of professional task (Franck, 2024). Generative AI tools such as ChatGPT, GitHub Copilot, and Gemini, aid in tasks from producing texts to writing code and creating CAD models (OpenAI, 2025; GitHub, 2023; Google Deepmind, 2024; ZOO, 2024). The adoption of

AI tools, on an individual level, is therefore not limited to functions such as programming, automatisation, and data analysis, but can be valuable throughout the entire organization (Bell, 2024).

Despite the potential benefits in efficiency offered by the implementation of AI and AI tools, the adoption of these new technologies is far from straightforward. The adoption of AI and AI tools faces barriers on both the organizational and individual level. Challenges such as bridging the skill gap and ensuring technological readiness, are identified as some of the most prominent barriers hindering organizational AI adoption (Gressel et al. 2021, p. 173). One study showed that individual level challenges include fears about job displacement, ethical concerns, and lack of transparency can impact the adoption of AI and AI tools (Kelley, 2022). The study also highlighted that employee training and support from management significantly impacts AI adoption as employees are more likely to adopt ethical AI practices when leadership visibly advocates for them (Kelley, 2022).

One significant concern that many organizations have regarding AI tools, such as ChatGPT, relates to data security. Several companies such as Apple, Spotify, and JPMorgan have limited their employees' access to ChatGPT and GitHub Copilot, citing fears of leaked confidential data (Mok, 2024). In order to combat the concerns regarding data security, while still offering professionals the benefits provided by AI tools, several AI tool providers have launched enterprise AI tools. Some enterprise solutions include Microsoft Copilot, Slack AI, and even an enterprise version of ChatGPT (Spataro, 2023; Slack, 2024; OpenAI, 2025b). These enterprise solutions have been largely successful with over 50% of Fortune 500 companies using Azure OpenAI, an enterprise solution provided by Microsoft (Ramel, 2024).

Although it is evident that there are enterprise AI tools, which mitigate organizations' fears about data security while still enabling individuals to gain access to AI tools, it is apparent that the individuals adoption of AI often is dependent on the organizations AI policy as well as the access to enterprise solutions. It should be noted that investing in an enterprise solution is not a guarantee for individual adoption as the employees still need to choose to use the technology. Organizations that want to utilize AI tools therefore need to provide both the appropriate technologies as well as facilitating what is necessary to drive their employees to choose to use the AI tools (Leonardi, 2023).

1.2 Problematization

AI tool adoption varies significantly across industries as well as organizational departments within the same organization. This variation is built up by a complex interplay of factors, including organizational culture, leadership dynamics, and individual attitudes toward new technologies (Gressel et al. 2021, pp. 165-181). Understanding the drivers and barriers of AI adoption is crucial for organizations that want to utilize AI tools. The factors which influence AI adoption are increasingly shaped by what the *Ecological Framework of Management Decision-Making* describes as an ecological system, wherein AI adoption is driven not only by external forces, such as technological advancements and industry norms (the macrosystem), but also by internal dynamics at the organizational and individual levels (the microsystem) (Gressel et al. 2021, pp. 165-181).

As AI tools are a new technological advancement, research regarding AI tool adoption is limited. Of the research that has been completed most of these take a macro-perspective and focus on organizational level barriers to AI adoption. One study regarding AI adoption provides a top down framework-based checklist for digital leaders (Tursunbayeva & Gal, 2024). Although this research takes the employees into consideration, it treats them as a homogeneous group. Assuming that employees are a homogeneous group with insignificant differences may lead to overgeneralized results which limit the practical applicability of the study for organizations when attempting to increase AI tool adoption in specific departments. The limited use of a micro-perspective when examining the adoption of AI tools is therefore identified as a knowledge gap.

Although the use of a micro-perspective is limited in research concerning the adoption of AI tools, this is not the case for research regarding the adoption of other technologies. One study which utilized a micro-perspective researched the individual adoption of digitalization among business owners/ managers in the context of European SMEs (Kwarteng et al. 2023). Another study which utilized a micro-perspective was a bachelor's thesis completed at LUSEM, which evaluated the drivers which impact accountants' use of big data systems (Thunberg, Svensson & Yngwe, 2022). Both of these studies utilized the Unified Theory of Acceptance and Use of Technology (UTAUT) in order to observe individuals’ drivers and barriers to the acceptance/ adoption of new technologies (Venkatesh et al. 2003).

The Theory of Acceptance and Use of Technology (UTAUT) highlights key challenges for the adoption of new technology (Venkatesh et al. 2003). This model utilizes four “predictor” nodes which are believed to influence an individuals adoption of new technologies. These predictor nodes include *Performance Expectancy, Effort Expectancy, Social Influence,* and *Facilitating Conditions* (Venkatesh et al. 2003). This theory explains that the belief that AI will improve their job performance is critical to the individual adoption of AI. How easy the AI-tool is to use may also affect the individual’s willingness to adopt the technology. If the individual finds the technology complex, due to steep learning curves or a lack of training, they may be less willing to use AI in their daily tasks. Support from the organization can significantly impact individual attitudes towards AI tools. With a lack of social encouragement or a culture resistant to technological change/ innovation barriers to adoption can arise. Furthermore, the access to technical infrastructure, expertise, and clear organizational policies, further influence AI tool adoption. Employees are more likely to embrace AI tools when they feel supported by robust IT systems, have access to skilled professionals, and work within a framework of clear guidelines for using AI responsibly (Venkatesh et al. 2003).

The predictors presented within the UTAUT-model can be hypothesized to contrast the assumption of homogeneity among different groups of employees within an organization. *Social Influence* predicts that employees which work in departments that have cultures of innovation are more likely to adopt new technologies. One study identified three types of innovation, product innovation, process innovation, and organizational innovation (Boer et al. 2001). Product innovation is most common within technical departments such as R&D while process innovation can be found throughout large parts of the organization. Organizational innovation is, in contrast to product innovation, most common in non-technical departments (Boer et al. 2001). Although the majority of departments within an organization have the potential of being innovative, the types of innovation differ between technical and non-technical departments. This difference in innovation can, according to the UTAUT-model, impact the culture of innovation in the different departments and thus the departmental adoption of AI tools.

It is also likely that *Facilitating Conditions* may differ between organizational departments. The UTAUT-model predicts that individuals who believe that they are supported during the adoption process are more likely to adopt new technologies. This implies that if an individual works in a department which has greater technical skills, they are more likely to feel supported, and thus adopt the new technology. As technological experience, and thus technical skills, are highest in technical departments such as R&D, Information Technology, and Data Science it is not unreasonable to expect a greater adoption in these technical departments (Farley, 2019).

The UTAUT-model also includes four moderating nodes, *Gender, Age, Experience,* and *Voluntariness of Use,* which are expected to influence the adoption of new technologies (Venkatesh et al. 2003). As mentioned above, technological experience is expected to be highest in technical departments such as R&D, Information Technology, and Data Science, which should influence the relative AI tool adoption. The demographic differences between technical and non-technical departments are also believed to impact their respective AI tool adoption. The moderating node *Age* implies that younger individuals are more likely to adopt new technologies (Venkatesh et al. 2003). *Age* is a demographic measurement which largely differs between technical and non-technical departments. The average age of an engineer in the US in 2021 was 40 with 48% of engineers being older than 40 (Zippia, 2021). The average age of a marketer in the US in 2021 was 36 with only 35% of marketers over the age of 40 (Zippia, 2021b). The difference in age between technical and non-technical departments should, according to the UTAUT-model, imply that individuals working in non-technical departments are more likely to adopt new technologies.

Gender is another moderating node which is expected to impact the adoption of new technologies. This demographic measurement largely differs between technical and non-technical departments. The gender gap in STEM fields is large with only 28% of the workforce being made up of women (Piloto, 2023). The gender gap in non-technological departments is much smaller. In 2023 women made up 51.8% of the consumer service field and 42.4% of the financial service field (World Economic Forum, 2023). The large demographic differences, with regard to gender, between technical and non-technical departments should, according to the UTAUT-model, lead to higher AI tool adoption rates in the technical departments.

While previous research on individual adoption of new technologies is well-established, research exploring the adoption of AI tools with a micro-perspective is significantly limited. Based on previous research and the commonly used UTAUT-model, it seems likely that the drivers and barriers to AI tool adoption will differ between different types of organizational departments. This study therefore seeks to fill the gap in the existing research and examine the differences with regards to AI tool adoption between departments with technical contra non-technical characteristics, while utilizing a micro-perspective.

1.3 Objectives

This study seeks to explore drivers/ barriers towards individual adoption of AI tools in technical and non-technical departments. The purpose of this is to better understand why the adoption levels, with regards to AI, might differ between departments with different technical characteristics. This understanding will provide insights to organizations regarding what they need to facilitate in order for AI tools to be implemented across departments with varying technical characteristics.

1.4 Research Question

In order to examine the described problem the study aims to resolve the following research question:
What are the drivers and barriers that impact the individual adoption of AI tools and how do these differ between individuals who work in technical and non-technical departments?

1.5 Study boundaries

In order to answer the research question, different organizational departments need to be able to be categorized as either technical or non technical. This study chooses to define technical departments as those which require higher education within STEM and or Information Technologies as a prerequisite. All of the departments which do not fit into this description are classified as non-technical departments. Although this definition can be discussed as some non-technical departments can, in some cases, be seen as technical it was decided that the definition is sufficient for the objective and scope of the study.

2. Theory

2.1 Ecological Framework of Management Decision-Making

Bronfenbrenner's model ecological systems was originally developed to understand human development within different environments, which later on has been applied to analyze decision-making processes within organizations (Bronfenbrenner, 1979). The ecological model explains that decision-making is influenced by several interconnected layers, from broader societal influences, all the way to individual characteristics (Gressel et al. 2021, pp. 165-181). These layers, the macrosystem, exosystem, mesosystem, microsystem, and individual level, interact and shape the extent of an organization's data-driven decision making. This study assumes that the more data-driven an organization's decision making is, the more likely to adopt AI tools they will be. To understand the adoption of AI tools in different types of organizational departments it is therefore of interest to consider the environmental factors influencing the potential adoption. The *Ecological Framework of Management Decision-Making* is, therefore, valuable for the study's theoretical framework as it describes several factors which are thought to impact the adoption of technologies, such as AI tools. These factors include personnel subsystems, technical subsystems and the structure of the organization (Gressel et al. 2021, pp. 165-181).

2.1.1 The Different Layers of Decision-Making

1. Macrosystem (Societal Level)
2. Exosystem (Industry and Academia Level)
3. Mesosystem (Organizational Level)
4. Microsystem (Team Level)
5. Individual Level

In Bronfenbrenner's ecological framework the macrosystem represents large-scale influences such as political, economic, and technological systems (Gressel et al. 2021, pp. 165-181). These forces define the conditions in which organizations operate, and can impact the level of data-driven decision making in organizations. The exosystem, on the other hand, focuses on indirect environmental factors such as industry standards, academic research, and collaborations between organizations and external institutions. These elements provide insights regarding the factors that influence managerial decision-making processes, often serving as a bridge between broad societal trends and the organizational environment (Gressel et al. 2021, pp. 165-181).

Within the organization itself, the mesosystem plays a great influence on technology adoption by encompassing internal structures, culture, and processes. Factors such as organizational strategy, openness to innovation, and interdepartmental collaboration create the context for managerial decision making (Gressel et al. 2021, pp. 165-181). The microsystem operates at the team level, emphasizing the impact of leadership styles, team dynamics, and resource availability. Finally, at the core of the model is the individual manager, whose knowledge, attitudes, and decision-making styles directly influence how decisions are made and implemented. Moreover, individual-level traits, such as a manager's openness to innovation, can amplify or act as a barrier on the effects of organizational culture.

By integrating these five levels of decision-making, the model offers a comprehensive perspective on data-driven decision-making. It highlights the dynamic interplay between external pressures, organizational contexts, and individual capabilities, demonstrating how the extent of which an organization's decision-making is data-driven is not an isolated event, but rather the outcome of continuous interaction across ecological layers.

2.1.2 The Mesosystem, Microsystem, and Individual Level

The interplay between the mesosystem, microsystem, and the individual level has a great influence on the success of the adoption of AI tools. The mesosystem, which describes the interplay between different microsystems, is largely influential when an organization aims to increase their level of data-driven decision-making. The mesosystem largely impacts the company culture and can therefore significantly impact the adoption of data-driven decision-making. A report by Erik Brynfjofsson and Andrew McAfee shows that fostering a culture of innovation and collaboration is critical to the successful adoption and integration of data-driven decision-making (Brynjolfsson & McAfee, 2017).

The microsystem, which focuses on the interactions between individuals and their environments, is also crucial in fostering a culture of innovation. According to the model the microsystem influences the higher hierarchies in the organization by challenging the processes. The dynamics within the team contributes to decisions not being created in isolation by leadership but instead implemented by the interplay between the two systems. At an individual level, like in the microsystem, employees provide insights that challenge the managers' perspectives. The individual level of decision-making is crucial for the adoption of new technologies. It can be summarized that the success of organizations' technology adoption is dependent on the levels of interconnection between leadership, teams, and individuals (Gressel et al. 2021, pp. 165-181).

Furthermore, one of the strengths of the framework is its ability to explain the interplay between the different levels. For example, societal regulations (macrosystem) often cause changes in organizational strategy (mesosystem), which in turn influence team-level operations (microsystem). A study by Rai et al. (2019) on digital platforms illustrates how macro-level pressures for transparency and accountability trickle down throughout the organizations, influencing internal workflows and decision-making. A key takeaway from the study is the emphasis on effective design and governance for achieving AI's full potential. Rai et al. highlights challenges in platform governance, ethical considerations in AI deployment, and the need for a balance between human judgment and AI-driven insights. The findings of Rai et al. (2019) align with the *Ecological Framework of Management Decision-Making*, particularly in highlighting the interaction between external macro-level forces (societal and industry trends) and internal organizational dynamics. This demonstrates how these different systems influence each other. Macrosystem affects the exosystem which in turn impacts the mesosystem. By understanding the interplay between the ecological systems the study can navigate and understand challenges and opportunities AI presents for companies.

2.2 UTAUT-model

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a theoretical model developed by Venkatesh et al. (2003) to explain and predict user acceptance and use of technology. It consolidates various existing models of technology acceptance, such as the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB), and has been widely applied in organizational and individual technology adoption studies. There is a lot of previous research regarding the applicability and usefulness of the UTAUT model when studying technology acceptance. The vast majority of these studies show results which indicate that the UTAUT model is the best model as it explains more variance than previous models, such as the TAM model (Cabrera-Sánchez & Villarejo-Ramos, 2020).

The UTAUT model has been applied in a wide range of contexts, including business, healthcare, education, and public administration, to understand and explain user adoption and acceptance of new technologies. It is particularly useful for analyzing the success or failure of technology implementations in organizational settings, where multiple factors interact to influence user behaviour (Taiwo et al. 2013).

The UTAUT model, as can be seen in figure 1, identifies four primary predictors that influence an individual's intention to use technology, and their usage behaviour. These predictors are in turn influenced by the moderating nodes.

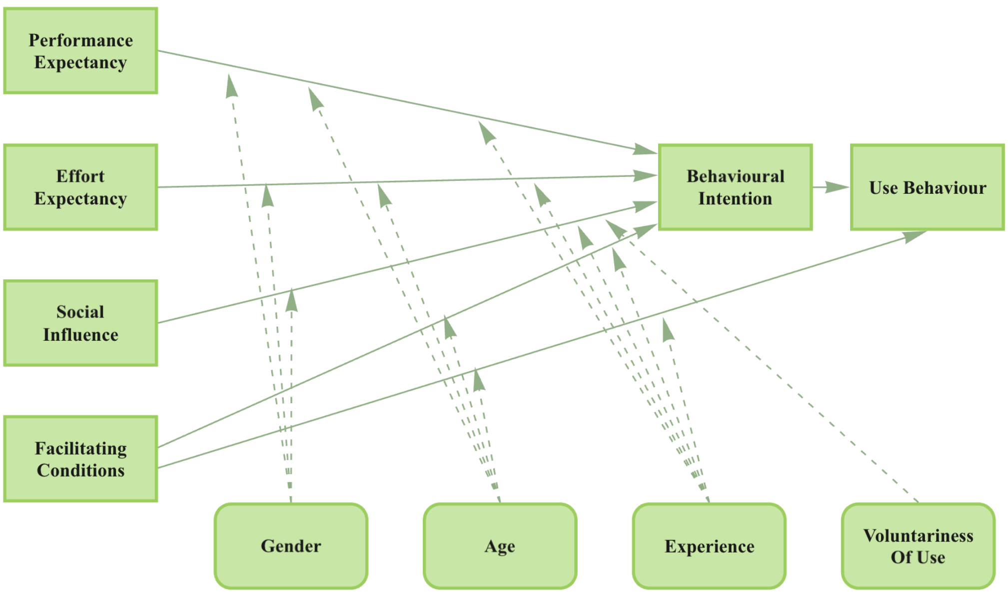

Figure 1. The UTAUT-model.

2.2.1 UTAUT Predictors

The UTAUT model includes four predictor variables. These predictors directly influence the behavioural intention to use the new technology, which in turn influences the use/ adoption of the technology (Venkatesh et al. 2003).

2.2.1.1 Performance expectancy

This predictor refers to the degree to which an individual believes that using a particular technology will improve their job performance or help them achieve their goals more efficiently. This predictor implies that employees are more inclined to adopt new technologies when they believe that these technologies will lead to performance gains such as an increase in productivity and efficiency. This indicates that individuals will be more likely to adopt the technology if they believe it has a direct application to their work and daily tasks (Davis, 1989; Venkatesh et al. 2003).

2.2.1.2 Effort expectancy

This predictor reflects the perceived ease of use of the technology. If users believe a technology is easy to learn and operate, they are more likely to adopt it (Venkatesh et al. 2003). Ensuring that the selected technology has an intuitive design with user-friendly interfaces and seamless integration with existing systems lowers the barrier to adoption. Tools that require minimal training and align with current workflows are more readily embraced by employees. If technologies are perceived as overly complex or difficult to use, employees may resist adoption (Venkatesh et al. 2003).

2.2.1.3 Social influence

This predictor relates to the extent to which an individual perceives that others, such as colleagues, supervisors, or friends, think they should use the technology. It captures the role of social norms and peer pressure in influencing technology adoption. This can play a significant role in departments where leadership strongly advocates for the use of AI tools (Venkatesh et al. 2003). Active promotion and endorsement of AI initiatives by organizational leaders significantly influence employee adoption. Leaders who demonstrate commitment to AI integration set a positive example and motivate their teams. A study by Du and Lv (2024) found that social influence, including leadership advocacy, plays a crucial role in shaping behavioural intentions toward AI use. Observing colleagues successfully using AI tools can encourage others to follow suit. Peer support and shared experiences facilitate a culture of learning and experimentation with AI technologies. An organizational culture that values innovation and continuous improvement supports AI adoption (Gressel et al. 2021, pp. 188-190).

2.2.1.4 Facilitating conditions

Facilitating conditions refers to the degree to which an individual believes that the organizational and technical infrastructure exist to support the use of the technology. This includes access to resources, compatibility with other systems, and the availability of training and support (Venkatesh et al. 2003).

2.2.2 UTAUT Moderators

The UTAUT model includes four moderating variables. These moderators influence the relationships between the predictor variables and the behavioural intention to use the new technology, which in turn influences the use/ adoption of the technology (Venkatesh et al. 2003).

2.2.2.1 Gender

Men and women are believed to have different responses to factors influencing technology use. Men's technology adoption is more influenced by their attitude toward using new technology, while women's decisions are more influenced by perceived behavioural control and subjective norms (Venkatesh, 2000).

2.2.2.2 Age

Younger and older users may have differing experiences with and attitudes towards technology (Venkatesh, 2003). According to a study by Meyer (2009), an older workforce is less likely to adopt new technology compared to a workforce younger than 30 years old.

2.2.2.3 Experience

Prior experience with technology can affect how constructs like effort expectancy influence behavioural intention. Venkatesh et al. (2003) found that experience mitigates perceived barriers to adoption, emphasizing the importance of hands-on experience.

2.2.2.4 Voluntariness of use

Whether technology adoption is voluntary or mandatory can affect how strongly factors such as social influence impact user intention. Studies indicate that voluntary adoption leads to higher natural motivation, while mandatory use can drive compliance but may result in lower engagement (Venkatesh et al. 2003).

2.2.3 UTAUT-model in the context of employee adoption

A paper titled "*Adoption and use of AI tools: a research agenda grounded in UTAUT*" presents a slightly altered version of the UTAUT-model (Venkatesh, 2021). This paper provides an altered UTAUT-model which is better adapted to the specific case of individual adoption of AI tools, which entails different challenges than other more traditional technologies. The challenges of the original UTAUT-model may not fully account for personal factors such as human bias and trust, which is crucial for AI technology adoption. Humans may have greater trust in their own or colleagues' judgment than AI (Venkatesh, 2021). Furthermore, AI is often seen as a "blackbox", meaning that the user has little to no insight into how the model works, this can further lower the trust in the technology (Venkatesh, 2021). Errors can also occur with the use of AI models and accumulating mistakes can diminish user trust and hinder long-term adoption (Venkatesh, 2021). Some employees inherently dislike or distrust algorithms, preferring manual processes regardless of the AI tool's accuracy or reliability (Venkatesh, 2021).

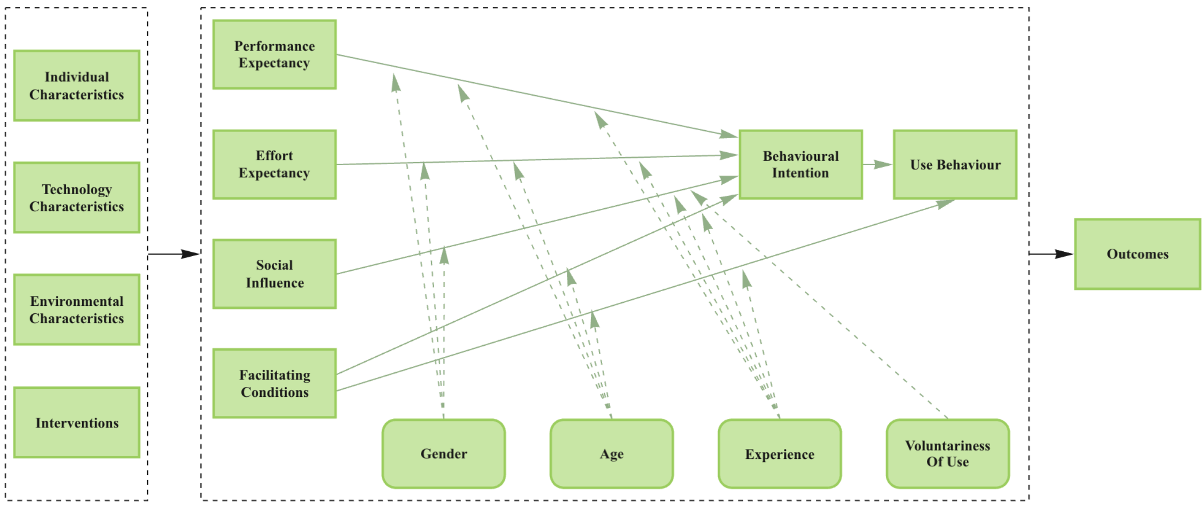

Figure 2. The altered UTAUT-model.

The altered model, which can be seen in figure 2, illustrates that individual characteristics, technology characteristics, environmental characteristics, and interventions, all impact the individual adoption of AI tools. These new nodes can be seen as additional moderators and impact different predictor nodes in the UTAUT-model (Venkatesh, 2021).

Individual characteristics significantly impact technology adoption, particularly in context involving AI tools where errors, uncertainty, and opaqueness are common. Traits like risk-seeking, tolerance for uncertainty and a desire to learn increase the likelihood of adoption (Venkatesh, 2021). Traditional technology-related traits such as computer self-efficacy and playfulness, along with general personal traits, also influence adoption by affecting key predictors in the UTAUT model (Venkatesh, 2021). Understanding these traits can help identify factors that foster or hinder AI adoption. This moderator node primarily impacts the performance expectancy, effort expectancy, and facilitating conditions predictor nodes (Venkatesh, 2021).

Technology characteristics can be analyzed through employee perceptions or objective attributes, depending on the study's focus. Factors like perceived model errors or the availability of complete information from the supply chain can impact UTAUT predictors, particularly performance expectancy (Venkatesh, 2021). Comparing multiple AI tools could involve evaluating their objective characteristics, such as error rates, to identify those with significant effects. Additionally, design aspects like model transparency can influence UTAUT predictors, such as effort expectancy, and affect employee adoption (Venkatesh, 2021).

Environmental characteristics, such as an organizational climate that fosters innovation and learning, can encourage employees to adopt and use AI tools over time. Studies on these characteristics can focus on employee perceptions or defined organizational attributes, depending on the scope (Venkatesh, 2021). Key environmental factors affecting UTAUT predictors include the number of stakeholders, data availability, uncertainty, biases, and the dynamic nature of the environment. These factors, independently or combined, create diverse situations that significantly influence AI tool adoption. The environmental characteristics impact primarily facilitating conditions and social influence (Venkatesh, 2021).

Interventions, such as generic training, gamification, or other innovative methods, can influence technology adoption and use. Effective management and support practices are especially crucial in environments with high system uncertainty, as they help achieve both projects and employee outcomes (Venkatesh, 2021). Including significant user involvement is generally beneficial but becomes even more critical in managing the complexities and uncertainties of systems (Venkatesh, 2021).

2.3 Modified Theoretical Framework

In order to be able to utilize a theoretical framework which encompasses the most relevant influences/ predictors, it is of interest to create a modified theoretical framework. This modified theoretical framework is based on the original UTAUT-model with additions from the altered UTAUT-model supported by the *Ecological Framework of Management Decision-Making*. In order to develop this modified theoretical framework, factors not applicable to this study will be removed from the UTAUT-model. The removal of excessive factors from the theoretical framework is desirable due to a couple of reasons. Reducing the amount of factors present in the theoretical framework will decrease the size of the survey, as fewer factors need to be examined, which in turn, will increase the response frequency (Rolstad et al. 2011). The removal of redundant variables also reduces the multicollinearity in the model which increases the quality of the results and the likelihood of obtaining statistically significant results (Hair et al. 2019).

2.3.1 Removals from the UTAUT-Model

The moderator node, "voluntariness of use", will be disregarded from the theoretical framework as it is deemed to be outside of the scope of this study. This study aims to observe what factors influence individual adoption of AI tools, which implies that the adoption of AI tools needs to be a choice. If the individual is forced to use the tool then the study will not be able to identify how the other predictors and moderators influence the adoption.

The moderator node, "gender", will also be disregarded from the theoretical framework as it is believed that this node will not have a significant impact due to the scope of the study. Previous research has found that gender does influence the use of technologies in different settings. One such study presented that women, in general, tend to attribute themselves with lower self-efficacy and higher perceived levels of effort expectancy (Venkatesh, 2000). The effects that gender has as a moderator between the different predictors in the UTAUT model and the adoption of the technology is however mitigated by the complexity of the technology (Sobieraj & Krämer, 2020). Although AI technologies might sound complex this is not true for AI tools, as one study reported that 90.9% of respondents answered that AI tools such as CoPilot are very user friendly (Miller et al. 2024). The user friendliness of mainstream AI tools is therefore very likely to significantly mitigate the effects which gender has on the adoption of AI tools. The scope of the study, focused on the adoption of AI tools which can be considered to be user friendly, therefore implies that the moderator node, "gender", can be disregarded.

The final node which will be disregarded from the traditional UTAUT model is *Behavioural Intention*. The purpose of this exclusion is, once again, based on the scope and the purpose of the study. As this study aims to observe drivers and barriers to the actual adoption of AI tools across organizational departments, observing whether or not individual employees want to adopt AI tools is not of interest.

2.3.2 Additions to the UTAUT-Model

In order to be able to utilize the valuable parameters in the altered UTAUT-model and influences presented within the *Ecological Framework of Management Decision-Making* it is of interest to include additional moderators. Since the aim of this study is to examine/ observe differences with regards to AI tool adoption between different organizational departments, it is of significant importance to include environmental aspects in the theoretical framework.

The first moderator which is to be added to the theoretical framework is environmental characteristics. This moderator was proposed in the paper, "*Adoption and use of AI tools: a research agenda grounded in UTAUT"* and incorporates factors such as organizational culture, industry norms, and regulatory environments (Venkatesh, 2021). The inclusion of this moderator will allow the study to attempt to capture the effect which different environmental characteristics have on the adoption of

AI tools. This is of interest as the study aims to observe differences in AI tool adoption within different organizational departments, which are likely to have different environmental characteristics. The addition of this moderator is not only supported by the UTAUT paper published in 2021 but also by the *Ecological Framework of Management Decision-Making.* Environmental characteristics are largely a result of the interplay between the mesosystem and the microsystem (Gressel et al. 2021, pp. 165-181). The inclusion of this new moderator node therefore provides the theoretical framework with a new more contextual perspective on the adoption of AI tools in different organizational departments.

The second moderator which is to be added to the theoretical framework is individual characteristics. Like environmental characteristics, this moderator was also proposed in the paper published in 2021. Individual characteristics such as risk-seekingness, tolerance for uncertainty and a desire to learn are all believed to significantly impact an individual's likelihood of adopting AI tools (Venkatesh, 2021). The inclusion of different individual characteristics not only allows the study to explore the moderating effects which these have, but also incorporate certain aspects from the *Ecological Framework of Management Decision-Making*. The interplay between the microsystem and the individual is believed to impact both the individual and the overall adoption of new technologies (Gressel et al. 2021, pp. 165-181). Individual characteristics, or personality traits, are likely to impact this interplay, which makes their inclusion valuable for the analysis.

The final moderator which is to be added to the theoretical framework is technology characteristics. Technology characteristics explain the inherent attributes of AI tools such as complexity, compatibility, and perceived usefulness, significantly impacting user adoption (Venkatesh, 2021).

2.3.3 The final theoretical framework

After making the modifications necessary to refine the theoretical framework the modified theoretical framework could be finalized. This final theoretical framework can be seen in figure 3.

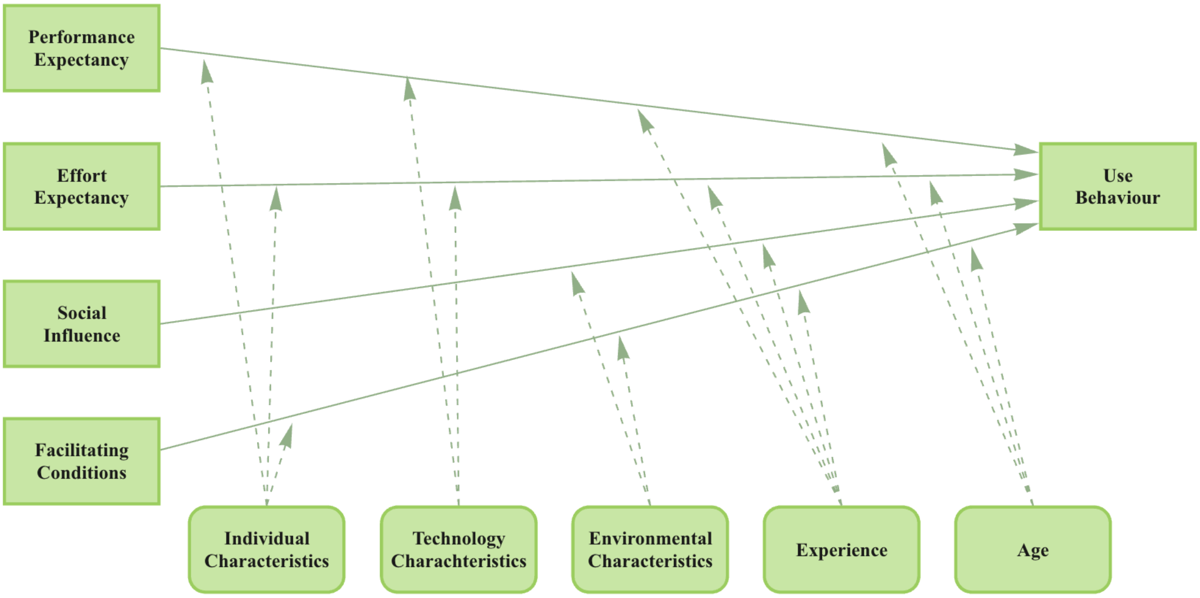

Figure 3. The final theoretical framework.

2.4 Hypothesis

Once the modified theoretical framework was completed it was possible to define hypotheses between the predictor variables, the moderating variables, and the outcome variable. The different hypotheses are illustrated and summarized in the figure below.

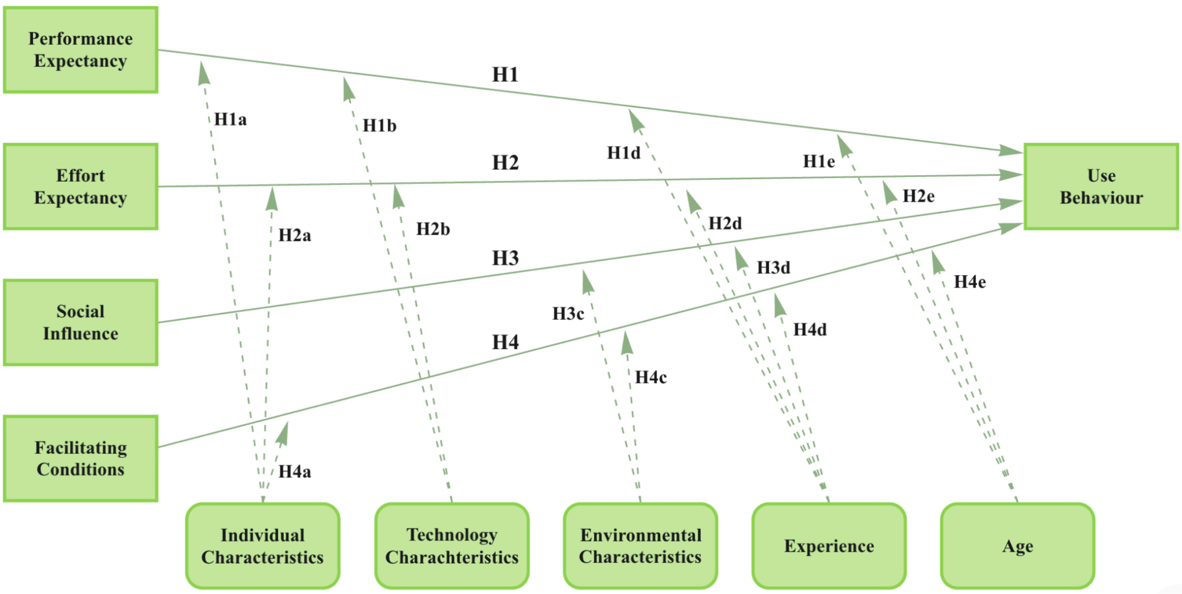

Figure 4. Summary of the hypotheses within the modified theoretical framework.

2.4.1 Performance Expectancy

According to the UTAUT theory it is hypothesized that if an individual believes that the utilization of a new technology will lead to increased levels of performance they are more likely to adopt and use the technology (Venkatesh, 2003). Based on this relationship the following hypothesis can be formulated:

H1: There will be a positive correlation between *Performance Expectancy* and *Use Behaviour.*

According to the altered theoretical framework different personality characteristics impact how likely people are to believe that new technologies will lead to improved performance. Higher levels of traits such as risk-seekingness, tolerance for uncertainty, and a desire to learn are thought to increase the perceived performance gain (Venkatesh, 2021). As increased levels of certain individual characteristics is thought to increase the *Performance Expectancy* the following hypothesis can be formulated:

H1a: The relationship between *Performance Expectancy* and *Use Behaviour* is positively moderated by *Individual Characteristics*.

The altered UTAUT-model predicts that the characteristics of the technology will impact its performance expectancy, and thus influence the use behaviour (Venkatesh, 2021). Technology characteristics such as reliability are thought to increase the perceived positive effect that the technology would have on performance. As the *Performance Expectancy* is increased with higher levels of technology characteristics such as reliability and data availability, the following hypothesis can be formulated:

H1b: The relationship between *Performance Expectancy* and *Use Behaviour* is positively moderated by *Technology Characteristics*.

As per the original UTAUT-model, it is predicted that experience will have a moderating effect on the relationship between *Performance Expectancy* and *Use Behaviour*. Individuals who have experience with the technology have more knowledge regarding the potential advantages the adoption of this technology might entail, thus impacting the *Performance Expectancy* (Venkatesh, 2003). This implies that the following hypothesis can be formulated:

H1d: The relationship between *Performance Expectancy* and *Use Behaviour* is moderated by *Experience*.

According to the UTAUT model the relationship between *Performance Expectancy* and *Use Behaviour* is negatively moderated by age. Previous studies have shown that an older workforce is less likely to adopt new technologies (Meyer, 2009). It is believed that the older an individual is, the lower their *Performance Expectancy* will be, thus influencing their *Use Behaviour* (Venkatesh, 2003). The following hypothesis can therefore be formulated:

H1e: The relationship between *Performance Expectancy* and *Use Behaviour* is inversely moderated by *Age.*

2.4.2 Effort Expectancy

According to the UTAUT-model there is a negative correlation between *Effort Expectancy* and *Use Behaviour*. As the perceived *Effort Expectancy* increases the *Use Behaviour* is expected to decrease (Venkatesh, 2003). This can be summarized by the following hypothesis:

H2: There will be a negative correlation between *Effort Expectancy* and *Use Behaviour.*

The altered UTAUT-model predicts that the relationship between *Effort Expectancy* and *Use Behaviour* is positively moderated by *Individual Characteristics*. It is believed that individuals with higher levels of traits such as risk-seekingness, tolerance for uncertainty, and a desire to learn will be less dissuaded by expected efforts with regards to the new technology (Venkatesh, 2021). This can be summarized by the following hypothesis:

H2a: The relationship between *Effort Expectancy* and *Use behaviour* is inversely moderated by *Individual Characteristics.*

According to the altered UTAUT-model it is expected that the relationship between *Effort Expectancy* and *Use Behaviour* is moderated by *Technology Characteristics*. Factors like perceived model errors or the availability of complete information are believed to impact the *Effort Expectancy* in such a way that the greater the perceived errors and the lower the availability of complete information, the greater the effort expectancy (Venkatesh, 2021). This can be summarized by the following hypothesis:

H2b: The relationship between *Effort Expectancy* and *Use behaviour* is positively moderated by *Technology Characteristics.*

It is predicted by the altered UTAUT-model that the relationship between *Effort Expectancy* and *Use Behaviour* is moderated by *Experience*. It is believed that individuals with varying levels of *Experience* with the technology will have different *Effort Expectancies*. Individuals with less experience are more likely to either under- or over-estimate the effort (Venkatesh, 2003). This can be summarized by the following hypothesis:

H2d: The relationship between *Effort Expectancy* and *Use behaviour* is moderated by *Experience.*

As per the UTAUT-model, it is believed that the relationship between *Effort Expectancy* and *Use Behaviour* is positively moderated by *Age*. This is due to older individuals likely over-estimating the complexity of new technologies, therefore increasing their *Effort Expectancy* (Venkatesh, 2003). This can be summarized in the following hypothesis:

H2e: The relationship between *Effort Expectancy* and *Use behaviour* is positively moderated by *Age.*

2.4.3 Social Influence

The UTAUT-model predicts that there is a positive relationship between *Social Influence* and *Use Behaviour*. This is due to the belief that an individual's colleagues, supervisors, friends, etc. feelings towards the use of AI tools will impact the individual's likelihood of adopting the technology (Venkatesh et al. 2003). It is also believed that leadership advocacy will greatly influence an individual to adopt the technology (Gressel et al. 2021, pp. 165-181). The prediction that *Social Influence* will have an impact on *Use Behaviour* leads to the following hypothesis:

H3: There will be a positive correlation between *Social Influence* and *Use Behaviour.*

As per the altered UTAUT-model, it is believed that the relationship between *Social Influence* and *Use Behaviour* is positively moderated by *Environmental Characteristics*. The relationship between *Social Influence* and *Use Behaviour* is expected to be strengthened when certain *Environmental Characteristics* are present. If an organization has an organizational environment/ culture which fosters innovation and values learning, it is believed that *Social Influence* will have an increasing effect on *Use Behaviour* (Venkatesh, 2021). This can be summarized by the following hypothesis:

H3c: The relationship between *Social Influence* and *Use Behaviour* is positively moderated by *Environmental Characteristics.*

It is expected that the relationship between *Social Influence* and *Use Behaviour* will be moderated by *Experience*. Individuals with more *Experience* are less likely to be significantly influenced by others opinions as they themselves have enough knowledge to not be significantly influenced by mechanisms such as peer pressure (Venkatesh et al. 2003). This notion can be expressed by the following hypothesis:

H3d: The relationship between *Social Influence* and *Use Behaviour* is inversely moderated by *Experience.*

2.4.4 Facilitating Conditions

It is believed that there will be a positive correlation between *Facilitating Conditions* and *Use Behaviour*. This is due to the belief that if an individual feels that the organization in which they work has the infrastructure to support the adoption of the technology the individual will be more likely to do so (Venkatesh et al. 2003):

H4: There will be a positive correlation between *Facilitating Conditions* and *Use Behaviour.*

The relationship between *Facilitating Conditions* and *Use Behaviour* is expected to be inversely moderated by individual characteristics. It is believed that individuals with higher levels of traits such as risk-seekingness, tolerance for uncertainty, and a desire to learn, will be less negatively impacted by poor *Facilitating Conditions* (Venkatesh, 2021). The relationship between *Facilitating Conditions* and *Use Behaviour* is therefore expected to be weaker for individuals with higher levels of the defined *Individual Characteristics*. This can be summarized in the following hypothesis:

H4a: The relationship between *Facilitating Conditions* and *Use Behaviour* is inversely moderated by *Individual Characteristics.*

The relationship between *Facilitating Conditions* and *Use Behaviour* is expected to be positively moderated by *Environmental Characteristics*. If an organization has good *Environmental Characteristics*, it is expected that the organization will provide the *Facilitating Conditions* required for the adoption of the new technology. The following hypothesis can therefore be formulated:

H4c: The relationship between *Facilitating Conditions* and *Use Behaviour* is positively moderated by *Environmental Characteristics.*

It is expected that the relationship between *Facilitating Conditions* and *Use Behaviour* is inversely moderated by *Experience*. Individuals with more *Experience* are expected to be able to find the support for the adoption of the technology within the company without any explicitly defined support channels. Individuals with less *Experience* are expected to require more structured support from the organization (Venkatesh et al. 2003). The following hypothesis can therefore be formulated:

H4d: The relationship between *Facilitating Conditions* and *Use Behaviour* is inversely moderated by *Experience.*

As per the UTAUT-model, it is expected that the relationship between *Facilitating Conditions* and *Use Behaviour* is moderated by *Age*. *Age* is expected to impact individuals' needs for external support, with regards to technology. Younger and older individuals may need more support than those who are closer to the median age (Venkatesh et al. 2003). This can be summarized in the following hypothesis:

H4e: The relationship between *Facilitating Conditions* and *Use Behaviour* is moderated by *Age.*

3. Methodology

3.1 Research Design

3.1.1 Deductive Approach

This study utilizes a deductive approach which implies that the study is based on the modified theoretical framework presented in section 2. This modified theoretical framework is based on the UTAUT-model and the *Ecological Framework of Management Decision-Making.* The UTAUT-model provides a framework which relates directly to the acceptance/ adoption of new technologies. This framework provides the theoretical basis which is needed to evaluate the individual adoption of AI tools. The *Framework of Management Decision-Making*, on the other hand, takes a more holistic approach and includes factors on many different levels which may affect the adoption of AI tools. The combination of these two models provides the study with a theoretical framework which allows for the application of the specific individual influences, presented within the UTAUT-model, while considering the holistic influences presented in the *Framework of Management Decision-Making*. The deductive approach therefore allows the study to utilize the aforementioned theories, via the modified theoretical framework, in order to quantify the adoption levels of AI tools, and the factors which influence individuals' adoption of said AI tools.

3.1.2 Quantitative Research

A quantitative approach is taken as it allows for the obtained data to be efficiently sorted and analyzed. The quantitative approach is also what makes it possible to utilize statistical analysis. A quantitative approach can be seen as appropriate as it reduces the level of bias within the study as well as potentially allowing for results which can be further generalized (Bryman & Bell, 2017). The utilization of both a quantitative and deductive approach allows the study to efficiently utilize theory, which makes it possible to efficiently evaluate the research question, while also ensuring that the collected data is of sufficient quality and is easily processed and analyzed (Bryman & Bell, 2017).

3.2 Data Collection

3.2.1 Survey Study

The data collection method utilized within this study is a survey. The purpose of a survey is to collect data from a group of people to receive a broader perspective on a subject. Bryman and Bell describe surveys as being a non-experimental method of data collection to understand group behaviours and perspectives regarding a subject (Bryman & Bell, 2017). Surveys can be seen as a desirable data collection method due to a variety of reasons. Surveys allow for efficient data collection as they can generate a lot of data within a short amount of time, can have a broad reach, and are cost effective, relative to other methods of data collection. Surveys also provide standardized responses, ensuring that the obtained data is both consistent and comparable. In addition to being consistent and comparable the responses are also quantifiable. The comparable and quantifiable nature of the obtained data is a requirement for efficient data analysis and thus the examination of the research question. (Bryman & Bell, 2017)

3.2.2 Research Survey

As the study utilizes a deductive approach, the data collection, and thus the survey, is created based on the modified theoretical framework presented in section 2.3. Once the modified theoretical framework was completed it was possible to define the hypothesis', which can be found in section 2.4. In order to be able to test each hypothesis, a minimum of two questions per node in the theoretical framework model were included in the survey. This theoretical base implies that each question serves a unique and important purpose, with regards to the goals of the data collection and the study as a whole.

The creation of a survey requires methodical question formulations in order to minimize the bias imposed on the study by the researchers. It is during the creation of the survey that personal bias from the researchers can influence the quality of the results and thus the quality of the study (Bryman & Bell, 2017). In order to minimize the extent that this bias could impact the study, questions which have previously been reviewed and validated in other studies were reused as often as possible. This implied that the questions which were included within the survey were of high quality, which should minimize the amount of bias within the data collection (Bryman & Bell, 2017). See Appendix A for a description of the included questions and their respective source.

The majority of the questions in the survey were designed using a likert scale. This implies that the respondents were asked to indicate their level of agreement to a statement on a scale between 1 and 5. The Likert scale is a tool which makes it easier to analyse and explore patterns in responses from participants (Bryman & Bell, 2017). In addition to the likert scale questions, some questions were formulated as closed-ended questions. The purpose of these questions were to obtain the required data about the respondent, such as age range, type of department, and AI tool *Use Behaviour*. In addition to providing the data required by the model in the modified theoretical framework, these questions also allowed the study to notice if any group was overrepresented. This enabled the study to make sure that an adequate amount of data was collected for each sub-part of the study population. See Appendix B and C for the collected responses.

3.2.3 Study Population

In order to make sure that the study does not significantly deviate from its purpose, the partaking organizations needed to be selected methodically. If for example, a highly data-literate organization and a more traditional organization were selected, the differences seen in the data may be due to organizational differences rather than general departmental differences, which is what the study aims to observe. It is therefore important that organizations which have somewhat similar organizational adoption levels, with regards to AI and AI tools, are selected. A correct definition of the study population should allow the study to isolate the desired phenomena, which in this case is AI tool adoption. The organizational adoption level of AI and AI tools is, therefore, the primary selection criteria when defining the study population. Other selection criteria include industry, location, and size (Defoes, 2024). All of these criteria aim to ensure that the obtained data is appropriate by minimizing the effects of factors which are outside the scope of the study and may influence the levels of AI tool adoption.

When defining the study population it is important to also consider the effects which this has on the possibility of generating a sufficient number of responses and thus collecting data (Kline, 2014). The ability of getting a high number of responses, as well as ensuring comparable AI tool adoption levels between organizations, enabled the definition of the study population. The study population includes individuals who work at mid- and large-cap industrial companies with offices in Sweden and provide access to enterprise AI solutions. The size of the companies, as well as them all being in similar manufacturing industries in the same region, ensures similar levels of organizational AI tool adoption as the different organizations exist within the same macrosystem and exosystem, which largely influence the organization's level of data-drivenness (Gressel et al. 2021, pp. 165-181). The location and size of these companies also aid in the efficient collection of data.

3.2.4 Sampling Strategy

In order to be able to obtain the required amount of data it was of importance to gather as many responses as possible within the relatively short time frame of the study. Selecting an efficient sampling strategy was therefore of critical importance for the completion of the study. The sampling strategy which was selected was a combination of snowball sampling and stratified sampling (Bryman & Bell, 2017). As the study aims to observe the drivers and barriers for AI tool adoption for both technical and non-technical departments it is crucial that a sufficient amount of responses are collected for both of these groups. The minimum sample size, for a study which aims to utilize PLS-SEM, which is the case for this study, is determined by multiplying 10 by the maximum number of indicators pointing to an inner or outer latent variable, known as the "rule of ten" (Hair, 2011). As the model presented in the modified theoretical framework contains a maximum of four indicators per latent variable, the minimum sample size for this study is forty responses per department type. The minimum sample size of forty for both technical and non-technical departments illustrates the need for incorporating stratified sampling into the sampling strategy.

Due to the need of quickly collecting large amounts of data quickly snowball sampling was used as the primary sampling method when it came to data collection.. Snowball sampling is a non-probability sampling method through which the survey is shared to different individuals who then forward the survey to their network (Nikolopoulou, 2022). This sampling strategy was utilized by the study as different individuals, at companies within the study population, were identified and contacted. These individuals were then able to forward the survey to their immediate colleagues which resulted in an efficient data collection. This sampling strategy also allowed the study to ensure adequate data collection for both of the studied groups as the contact people could be selected with regards to which department they work in.

Although this sampling strategy was very advantageous for the study, as it allowed a significant amount of data to be collected within the limited timeframe, it does imply clear limitations. One limitation with snowball sampling is that it makes it impossible to identify the frequency of nonresponse. This is not believed to significantly impact the quality of the results of this study as nonresponse poses minimal bias when it is unrelated to the study variables (Groves et al. 2009). The object of study in this research is individuals who work in either technical or non-technical departments. The study population is defined to include individuals who work at organizations with similar levels of organizational AI adoption, which implies that the technical and non-technical departments should be quite similar between organizations, with regards to AI tool usage. This implies that the possibility of nonresponse occurring at one organization, via one contact person, shouldn't affect the quality of the collected data as it is not the organizations which are being studied, but rather the individuals who work in the comparable organizational departments.

3.3 Operational Definition

3.3.1 Outcome Variable

The objective of this study was to examine which factors influence the adoption of AI tools. This study differs from previous research, which also utilized the UTAUT model, as the number of dependent/ outcome variables was reduced from two, *Behavioural Intention* and *Use Behaviour*, to one dependent/ outcome variable, *Use Behaviour*. This simplification was done due to the scope of the study aiming to observe factors which influence the actual adoption of AI tools, rather than individuals intentions regarding the adoption of AI tools.

To be able to observe which factors influence use behaviour with regards to AI tools, and thus the adoption of AI tools, a measurement for use behaviour was required. In order to measure different repondants' use behaviour the survey included a question which asked the respondents to approximate the frequency of their AI tool use when faced with tasks which AI tools can assist with. It is believed that the frequency with which individuals use AI tools, in cases where the use of AI tools is possible, can be seen as an adequate representation, and thus measurement, of their use behaviour (Venkatesh et al. 2003). The respondents answered this question with the help of a percentage, implying that the measurements created by this question has a ratio scale.

3.3.2 Predictor Variables

A latent variable in a statistical model is a theoretical concept that cannot be directly observed, but can be measured via their impact on observable or measurable variables (Taylor & Francis, 2021). There are four latent variables, which act as predictors, in the modified theoretical framework used in this study, *Performance Expectancy*, *Effort Expectancy*, *Social Influence*, and *Facilitating conditions*. As this study aims to observe the effects that these latent variables, as drivers and barriers, have on the adoption of AI tools it is of interest to measure their influence on the outcome variable, use behaviour. Questions which aimed to evaluate the latent variables were included in the survey and acted as observable indicators, which is the primary way that latent variables can be measured (ScienceDirect, 2024). These questions were sourced from previous studies which had reviewed and validated the questions. This method of selecting already controlled questions provides the study with greater validity and trustworthiness (Bryman & Bell, 2017). The questions which were sourced and utilized as observable indicators for the latent variables can be seen in Appendix A.

3.3.3 Moderating Variables

The modified theoretical framework used in this study contains five moderating variables, *Individual Characteristics*, *Technology Characteristics*, *Environmental Characteristics*, *Experience*, and *Age*. Apart from *Age*, the moderating variables are all latent variables. This implies that they needed to be measured in a similar manner as the latent predictor variables, via observable indicators.

3.4 Data Quality

The goal of the data collection was to achieve the most representative and high quality sample as possible. It was therefore of interest to collect a broad range of responses from respondents with ranging ages and department of work. The collection of a broad range of data strengthens the study by reducing the risk of bias, leading to stronger validity in the study (Bryman & Bell, 2017).

3.4.1 Internal Validity

Internal validity is a measure of the extent of which it is possible to be confident that the causal relationship within the study is not affected by other factors (Tofan et al. 2014). In other words, it is a measure of whether or not the study is measuring what it sets out to measure. To minimize the risk of poor internal validity, it was important to ensure that the data collection was done in a correct manner. This included making sure that the questions used in the survey were of high quality. As previously mentioned, the questions used within the survey were, when possible, sourced from previous research, which utilized similar theoretical frameworks. As these questions have already been reviewed and validated, their inclusion in this study strengthens this study's internal validity (Bryman & Bell, 2017). In addition to strengthening this study's internal validity the use of sourced questions also reduces the risk of measurement bias (Bryman & Bell, 2017).

3.4.2 External Validity

External validity refers to the ability of being able to generalize the findings from a study to a broader context (Oriol et al. 2014). External validity can be improved via several actions. The use of a representative sample is of significant importance as this aids in the generalizability of the results of the study. This was considered during the development of this study's sampling strategy. This study aimed to create a sample size which was as large as possible in order to reduce the variability of the results, and thus enhance the external validity (Oriol et al. 2014).

The external validity of this study is, however, likely weakened by the use of snowball sampling for the collection of responses. This is due to the possibility that certain organizations may be overrepresented in the produced sample if the contact person at a certain organization was more diligent in the distribution of the survey to their colleagues. The overrepresentation of respondents who work at certain organizations in the sample is impossible to measure due to the nature of snowball sampling. This is a clear limitation of the study.

The relationship between internal and external validity needs to be considered when defining the study population and the sampling strategy. This is due to the tradeoff that exists between internal and external validity (Busch, 2017). If the external validity, and thus the generalizability of the study, is to be increased, it is of interest to have a study population which is as broad as possible from both a population and ecological perspective (Bhandari, 2020). If the broadness of the study population, and thus the sample, is increased it presents a challenge with regards to the internal validity of the study as the broader sample introduces additional parameters which impacts the internal validity of the study. The desired level of internal and external validity therefore needs to be defined when designing the study. This study was designed to slightly prioritize internal validity over external validity in order to be able to hopefully produce significant results within the limited timeframe of the study.

3.4.3 Reliability

Reliability refers to the consistency of a measure of a concept (Bryman & Bell, 2017). High reliability ensures that measurements are not affected by the researchers conducting the study. A high reliability ensures that if the study would be conducted repeatedly it would provide consistent results. Poor reliability can arise if the study is set up in such a way that gives a higher variance due to the measurement method rather than what is being measured, this is called common method bias (Podsakoff et al. 2003). Common method bias is a study error which can largely be mitigated via a proper construction of the research method. This study aimed to reduce the prevalence of this type of bias via a couple of decisions related to the research design/ methodology. The definition of the study population was defined in order to ensure sample consistency, which should reduce the variability of the results, and thus strengthen the reliability.

Reliability was also largely considered during the creation of the survey. As previously mentioned, the large majority of the questions included in the survey were sourced from previous research which had reviewed and validated the question formulations. This strengthens the reliability of the study as it reduces the risk of including loaded and unclear questions in the survey, which would likely lead to common method bias. The questions were also formulated with likert scales of the same size, ensuring that the scale could not impact the respondents answers. Furthermore, information regarding the context of the study as well as definitions needed to understand the survey was included in the beginning of the survey. This was done in order to provide both the context and the instructions needed to successfully respond to the survey. Finally, individual anonymity was guaranteed in order to minimize participant bias. (Krosnick, 1999; Brown, 2023)

Due to respondents' tendencies of answering the question from the same survey in a similar way, there is an increased risk of common method bias if several or all the variables are measured within the same survey (Podsakoff et al. 2003). Although utilizing several surveys during the study can be advantageous and reduce the risk of common method bias this was not possible for this study. As this study needed to produce a significant amount of responses in a relatively short period of time, it was impossible to utilize multiple surveys. While multiple surveys could provide more reliable results, the burden on participants would be too high and due to the short amount of time the data would have a higher risk of being incomplete. To mitigate risk of common bias for the study, keeping the survey easy to complete was prioritized (Krosnick, 1999).

3.4.4 Coverage Error

Coverage error occurs when there is a difference between the study population and the sampling frame (Bryman & Bell, 2017). Coverage error therefore leads to the exclusion of some parts of the study population from the sampling frame, limiting the study's generalizability (ScienceDirect, 2024b). In order to minimize the coverage error in the study the study population was clearly defined. This clear definition of the study population limits the number of sub-groups which could be either overlooked or overrepresented, mitigating the risk of overcoverage and mismatch in representation.

3.4.5 Nonresponse

Nonresponse refers to the failure of some respondents to complete or return the survey, which could reduce the representativeness of the sample (Fowler, 2014). There are two main types of nonresponse, partial non response and total nonresponse. Total nonresponse is when the respondents do not answer or return the study, partial nonresponse is when the respondents answer some parts of the survey, but not the entire survey. In survey studies, nonresponse is generally a significant issue that can lead to biased results (Dahmström, 2011). To minimize the total nonresponse, the survey was designed to emphasize clarity and reduce the respondent's workload. To enhance clarity, the answer options were presented in a consistent format throughout the survey. The survey was designed to be as quick to complete as possible, reducing the burden on the respondent, and thus reducing the non-response. The risk of partial nonresponse was eliminated by requiring respondents to complete the entire questionnaire before submitting.

One of the primary limitations of utilizing snowball sampling within the sampling strategy is that it makes it impossible to measure the nonresponse of the study. This implies that it isn't known which company the respondents work for, possibly leading to the under/over-representation of some organizations. As the study variable in this research is the individual rather than the organization it is not believed that the possibility of nonresponse occurring at an organization in this study will affect the quality of the collected data. This is because nonresponse poses minimal bias when it is unrelated to the study variables (Groves et al. 2009).

3.5 Data Analysis Techniques

3.5.1 PLS-SEM Partial Least Square

Partial Least Square Structural Equation Model (PLS-SEM) is a *Structural Equation Model* used for analyzing complex relationships between latent variables and their indicators, commonly used in social sciences, marketing, and information systems research (Hair et al. 2021). PLS-SEM is primarily concerned with maximizing the explained variance in the dependent variable, which in this case is the outcome variable, *Use Behaviour,* making it well suited for prediction-oriented and exploratory research (Hair et al. 2021; Hair et al. 2019). PLS-SEM combines *Principal Component Analysis* together with regression-based path analysis to estimate the parameters of multiple equations in a structural equation model (Mateos-Aparicio, 2011; Hair et al. 2021). The model calculates the effect of each independent variable on the dependent variable, with greater coefficients indicating a stronger influence. The independent variables are ranked based on the magnitude of their impact on the dependent variable (Hair et al. 2019b). In PLS-SEM, principal component analysis concepts are used to create latent variables, the predictors, and the moderating variables, which represent abstract or theoretical constructs that cannot be measured directly. Latent variables are inferred from multiple measurable indicators, the survey questions in this study, and are commonly used to represent subjective beliefs, perceptions, or behaviours (Hair et al. 2019). This study aims to compare two groups, *Non-technical* and *Technical*, which is done with a multigroup analysis that allows for identification of model relationships that differ significantly between groups (Hair et al. 2021b).

3.5.2 Structural and Measurement Model in PLS-SEM

The model is divided into two main components; a structural model and a measurement model (Hair et al. 2021). The structural model, or also referred to as the “inner model”, connects the latent variables together and also describes the relationships between these latent variables (Hair et al. 2021). In this study, the latent variables are the predictor variables, outcome variable, and moderating variables, presented in section 3.3. *Age,* on the other hand, is not a latent variable, but rather a control variable. The measurement model captures the relationship between the latent variables and the indicators (Hair et al. 2021).

3.5.3 Bootstrapping

PLS-SEM incorporates a method called *Bootstrapping* which is a nonparametric method used to evaluate the variability of a parameter by examining the distribution of its estimates through resampling from the original sample data, rather than relying on parametric assumptions to assess its precision (Becker et al. 2022). This process involves generating many random subsamples from the original data set. The model estimates derived from these subsamples are then used to conduct standard statistical inference, such as calculating confidence intervals or p-values (Becker et al. 2022). This is useful as it does not require the data to follow normal distribution, like survey data with Likert scales and a small sample size. To simplify bootstrapping, it is like running the analysis over and over with slightly different versions of the data to see how stable the results are.

3.5.4 Data Quality Assurance and Model Evaluation

To ensure that the data used in the study is of high quality it is important to validate the results. In order to evaluate the results of the PLS-SEM, two stages needed to be completed (Hair et al. 2021). The first stage is to evaluate the measurement model and the second stage is the evaluation of the structural model (Hair et al. 2021).

The first examination is the reliability of the indicators. The latent variables explain more than 50% of the indicator's variance when the loading factor is above 0.708, thus demonstrating a satisfactory degree of reliability (Hair et al. 2021). However, factor loadings in the interval 0.4 - 0.708 should only be considered to be removed if the consistency reliability and convergent validity increases to over the recommended threshold (Hair et al. 2021b). The second examination assesses the latent variables' internal consistency reliability. This is measured through *Composite Reliability* in which higher values indicate greater reliability (Hair et al. 2021). Values between 0.6 - 0.7 are considered as acceptable values in exploratory research. Values between 0.7 - 0.95 are considered as good reliability. Values above 0.95 indicate identical or redundant items, and are therefore problematic (Hair et al. 2021). Convergent validity indicates to what extent latent variables converge in its indicators by describing the items' variance (Hair et al. 2021). This is done by the *average variance extracted* (AVE). The threshold for an acceptable AVE is 0.5 (Hair et al. 2021). The next step is to evaluate the latent variables discriminant validity. This explains how latent variables correlate with other latent variables and how the distinct indicators only correspond to this specific latent variable (Hair et al. 2021). This is done by analyzing the correlation *hetero-trait-monotrait ratio* (HTMT). If latent variables are considered conceptually close to one another a suiting HTMT-threshold value is 0.85 (Hair et al. 2021). Meaning that values 0.85 and above indicate a lack of discriminant validity.

Multicollinearity poses a challenge because it causes the independent variables to influence each other, reducing the likelihood that the variables will be statistically significant (Hair et al. 2021). Beyond decreasing the significance of individual variables, multicollinearity can also negatively affect the model's predictive accuracy (Hair et al. 2021). To assess the presence of multicollinearity, a *Variance Inflation Factor* (VIF) test is conducted. According to Hair et al. (2021), a commonly accepted threshold for problematic multicollinearity is a VIF value of 5. If the VIF exceeds this value, multicollinearity exists, which can distort the model and affect the significance of individual predictors. However, even VIF values under 5 may indicate substantial multicollinearity. As VIF values over 3 can point to high multicollinearity, which can influence the model's outcome, a suggested VIF value threshold is 3 (Hair et al. 2021b).

The path coefficients are estimated after assessing the measurement model, testing the hypothesized relationships between variables. Path coefficients are generally in between the values of -1 and +1. Coefficients closer to +1 indicate a strong positive relation and coefficients closer to -1 represent a strong negative relation (Hair et al. 2021). The *Coefficient of Determination* (R^2) measures the proportion of variance in the endogenous variable explained by the model, reflecting its explanatory power (Hair et al. 2021). R^2 ranges from 0 to 1, where higher values indicate greater explanatory power. Generally, values of 0.75, 0.50, and 0.25 are considered substantial, moderate, and weak, respectively (Hair et al. 2021). However, depending on the context, acceptable R^2-values may be lower. Values as low as 0.1 can be considered acceptable when, for example, predicting stock prices (Hair et al. 2021). To evaluate the predictive power of the model, *Root-mean-square Error* (RMSE) and *Mean Absolute Error* (MAE) are used. These values have to be compared to a naive *Linear Regression Model* (LM) benchmark (Hair et al. 2021b). If the RMSE and MAE values, of the outcome variable, are lower in the PLS-SEM model compared to the LM, the PLS-SEM model can be considered to have a high predictive power. If the values for the PLS-SEM are higher than the LM, the model can be considered to lack predictive power (Hair et al. 2021b). Q^2 can also be evaluated, which determines whether the PLS-SEM model's predictions outperform a simple baseline. Specifically, the mean of the indicator values from the holdout sample. A value greater than 0.0 indicates that the model provides better predictive accuracy than the basic benchmark (Hair et al. 2021).

3.5.5 Justification of PLS-SEM

The use of *Structural Equation Modelling* (SEM) is well suited for this study since it aims to examine the reliability and validity of latent variables that consist of multiple indicators (Hair et al. 2017). It allows for the assessment of the measurement and structural model simultaneously (Hair et al. 2017). SEM also describes the variance in the outcome variable better than multiple regression since it factors in both direct and indirect effects (Hair et al. 2017).

There are two established SEM-models, PLS-SEM and *Covariance-Based SEM* (CB-SEM). CB-SEM is mostly used when confirming established theories and explaining them. Meanwhile, PLS-SEM is often used when doing exploratory research (Hair et al. 2017). CB-SEM is based on the common factor model that assumes that the analysis is based on the common variance in the data and its purpose is to minimize the differences between the measured and estimated sample covariance matrix (Hair et al. 2017). PLS-SEM, on the other hand, is based on the composite model that aims to maximize the variance explained in the outcome variable (Hair et al. 2017). Some of the common reasons for using PLS-SEM over CB-SEM is when the sample size is below 100, the study is exploratory research or theory development, and non-normal data (Hair et al. 2017). This study fits all of the mentioned reasonings and therefore proceeded with PLS-SEM as the method to analyse the theoretical framework presented in section 2.4.

3.5.6 Criticism of PLS-SEM

PLS-SEM is a statistical tool which has been applied for many years in order to estimate complex interrelationships between constructs and indicator variables (Hair et al. 2021). One advantage with PLS-SEM, which also can become a limitation, is the presence of bootstrapping in the model. Bootstrapping allows PLS-SEM to be used with relatively small sample sizes compared with other statistical methods. One study argued that researchers often misuse this advantage of PLS-SEM by utilizing too small sampling sizes and relying excessively on the statistical tool to find significant results (Hair et al. 2012). Excessively relying on a statistical model to generate significant results, rather than the volume and quality of the study sample can lead to significant errors due to data quality issues such as coverage error. The minimum sample size, for a study utilizing PLS-SEM, is determined by multiplying 10 by the maximum number of indicators pointing to an inner or outer latent variable, known as the "rule of ten" (Hair, 2011). This implies that the minimum sample size for this study is 40, which was adequately met.

Apart from criticisms related to the misuse of the small required sample size there are also technical criticisms with regards to PLS-SEM. As the latent variables, within a PLS-SEM model, cannot be directly observed but rather have to be measured via observable indicators, the measurement of these variables imply a certain degree of measurement error (Hair, 2021b). Asking individuals to self-report their experiences in order to be able to generate the observable indicators introduces some degree of uncertainty into the statistical model (Hair, 2021b; Yates et al. 2022). This study aimed to minimize the effects of this error by designing the survey to be as clear and and understandable as possible, reducing the risk of misunderstanding. The use of pre-formulated questions, when possible, also aimed to ensure that the quality of the survey, and thus the collected data, was of sufficient quality when compared to other studies. These actions should reduce the level of error in the PLS-SEM model.

3.6 Ethical Considerations

When conducting research it is of significant importance to consider the ethical implications during the research design. There are four ethical principles which researchers should adhere to. These include, avoidance of harm, informed consent, protection of privacy through confidentiality, and preventing deception (Bryman & Bell, 2017). The consideration of these ethical principles led to a number of actions during the design of this study. It was decided that the survey would be anonymous for both the individual respondent and the organization for which they work. Anonymity for the individual respondent ensures their privacy, and thus avoids potentially harming their career if it was found that they utilize AI tools in a way not seen as acceptable by their employer. As previously mentioned, individual anonymity also encourages respondents to answer honestly, mitigating the possibility of bias in the study. During the process of designing the study it was learned that many organizations don't want to publicly disclose their use of AI tools and their policies regarding AI tool usage. As the successful implementation of AI tools, on an organizational level, can be seen as a competitive advantage it is possible that sharing an organization's use of AI tools can cause them harm, anonymity for the organizations was therefore also guaranteed. In addition to avoiding harm and guaranteeing privacy through confidentiality the study was also designed to ensure informed consent and prevent deception. In order to prevent deception in the study, information regarding the context of the study, and thus the survey, was provided in the beginning of the survey. This was done with the purpose of guaranteeing that the respondents understood what they were participating in by responding to the survey. Informed consent was obtained via a question in the survey which asked the respondents to consent to the use of their response as well as their data being stored until 30/05/2025.

In addition to considering the four ethical principles it is also important for studies, which collect and store data, to be GDPR compliant (Wolford, 2024). In order to ensure that this study’s data collection and data storage complies with GDPR a guide to GDPR compliance for surveys was followed during the data collection design (Maptionnaire, 2022). In order to maintain GDPR compliance only necessary data was collected, the information presented in the beginning of the survey ensured transparency, no identifiable information was presented in the results, and publication consent was obtained in the survey. Furthermore, in order for the data collection to be GDPR compliant the respondents need to be able to modify or delete any of the personal information collected through the survey. For this purpose, personal identifiers were provided by the respondents. These identifiers were known only by the respondents, not the research team, ensuring anonymity while still making it possible for the respondents to modify or delete their data.

3.7 The Use of AI in the Study

AI was utilized as a supportive tool throughout the research process to enhance efficiency and ensure the findings of relevant literature. Two AI tools, ChatGPT and Consensus, were used for brainstorming, development of structure, and finding relevant and reliable sources. ChatGPT was used to assist in brainstorming ideas, exploring theoretical concepts and drafting a structure for the paper. The model provided suggestions for key topics, research questions, relevant theory and methodology. These outputs were analyzed and reviewed and built further upon. This iterative process helped develop a structured framework for the study. The AI tool "Consensus" was used to identify relevant academic sources for the paper. Consensus specializes in finding literature and evidence-based content that aligns with specific research topics (Consensus, 2024). Using keywords and research questions, the model was used to find studies, articles, and frameworks directly related to AI adoption, organizational behaviour, and the UTAUT model. One key feature of Consensus is that it provides a trustworthiness score for each piece of literature which it recommends. This trustworthiness score is based on parameters such as the number of other high quality papers which have cited the recommended literature, the status of the entity which published the literature, and whether it has been significantly peer reviewed (Consensus, 2024). The outputs from Consensus were critically reviewed to ensure they met the standard for relevance and quality.

The use of AI in this research was guided by principles of transparency and integrity. Outputs from the AI models were used as supplemental inputs and were critically evaluated to ensure their validity. The use of AI was documented to provide full disclosure and maintain accountability in the research process. The use of AI in this study adheres to the guidelines provided by Lund University School of Economics and Management (LUSEM, 2025). The prompts used in this study can be seen in Appendix D.

4. Results & Analysis

4.1 Descriptive Statistics

4.1.1 The Entire Sample

Measurement	Values	Frequency	Percentage
Age	18-25	13	13.7 %
	26-35	33	34.7 %
	36-45	26	27.4 %
	46-55	16	16.8 %
	56-65	7	7.4 %
	65+	0	0 %
Department	Technical	47	49.5 %
	Non-Technical	48	50.5 %
AI Tool Use Behaviour	0 %	7	7.4 %
	1-10 %	18	18.9 %
	11-20 %	6	6.3 %
	21-30 %	9	9.5 %
	31-40 %	3	3.2 %
	41-50 %	7	7.4 %
	51-60 %	9	9.5 %
	61-70 %	9	9.5 %
	71-80 %	14	14.7 %
	81-90 %	12	12.6 %
	91-100 %	1	1.1 %
Total		95	100%

Table 1. Descriptive Statistics for the entire study population.

Table 1 presents the descriptive statistics for the entire sample. The purpose of examining the descriptive statistics is to ensure that the obtained sample is appropriate for the purpose of the study. If the obtained sample over or under represents a certain sub-population it is possible that this will impact the quality of the results produced by the study. This was highlighted in section 3.4.4 regarding coverage error. In the table above it can be seen that the study managed to obtain a total sample size of 95 respondents, with 47 respondents working in technical departments and 48 respondents working in non-technical departments. This illustrates that the study managed to collect sufficient data for both of the studied groups, as the minimum sample size was 40 respondents per group. The collected data is also evenly distributed between the two groups. The descriptive statistics also show that the age range of the respondents is reasonably distributed. It can be seen that there was no respondent over the age of 65, which is to be expected as the retirement age in Sweden is between 61 and 67 (Pensionsmyndigheten, 2024).

4.1.2 The Technical Departments

Measurement	Values	Frequency	Percentage
Age	18-25	7	14.9 %
	26-35	9	19.1 %
	36-45	14	29.8 %
	46-55	12	25.5 %
	56-65	5	10.6 %
	65+	0	0 %
AI Tool Use Behaviour	0 %	7	14.9 %
	1-10 %	16	34.0 %
	11-20 %	4	8.5 %
	21-30 %	6	12.8 %
	31-40 %	1	2.1 %
	41-50 %	3	6.4 %
	51-60 %	2	4.3 %
	61-70 %	3	6.4 %
	71-80 %	5	10.6 %
	81-90 %	0	0 %
	91-100 %	0	0 %
Total		47	100%

Table 2. Descriptive Statistics for the respondents who work in technical departments.

Table 2 presents the descriptive statistics for the respondents who work in technical departments. It can be seen that the age distribution in this model is reasonable with the majority of the respondents being between 36 and 55. The age distribution likens a binomial distribution as the majority of the respondents are located in the center of the distribution with increasingly fewer respondents further away from the average age.

Figure 5 illustrates the distribution of the AI tool use behaviour for the respondents who work in technical departments. This figure illustrates that there is a peak between 1 and 10%, indicating that a significant portion of the respondents in this model utilize AI tools between 1 and 10% of the time when the use of AI tools is possible. The boxplot shows that the average AI tool use behaviour is 28.51% while the median use behaviour is 20%.

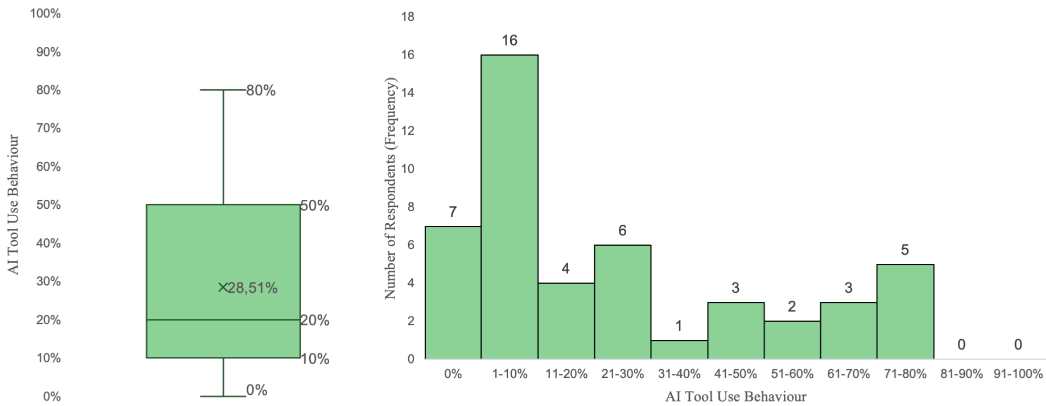

Figure 5. A boxplot (left) and a frequency graph (right) illustrating the AI tool use behaviour of the respondents who work in technical departments.

The figure below illustrates the distribution of the respondents, who work in technical departments, answers to the question regarding how much the respondent believes that there are AI tools which are applicable for their work.

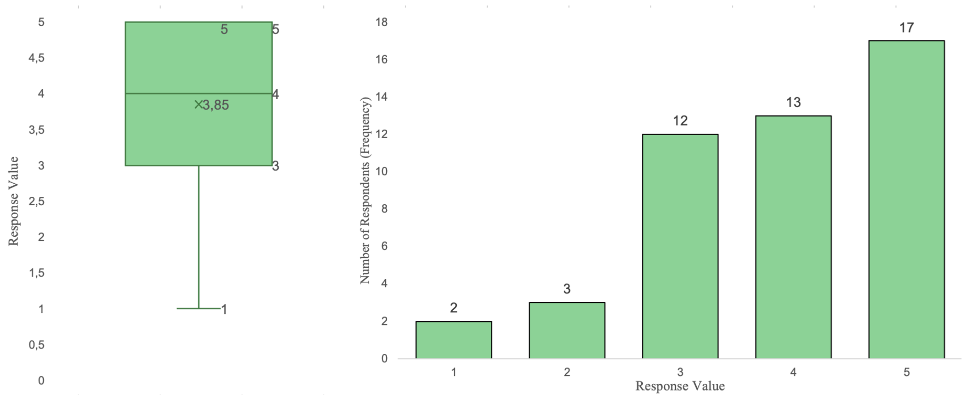

Figure 6. A boxplot (left) and a frequency graph (right) illustrating the answers to the survey question regarding AI tool applicability for the respondents who work in technical departments.

When comparing figure 6 and 5 it can be seen that there is a discrepancy between perceived applicability and AI tool use behaviour. While figure 6 shows that 64% of the respondents, in this group, believe that there are AI tools which are applicable or very applicable to their work, figure 5 shows that the average AI tool use behaviour is only 28.51%. This seems to indicate that there are barriers to adoption as although the respondents generally seem to believe that there are AI tools which are applicable for their work they are not using these tools when possible almost 75% of the time.

4.1.3 Non-Technical Departments

Measurement	**Values**	**Frequency**	**Percentage**
Age	18-25	6	12.5 %
	26-35	24	50.0 %
	36-45	12	25.0 %
	46-55	4	8.3 %
	56-65	2	4.2 %
	65+	0	0 %
AI Tool Use Behaviour	0 %	0	0 %
	1-10 %	2	4.2 %
	11-20 %	2	4.2 %
	21-30 %	3	6.25 %
	31-40 %	2	4.2 %
	41-50 %	4	8.3 %
	51-60 %	7	14.6 %
	61-70 %	6	12.5 %
	71-80 %	9	18.8 %
	81-90 %	12	25.0 %
	91-100 %	1	2.1 %
Total		48	100%

Table 3. Descriptive Statistics for the model (non-technical departments).

The table above presents the descriptive statistics for the respondents who work in non-technical departments. As 50% of the respondents are between the ages of 26 and 35 it can be seen that the age distribution in this group is younger than that for the technical departments. The lower average age for this group is to be expected as it is in line with industry differences which implies that the sample is sufficient with regards to age (Zippia, 2021; Zippia, 2021b).

Figure 7 illustrates the distribution of the AI tool use behaviour for the respondents who work in non-technical departments. It can be seen that the frequency increases as the use behaviour increases until it reaches its maximum at 81-90%. The boxplot shows that the average AI tool use behaviour is 66.04% while the median use behaviour is 70%.

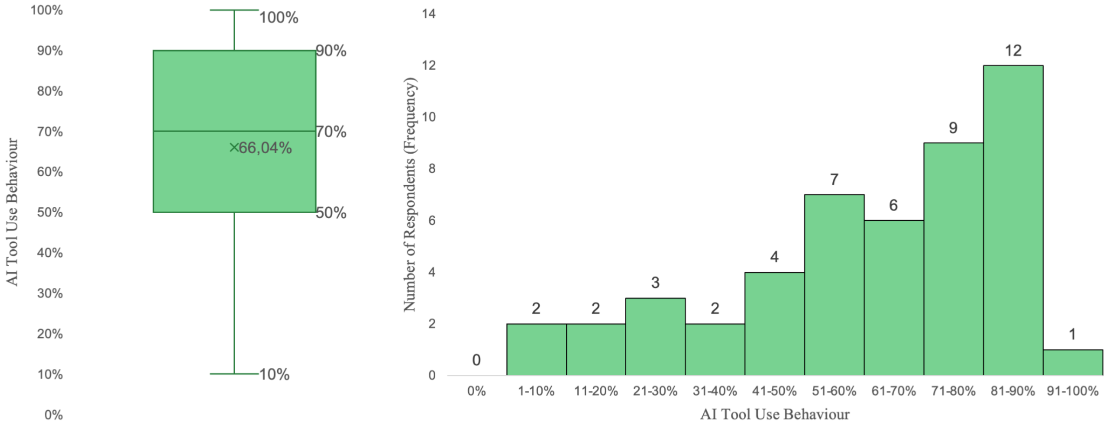

Figure 7. A boxplot (left) and a frequency graph (right) illustrating the AI tool use behaviour of the respondents who work in technical departments.

Figure 8 illustrates the distribution of the respondents, who work in non-technical departments, answers to the question regarding how much the respondent believes that there are AI tools which are applicable for their work.

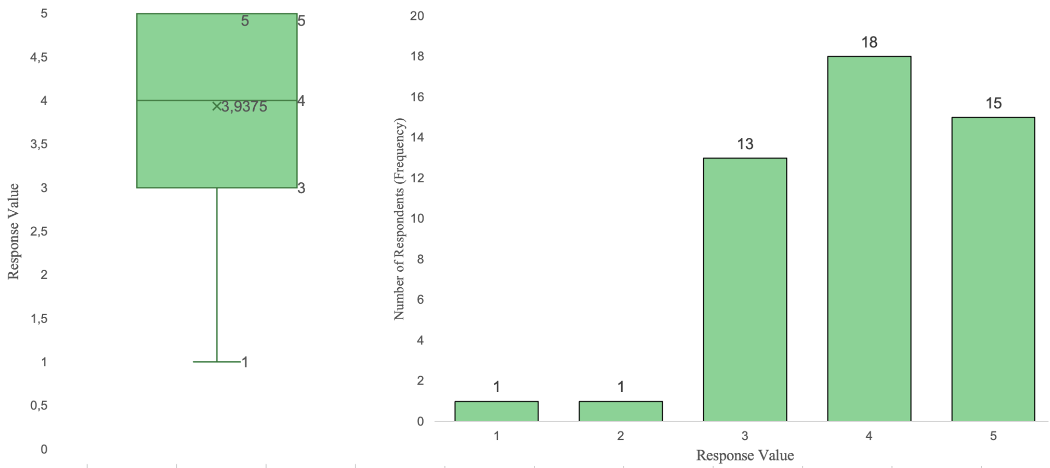

Figure 8. A boxplot (left) and a frequency graph (right) illustrating the answers to the survey question regarding AI tool applicability for the respondents who work in non-technical departments.

The figure above shows that 68.75% of the respondents, who work in non-technical departments, believe that there are AI tools which are applicable or very applicable to their work, with 27.1% of the respondents choosing to answer neutrally.

4.2 Data Quality and Model Evaluation

The latent variable *Experience* was removed from the model due to multicollinearity, identified during the collinearity diagnostics using the VIF-value. As mentioned in section 3.5.4, a commonly accepted threshold for VIF is 3, beyond which multicollinearity can be considered problematic (Hair et al. 2021b). In this case, *Experience* exhibited VIF-values exceeding 3 on three independent variables; *Facilitating Conditions, Effort Expectancy, and Performance Expectancy*. To address this issue and ensure robustness of the structural model, *Experience* was removed from the model. This adjustment helped to reduce multicollinearity and improve overall reliability of the remaining variables. Removing *Experience* aligns with best practices in PLS-SEM, where problematic latent variables with high collinearity are excluded to enhance model validity (Hair et al. 2021b). As a consequence of removing *Experience*, four hypotheses; H1d, H2d, H3d, H4d, that were directly related to this latent variable had to be eliminated and the moderating effect was not possible to test.

In table 4, the factor loadings of each indicator is presented alongside composite reliability and AVE value for each latent variable. As mentioned in section 3.5.4, when the loading factor is below 0.708 but above 0.400, the indicator should only be removed if the reliability and validity increase over the recommended threshold (Hair et al. 2021b). Based on this, six indicators were removed from the model due to them falling below the recommended value. The indicators removed were; EE1, EE3, FC1, IC3, and EC2. This led to two latent variables being measured by only one indicator which means that these latent variables are formed entirely by one indicator, thus decreasing the reliability of the model. The reliability and validity can be further examined by the composite reliability and AVE for each latent variable. The composite reliability examines the latent variables' internal consistency reliability. *Performance Expectancy, Social Influence, Facilitating Conditions, Individual Characteristics* and *Technology Characteristics* all had values between 0.7 - 0.9 which is considered reliable (Hair et al. 2021). The remaining two latent variables had a composite value of 1 due to them being formed by only one indicator. Values above 0.95 indicate identical or redundant variables and are problematic (Hair et al. 2021). The reliability of the latent variables *Effort Expectancy* and *Environmental Characteristics* can therefore be questioned. The AVE-values describe the variance of the indicators for each latent variable. Five of the latent indicators had values higher than the recommended threshold of 0.5 (Hair et al. 2021), which is considered acceptable. The remaining latent variables, *Effort Expectancy* and *Environmental Characteristics,* had an AVE-value of 1. *Age* is also included in this model but not shown in table 4 due to it not being considered a latent variable, but rather a control variable. Its inclusion would have resulted in a value of 1 in factor loading, composite reliability, and AVE.

Latent Variable	Indicators	Factor Loading	Composite Reliability	AVE
Performance Expectancy			0.760	0.617
	PE1	0.668		
	PE2	0.888		
Effort Expectancy			1	1
	~~EE1~~	~~0.176~~		
	EE2	1		
	~~EE3~~	~~-0.768~~		
Social Influence			0.828	0.620
	SI1	0.767		
	SI2	0.672		
	SI3	0.905		
Facilitating Conditions			0.749	0.505
	~~FC1~~	~~0.512~~		
	FC2	0.845		
	FC3	0.676		
	FC4	0.587		
Individual Characteristics			0.837	0.719
	IC1	0.829		
	IC2	0.867		
	~~IC3~~	~~-0.705~~		
Technology Characteristics			0.751	0.503
	TC1	0.835		
	TC2	0.718		
	~~TC3~~	~~0.633~~		
Environmental Characteristics			1	1
	EC1	1		
	~~EC2~~	~~0.106~~		
~~**Experience**~~				
	~~E1~~			
	~~E2~~			

Table 4. Reliability and validity test for latent variables and indicators for the entire study population.

The hetero-trait-monotrait ratio can be seen in table 5. These values describe the correlation between the latent variables and should be below 0.85, as mentioned by Hair et al. (2021). The results show that all HTMT-values are below 0.85 except one. The correlation between *Facilitating Conditions* and *Technology Characteristics* showed a value of 0.938. Values above 0.85 indicate a lack of discriminant validity and will be taken into consideration when analyzing the results.

	EC	EE	FC	IC	PE	SI	TC	UB	TC x EE	TC x PE	IC x PE	IC x EE	IC x FC	EC x FC	EC x SI
EC															
EE	0.310														
FC	0.823	0.426													
IC	0.421	0.442	0.225												
PE	0.378	0.069	0.530	0.215											
SI	0.802	0.084	0.614	0.307	0.485										
TC	0.633	0.152	0.938	0.498	0.530	0.821									
UB	0.249	0.167	0.561	0.302	0.547	0.224	0.764								
TC x EE	0.251	0.342	0.358	0.373	0.258	0.036	0.243	0.175							
TC x PE	0.124	0.122	0.210	0.154	0.480	0.155	0.280	0.195	0.176						
IC x PE	0.229	0.096	0.435	0.049	0.057	0.187	0.164	0.039	0.111	0.131					
IC x EE	0.437	0.333	0.265	0.327	0.167	0.438	0.293	0.167	0.395	0.028	0.029				
IC x FC	0.294	0.238	0.414	0.400	0.654	0.197	0.274	0.290	0.228	0.185	0.199	0.363			
EC x FC	0.485	0.216	0.608	0.295	0.201	0.298	0.396	0.170	0.318	0.122	0.251	0.303	0.376		
EC x SI	0.421	0.209	0.400	0.302	0.080	0.460	0.473	0.115	0.329	0.139	0.404	0.532	0.223	0.580	

Table 5. HTMT-values for the entire study population.

The VIF-values are presented in table 6. As mentioned in section 3.5.4, VIF-values describe the collinearity between the latent variables and a suggested threshold, to exclude a latent variable due to collinearity, is a VIF-value of 3 (Hair et al. 2021). None of the latent variables exceeds this threshold, indicating that the presence of collinearity is not an issue for this altered model with *Experience* removed.

Latent Variable	VIF-value
PE	1.659
EE	1.435
SI	2.382
FC	2.043
IC	1.505
TC	1.700
EC	2.777
Age	1.871

Table 6. VIF-values for the entire study population.

4.3 Results

4.3.1 Descriptive Statistics

	Technical Departments	Non-Technical Departments
Perceived AI Tool Applicability (% of respondents)	64.00 %	68.75%
Average AI Tool Use Behaviour	28.51 %	66.04 %
Difference	48.49 %	2.71 %

Table 7. A summary of the descriptive statistics.

Table 7 summarizes the descriptive statistics which were illustrated by the figures in section 4.1.2 and 4.1.3. The table highlights the discrepancy between the perceived AI tool applicability and the average AI tool use behaviour. It can be seen that this discrepancy is much larger in the technical departments than in the non-technical departments. Although the perceived AI tool applicability only differs by 4.75% between the two types of departments, the average use behaviour differs by more than 45%. This seems to indicate that there are differences between technical and non-technical departments which influences the use behaviour, and thus the adoption of AI tools. The descriptive statistics seem to indicate that almost everyone who believes that the use of AI tools is possible in non-technical departments is able to utilize the tools. In contrast, it seems that although the perceived applicability of AI tools is similar in technical departments there is a barrier which hinders or prevents the respondents working in technical departments from utilizing the tools.

4.3.2 Model Results

4.3.2.1 The Entire Sample

First, the entire sample was evaluated from the created PLS-SEM model. Figure 9 illustrates the model results with the moderating nodes included. When the moderating nodes are included in the model the moderating effects are considered. This model therefore tests the study's sub-hypothesis' (not hypothesis H1, H2, H3, or H4).

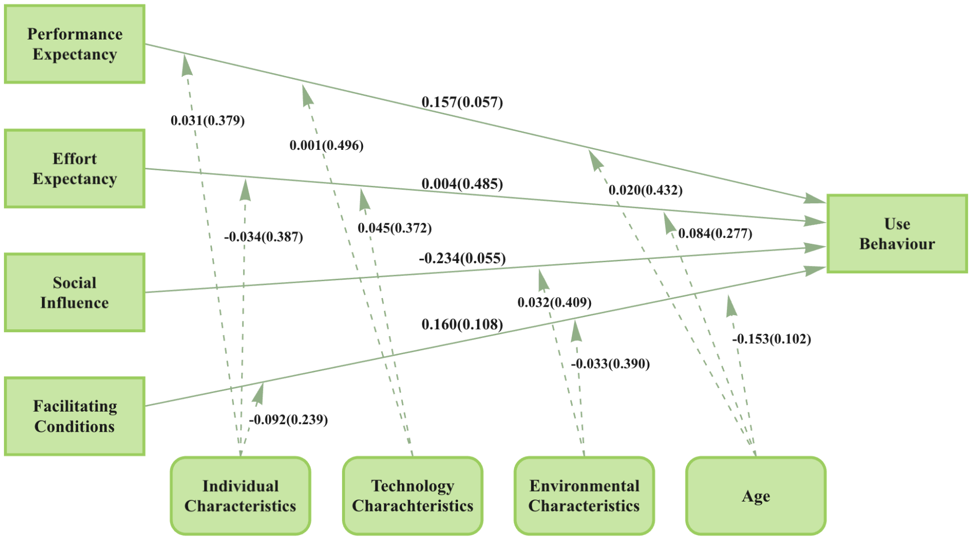

Figure 9. The model results with moderators included.

Figure 10 illustrates the model results when the moderating nodes are removed from the model, in order to disregard the moderating effects. The moderating nodes, and thus the moderating effects, are removed from the model in order to examine the direct influence which the predictor nodes have on the outcome node, *Use Behaviour*. This tests the four primary hypotheses, H1, H2, H3, and H4.

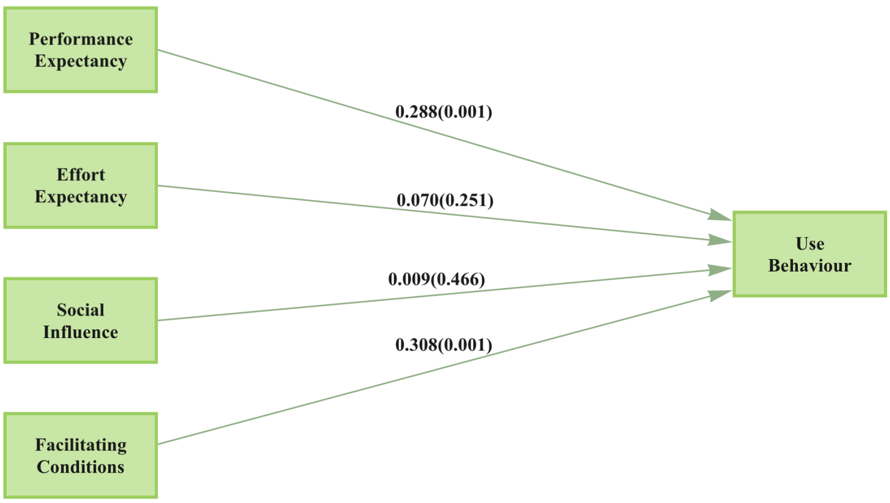

Figure 10. The model's results with regards to the predictors.

Hypothesis	Path Coefficient	P-value	Accepted
H1: Performance Expectancy (PE) - Use Behaviour (UB)	**0.288**	**0.001**	**Yes**
H1a: Individual Characteristics x PE - UB	0.027	0.382	No
H1b: Technology Characteristics x PE - UB	-0.013	0.438	No
~~H1d: Experience x PE - UB~~			
H1e: Age x PE - UB	0.020	0.432	No
H2: Effort Expectancy (EE) - Use Behaviour (UB)	**0.070**	**0.251**	**No**
H2a: Individual Characteristics x EE - UB	-0.058	0.299	No
H2b: Technology Characteristics x EE - UB	0.038	0.367	No
~~H2d: Experience x EE - UB~~			
H2e: Age x EE - UB	0.084	0.277	No
H3: Social Influence (SI) - Use Behaviour (UB)	**0.009**	**0.466**	**No**
H3c: Environmental Characteristics x SI - UB	0.026	0.419	No
~~H3d: Experience x SI - UB~~			
H4: Facilitating Conditions (FC) - Use Behaviour (UB)	**0.308**	**0.001**	**Yes**
H4a: Individual Characteristics x FC - UB	-0.095	0.204	No
H4c: Environmental Characteristics x FC - UB	0.031	0.356	No
~~H4d: Experience x FC - UB~~			
H4e: Age x FC - UB	-0.153	0.102	No

Table 8. Model estimation with hypothesis testing.

Table 8 above summarizes the results presented in figure 9 and 10. This table illustrates the values of the path coefficients and the statistical significance. There are two accepted hypotheses: H1 and H4. According to the model, *Performance Expectancy* and *Facilitating Conditions* statistically significantly increase *Use Behaviour*. The coefficient of determination (R^2) for the two models, presented above, were calculated to $R^2 = 0.477$ for the model with moderators included (figure 9), and $R^2 = 0.240$ for the model lacking moderators (figure 10). R^2-values of 0.50 and 0.25 can be seen as moderate and weak, respectively (Hair et al. 2021). The explanatory power of the model regarding actual *Use Behaviour* can therefore be seen as close to moderate for the model presented in figure 10 and weak for the model presented in figure 9.

The two tables, 9 and 10, below present the model's predictive power. As mentioned in section 3.5.4 the PLS-SEM model’s predictive power can be assessed with the RMSE- and MAE-value. If the RMSE and MAE value for the PLS-SEM model is lower than the linear model value, the model has a high predictive power (Hair et al. 2021). This is true for the model with the moderators removed, as both the RMSE and MAE-value are lower. This is, however, not the case for the model with moderators present as both the RMSE and MAE-value are higher than the linear model, indicating that this model lacks predictive power. The Q^2 value is above 0.0 in both tables, indicating that the model outperforms the basic benchmark (Hair et al. 2021).

Variable	Q^2	PLS-SEM RMSE	PLS-SEM MAE	LM RMSE	LM MAE
UB	0.146	2.935	2.346	2.741	2.261

Table 9. Model prediction (Model 1).

Variable	Q^2	PLS-SEM RMSE	PLS-SEM MAE	LM RMSE	LM MAE
UB	0.144	2.939	2.492	3.079	2.600

Table 10. Model prediction with moderators removed (Model 2).

4.3.2.2 Multigroup Analysis (Technical vs Non-Technical Departments)

After the model for the entire population was created and evaluated, a multigroup analysis was performed. The purpose of this was to examine the difference between the technical and non-technical departments. The comparison of the two types of departments aimed to observe whether or not the strength of influence between the different nodes in the model differed in a statistically significant manner between the two groups.

Figure 11 presents the multigroup analysis results with the moderating effects included. The inclusion of the moderating effects implies that this model tests differences between the two groups with regards to the sub-hypothesis'. Figure 11 corresponds to the model that includes moderating effects, while figure 12 corresponds to the model that excludes moderating effects, in the previous section.

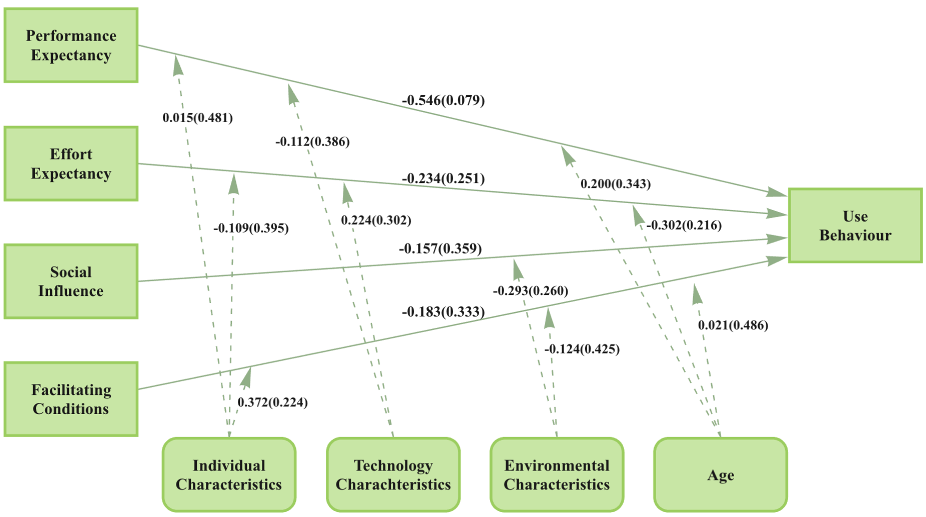

Figure 11. The model results with moderators included. (Model 1)

The following figure illustrates the multigroup analysis results when the moderating effects are not considered. The exclusion of the moderating effects implies that this model tests the differences between the two groups with regards to the primary hypothesis', H1, H2, H3, and H4.

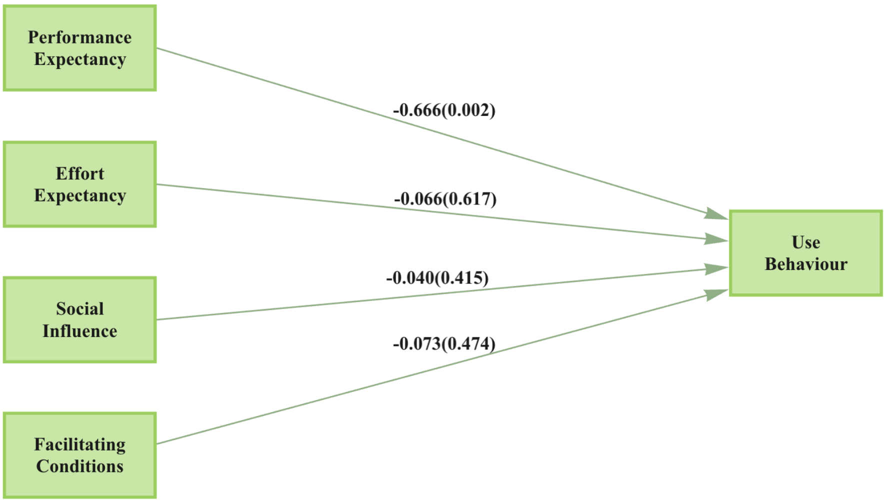

Figure 12. The model's results with regards to the predictors. (Model 2)

Hypothesis	Path Coefficient (NT* - T**)	P-value	Accepted
H1: Performance Expectancy (PE) - Use Behaviour (UB)	**-0.666**	**0.002**	**Yes**
H1a: Individual Characteristics x PE - UB	0.012	0.472	No
H1b: Technology Characteristics x PE - UB	-0.258	0.190	No
~~H1d: Experience x PE - UB~~			
H1e: Age x PE - UB	0.200	0.343	No
H2: Effort Expectancy (EE) - Use Behaviour (UB)	**-0.066**	**0.383**	**No**
H2a: Individual Characteristics x EE - UB	-0.088	0.401	No
H2b: Technology Characteristics x EE - UB	0.227	0.264	No
~~H2d: Experience x EE - UB~~			
H2e: Age x EE - UB	-0.302	0.216	No
H3: Social Influence (SI) - Use Behaviour (UB)	**-0.040**	**0.415**	**No**
H3c: Environmental Characteristics x SI - UB	0.014	0.499	No
~~H3d: Experience x SI - UB~~			
H4: Facilitating Conditions (FC) - Use Behaviour (UB)	**-0.073**	**0.474**	**No**
H4a: Individual Characteristics x FC - UB	0.303	0.219	No
H4c: Environmental Characteristics x FC - UB	0.066	0.424	No
~~H4d: Experience x FC - UB~~			
H4e: Age x FC - UB	0.021	0.486	No

*Table 11. Model estimation with hypothesis testing. *Non-technical, **Technical.*

Table 11, above, summarizes the results presented in the figures 11 and 12. This table illustrates the differences between the two groups with regards to the different hypotheses. The model is defined in such a way that values presented in the table, with regards to the path coefficient, are negative if the hypothesis is stronger for the technical departments. It can be seen that the relationship between all of the predictor variables and the outcome variable is stronger for the technical department. The only statistically significant result which was obtained from the multigroup analysis is that the effect of *Performance Expectancy* on *Use Behaviour* is stronger for individuals who work in technical departments. The explanatory power of *Use Behaviour* for the two models can be seen in table 12. The results indicate that the two models explained the actual *Use Behaviour* for technical individuals greater than for non-technical individuals.

Model	**R^2***	**R^2****	**R^2-difference*****	**p - value**
Moderating effects included	**0.293**	**0.620**	**-0.326**	**0.009**
Moderating effects excluded	**0.107**	**0.413**	**-0.306**	**0.017**

*Table 12. Coefficient of determination (R^2). *Non-Technical, **Technical, ***Non-technical - Technical*

5. Discussion and Conclusion

5.1 Discussion

The purpose of this study was to explore the drivers/ barriers which impact the individual adoption of AI tools as well as comparing how these might differ for individuals working in technical and non-technical departments. This was of interest due to the belief that the differing characteristics of technical and non-technical departments implies differing drivers/ barriers to AI tool adoption. The descriptive statistics, section 4.3.1, presents an insight regarding differing use behaviour between the two types of departments. The results show that 64% of the respondents who work in technical departments and 68.75% of the respondents who work in non-technical departments believe that there are AI tools which are applicable or very applicable to their work. Although the perceived applicability of AI tools is very similar between the two types of departments, the use behaviour largely differs. The average AI tool use behaviour for respondents working in technical departments was 28.51% while the average AI tool use behaviour was 66.04% for respondents working in non-technical departments.

When comparing the average use behaviour and the perceived applicability it can be seen that these values are very similar for the non-technical respondents. This seems to imply that the respondents working in non-technical departments, who believe that there are AI tools which are applicable to their work, are largely able and willing to adopt these AI tools. The respondents working in technical departments, on the other hand, seem to face greater barriers to adoption. It is somewhat surprising that their average use behaviour is 28.51% when they have access to enterprise AI tools and 64% of these respondents believe that there are AI tools which are applicable to their work. There are several possible explanations regarding why the technical departments face greater barriers than the non-technical departments. One possible difference between the two types of departments is the extent to which the available enterprise solutions meet the needs of individuals working in technical departments. It can be hypothesized that individuals working in technical departments might require more niche AI tools than what is offered by enterprise solutions, such as the computer drafting AI tool, ZOO (ZOO, 2024). This is, however, not necessarily the case as technical departments, such as R&D, are required to perform rigorous market research, write project documentation, test protocols, etc. all of which can be significantly aided with the use of an enterprise AI (Osama Akhlaq, 2024). What is more likely is differing departmental cultures as well as other individual factors, which can significantly impact the individual adoption (Gressel et al. 2021, pp. 165-181; Venkatesh et al. 2003).

The results produced in section 4.3.2.1 show that *Performance Expectancy* and *Facilitating Conditions* have a statistically significant positive effect on *Use Behaviour* for the study population, see section 4.3.2.1. This implies that if an individual believes that AI tools will have a positive impact on their professional performance, they will be more inclined to use the technology. This result also highlights the importance of the organization having the required organizational and technological infrastructure. If the individual believes that the organization has the technological infrastructure, which enables the use of AI, and the organizational infrastructure, which is capable of supporting the individual through the adoption process, the individual is more likely to choose to adopt AI tools. Of the two statistically significant results it is *Facilitating Conditions* which has the largest impact on *Use Behaviour*. No significant results were obtained for any of the other predictors/ moderators proposed by either the UTAUT model or the altered UTAUT model (Venkatesh et al. 2003, Venkatesh 2021). As previously mentioned, *Performance Expectancy* and *Facilitating Conditions* are not binary variables but rather represent the individual's beliefs concerning these variables. That is to say, it is not sufficient for the AI tool to actually perform well, the individual needs to believe that the tool performs well. In a similar manner, it is not sufficient for the organization to ensure that they have the required organizational and technological infrastructure, they need to convince their employees that this is the case, in order for the individual AI tool adoption to increase. This highlights the critical importance which clear communication from leaders has in organizations which want to adopt AI tools. This is in line with the results presented in the study by Kelley (2022).

As the goal of this study was to not only observe the drivers/ barriers to AI tool adoption, but also compare these drivers/ barriers between the technical and non-technical departments, a multigroup analysis was performed. The results from this analysis, see section 4.3.2.2, showed that the impact which *Performance Expectancy* has on *Use Behaviour* is statistically significantly stronger for individuals working in technical rather than non-technical departments. This implies that the *Use Behaviour* of individuals working in technical departments, in organizations similar to those in the study population, will be more impacted if they are convinced that AI tools will perform well than individuals working in non-technical departments. The results presented in table 11, section 4.3.2.2, illustrates that the relationship between all of the predictors and *Use Behaviour* is stronger for technical departments. However, only the relationship between *Performance Expectancy* and *Use Behaviour* was stronger in a statistically significant manner. This result implies that organizations should place extra emphasis on highlighting the positives associated with AI tools when attempting to increase AI adoption in technical departments, as this will result in a higher effect.

As previously mentioned, very little research has been performed applying the UTAUT model in order to observe drivers/ barriers to AI tool adoption, as well as comparing these drivers/ barriers between departments. This lack of previous research makes it difficult to validate the results produced by this study in a larger context. Previous research applying the UTAUT model in order to study individual adoption of new technologies has however been completed. Comparing the results produced by this study with these, more general studies, can aid in the evaluation of the results by evaluating the theory. When comparing the results found in this study to those found in the study regarding the individual adoption of digitalization among business owners/ managers in the context of European SMEs several similarities can be seen (Kwarteng et al. 2023). Both of these studies found the relationship between *Performance Expectancy*/ *Facilitating Conditions* and *Use Behaviour* to be positively statistically significant. Both of these studies also found the relationship between *Effort Expectancy* and *Use Behaviour* to be statistically insignificant. The general similarities which can be seen in the results produced in this study and the study by Kwarteng, et al. (2023) suggest some level of reasonability in the produced results.

The bachelor's thesis, completed at LUSEM, which utilized the UTAUT model in order to evaluate the drivers which impact accountants' use of big data systems, produced results which contrast the results produced by this study (Thunberg, Svensson & Yngwe, 2022). This study presented a statistically significant relationship between *Facilitating Conditions/ Social Influence* and *Use Behaviour*. Although the relationship between *Facilitating Conditions* and *Use Behaviour* was seen in this study as well, the relationship between *Social Influence* and *Use Behaviour* could not be seen. This discrepancy could be caused by a number of factors such as differences in the study population as well as the technology which is being studied.

Although the lack of previous research regarding the adoption of AI tools, as well as comparisons between technical and non-technical departments, imposes a challenge to the comparison and wider validation of this studies results, it also implies that this study is valuable to the research context surrounding the adoption of AI tools. As this study managed to identify some drivers/ barriers to AI tool adoption, as well as differences in drivers/ barriers between the two different types of departments, this study fills an identifiable research gap. This study can therefore act as a starting point for future research which aims to dive deeper into the area of study which is the individual adoption of AI tools in different departments.

The framework for this study was primarily grounded in the UTAUT model with additions from the *Ecological Framework of Management Decision-Making*. UTAUT is regarded as a robust model for understanding technology adoption. By integrating additional moderators relevant to AI tools, the framework was adapted to better reflect the unique challenges of AI adoption. Despite these theoretical strengths, the PLS-SEM analysis gave no significant results for both the traditional and the additional moderators. As this was also true for the study by Thunberg et al. (2022) it is possible to question the theoretical significance which the moderators are believed to possess with regards to AI tool and big data adoption.

There are several limitations in this study which need to be taken into consideration when observing the results. One significant limitation with this study is, as mentioned in sections 3.2.4 and 3.4.5, its sampling strategy. Due to the relatively short time frame of both the study and the data collection phase, an efficient sampling strategy which generates large response rates quickly was imperative to the study's completion. It was due to this that snowball sampling was included in the sampling strategy. This sampling strategy implies one significant limitation, a lack of data regarding nonresponse. This lack of data implies that it is not entirely known who the survey reached, and thus which respondents constitute the sample. In the context of this study it can only be stated that it is known, with complete certainty, which department the respondents work in, but not which company. This in itself is not an issue as it is not the organization which is the measurement entity, but rather the department. This mitigates the limitation with nonresponse as nonresponse poses minimal bias when it is unrelated to the study variables (Groves et al. 2009). The lack of knowledge regarding the organizations which the respondents work for does however make it impossible to guarantee that the survey hasn't been shared outside of the study population. Although this is a risk, it is not believed that this is the case in this study as it was observed that the majority of contact people led to a limited number of responses, seemingly indicating that, as requested, the survey hadn't been shared outside of the contact persons closest team.

Another potential limitation with this study is the grouping of technical and non-technical departments. This grouping was made largely due to demographic statistics and potential cultural differences, which are believed to impact technology adoption/ use. The grouping of technical and non-technical departments implies a belief that there is some level of homogeneity within the two groups. If one of the included departments varies significantly with regards to its characteristics, from the others in its group, it is possible that this could have a negative impact on the collected data, and thus the quality of the results. Furthermore, the generalisation of defining departments as either technological or non-technological may decrease the value and usability of the results as they cannot be seamlessly applied to any singular department.

A third limitation of this study is the reliability and validity in the constructed model. Due to the potential lack of invariance across the different groups, the results presented by the multigroup analysis might be compromised (Liengaard, 2024). The two groups might interpret the indicators differently, therefore indicating that the latent variables are perceived differently across the two groups. Thus implying that the result of the multigroup analysis might be compromised and further research is needed. This can be further explained by the results presented in table 12, section 4.3.2.2, in which the R^2 values for the two groups differ significantly. This indicates that the model better explains *Use Behaviour* for the technical group compared to the non-technical group. Another limitation with the model are the latent variables which are described by only one indicator, *Effort Expectancy* and *Environmental Characteristics*. This is problematic as these latent variables essentially behave as observed variables, meaning their measurements entirely depend on a single indicator, which can result in an increase of measurement error. Although none of these latent variables indicated statistical significance, this may have been caused by potential measurement error, thus limiting them from having statistical significance in the model. Additionally, the constructed model with moderators included lacked predictive power, as reported in table 10 in section 4.3.2.1. This indicates that the model's ability to predict new or future observations is weak (Hair et al. 2021b). Although the minimum sample size was adequately met for both of the groups, the aforementioned limitations might be resolved with a larger sample as a larger sample size will increase the precision of the PLS-SEM estimations (Hair et al. 2021b). Another possible improvement would be to revise and improve the indicators to better reflect the latent variables, thus providing more representative results for the two groups (Wurpts and Geiser, 2014).

5.2 Conclusion

The objective of this study was to explore drivers/ barriers to the individual adoption of AI tools in technical and non-technical departments. The purpose of this was to both observe what drivers/ barriers there are, as well as how these differ between departments with different technical characteristics. To this end, the study drew upon a modified theoretical framework founded on the UTAUT model with elements from the *Ecological Framework of Management Decision-Making*.

The results produced by the PLS-SEM analysis for the entire study population showed that *Performance Expectancy* and *Facilitating Conditions* have a statistically significant positive effect on *Use Behaviour*. This implies that individuals who believe that AI tools perform well and can aid them in their work will be more willing to adopt the technology. The results also show that employees who believe that the organization has the technological infrastructure, which enables the efficient use of AI tools, and the organizational infrastructure, which is capable of supporting the individual through the adoption process, are more likely to choose to adopt AI tools. The results from the multigroup analysis shows that the effect which *Performance Expectancy* has on *Use Behaviour* is statistically significantly stronger for individuals working in technical rather than non-technical departments.

Organizations, similar to those included in the study population, which want their employees to utilize AI tools need to not only provide their employees with the required AI tools and ensure that the necessary organizational and technological infrastructure is in place, but also actively communicate this with their employees. If the organization can convince their employees that the adoption of AI tools can lead to increased performance it is likely that the adoption of these technologies will increase. The same is true if the organization manages to convince the employees that the organization has the required technological and organizational infrastructure. Furthermore, the result from the multigroup analysis provides slight insight to organizations as to how they can distribute their efforts in order to most efficiently boost AI tool adoption across technical/ non-technical departments.

6. Recommendations for Future Research

Based on the results presented in this study there is reason to make a couple of recommendations for future research. Out of 18 presented hypotheses, only three were found significant; two for the general study population and one for the multigroup comparison. This outcome suggests potential areas for further investigation to better understand the dynamics of AI tool adoption.

Several factors could explain the limited number of significant results, one being model errors. To reduce model errors future research should focus on the improvement of the latent variables and observable indicators. Since AI tool adoption is a new topic, general improvements to the indicators to better capture the individual's perception of AI tools will increase the reliability of the latent variables. Increasing the sample size would increase the statistical power of the analysis and help identify patterns that may not have been evident in this study.

As a consequence of removing the latent variable *Experience*, due to multicollinearity, four hypotheses that were linked to this variable were disregarded. The removal of these hypotheses, while necessary to improve model robustness, suggests an avenue for future research. If a refined set of indicators, with lower multicollinearity, can be developed with AI tool adoption in mind, it may be possible to reintroduce *Experience* in future research to better understand the potential impact this moderator has on AI tool adoption.

Future research is recommended to minimise the generalisation about technical and non-technical categories at department level. A more focused/ direct approach is recommended to examine differing drivers/ barriers within departments such as marketing, finance, software development, and R&D to further improve the research. This would provide organizations with the results needed for specific departments to implement AI tools in a way that best suits their employees.

Lastly, the study's inability to measure nonresponse due to the use of snowball sampling was identified as a limitation. Future research, with more time and greater resources, are therefore emplored to utilize a more methodical sampling strategy in order to increase the robustness of the results.

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8. Appendix

8.1 Appendix A

The table below illustrates the used survey questions and their sources.

Variable	Index	Question/ Statement	Source
NA			
	NA	Do you consent to the use of your response for this research and to the storage of your response for this purpose until 2025-05-30?	NA
	NA	Please provide an anonymous identifier (remember this identifier in case you want to modify or delete the data we have gathered about you).	NA
	NA	Which department do you work in?	NA
	NA	How old are you?	NA
	NA	I believe that there are AI tools which are applicable for my work.	NA
Performance Expectancy			
	PE1	The use of AI tools does/would increase my efficiency.	Moore and Benbasat, 1991
	PE2	The use of AI tools does/would increase the quality of my work.	Thompson et al. 1991
Effort Expectancy			
	EE1	Learning to use AI tools would be easy for me.	Davis et al. 1989
	EE2	Overall, I believe that AI tools are easy to use.	Moore and Benbasat, 1991
	EE3	It takes too long to learn how to use AI tools to make it worth the effort.	Thompson et al. 1991
Social Influence			
	SI1	My colleagues support/ encourage the use of AI tools.	Davis et al. 1989
	SI2	My supervisor is supportive of the use of AI tools for my job.	Thompson et al. 1991
	SI3	I use AI tools because of the proportion of colleagues that use AI tools.	Thompson et al. 1991
Facilitating Conditions			
	FC1	The organization in which I work has the technical infrastructure enabling me to use AI tools.	Venkatesh et al. 2003
	FC2	The organization in which I work has standard practices which enables the adoption of new technologies.	Venkatesh et al. 2003
	FC3	The organization in which I work does/ can provide me with support when learning how to use new technologies.	Thompson et al. 1991
	FC4	I have the knowledge necessary to use AI tools.	Ajzen, 1991
Individual Characteristics			
	IC1	I tend to be risk tolerant.	Based on Venkatesh, 2021
	IC2	I tend to tolerate uncertainty.	Based on Venkatesh, 2021
	IC3	Learning new things motivates me.	Based on Venkatesh, 2021
Technology Characteristics			
	TC1	I find that the AI tools I use are reliable	Based on Venkatesh, 2021

	TC2	I am able to provide the AI tool I use with complete information	Based on Venkatesh, 2021
	TC3	I get the required information I need, from both within and outside of the department I work, in order to efficiently utilize the AI tools	Based on Venkatesh, 2021
Environmental Characteristics			
	EC1	The department in which I work has an environment/ culture which fosters the use of new technologies, such as AI tools	Based on Venkatesh, 2021
	EC2	The department in which I work has a culture which fosters innovation and learning	Based on Venkatesh, 2021
Experience			
	E1	I am experienced with AI tools	Based on Venkatesh et al. 2003
	E2	I am experienced with learning and using new technologies/ tools	Based on Venkatesh et al. 2003
Use Behaviour			
	UB1	When faced with tasks/ challenges which can be solved with the help of AI tools, I utilize AI tools approximately x% of the time	NA

8.2 Appendix B

The table below illustrates the responses obtained from the respondents working in technical departments.

	Respondent Answers (Frequency)				
Index	**1**	**2**	**3**	**4**	**5**
PE1	1	2	11	19	14
PE2	1	8	18	17	3
EE1	3	4	13	20	7
EE2	6	17	16	5	3
EE3	6	25	10	5	1
SI1	4	6	19	12	6
SI2	3	9	10	18	7
SI3	7	11	9	12	8
FC1	6	8	8	18	7
FC2	6	15	11	13	2
FC3	6	10	15	13	3
FC4	5	9	7	8	18
IC1	4	8	11	18	6
IC2	5	15	10	12	5
IC3	0	0	3	15	29
TC1	2	9	28	7	1
TC2	4	19	15	8	1
TC3	7	14	13	12	1
EC1	7	5	12	15	8
EC2	0	4	5	24	14
E1	9	14	5	12	7
E2	0	5	4	17	21

8.3 Appendix C

The table below illustrates the responses obtained from the respondents working in non-technical departments.

	Respondent Answers (Frequency)				
Index	**1**	**2**	**3**	**4**	**5**
PE1	0	0	15	20	13
PE2	0	1	21	21	5
EE1	1	3	21	19	4
EE2	0	0	25	19	4
EE3	0	5	22	19	2
SI1	2	2	14	26	4
SI2	1	1	19	25	2
SI3	1	1	14	27	5
FC1	2	2	21	18	5
FC2	1	2	21	19	5
FC3	1	1	23	22	1
FC4	0	1	24	21	2
IC1	0	2	24	16	6
IC2	0	2	19	22	5
IC3	0	0	16	24	8
TC1	1	0	16	24	7
TC2	2	2	23	19	2
TC3	2	4	25	16	1
EC1	1	0	14	28	5
EC2	0	0	16	26	6
E1	1	0	26	18	3
E2	0	0	21	26	1

8.4 Appendix D

The AI prompts which were used in this study:

ChatGPT:

- What should be included in the discussion section?
- What should be in a conclusion?
- What to include in recommendations for future research?
- What to include in problematization?
- How does the adoption of ai differ between organizational functions?
- What are your sources?
- How should I structure an introduction for a thesis in economics?
- What are the different types of AI?
- What about LLMS?
- What type of AI is github copilot?
- What are the main barriers to the corporate adoption of AI?
- How do skill gaps affect organisations ability to successfully adopt new technology?
- How to structure the method part of a report?
- Which organisational departments are the most innovative and value learning?
- Vad ska stå med i en operationalisering?
- What is a latent variable?
- What are the latent variables in the UTAUT model?
- What is the difference between dependent and outcome variables?
- What are your sources for the different points?
- What are moderating variables?
- How are the latent variables in the UTAUT model measured?
- What rubriks should be included in the data quality section?
- What is internal validity?
- How can I improve the external validity of a study?
- If the external validity is high can the results of the study be generalized outside of the study population?
- How to ensure high reliability of a study?
- Ensure reliability in a survey study?
- What is coverage error?
- Does coverage error limit a study's generalizability?
- What are some criticisms towards the use of PLS-SEM?

Consensus:

- AI tools used in R&D processes?
- AI tools used for mechanical engineering?
- How can AI help accountants?
- What affects individual usage of AI at work?
- Utilizing AI, a future must?
- Utilizing AI, a future must to remain competitive?
- Corporate AI applications?
- AI applications r&d?
- AI applications engineering?
- AI applications software engineering?
- AI applications marketing and sales?
- AI applications sales?
- Adoption of new technologies trends across organizational departments?
- How does acceptance of new technology differ between organisational functions?
- How does acceptance of new technology differ between organisational departments?
- How does ai adoption differ between different departments?
- How does AI usage vary across different organizational departments?
- The use of ai across departments?
- Does age affect acceptance of new technologies?
- Does age affect acceptance of new technologies utaut?
- Does gender affect acceptance of new technologies utaut?
- Does gender affect acceptance of new technologies?
- How does gender affect acceptance of new technologies?
- Are AI tools complex to use?
- Are AI tools hard to use?
- Are AI tools like chat gpt hard to use?
- Are AI tools like copilot hard to use?
- How user-friendly are AI programming tools like Copilot?
- Are AI tools like copilot easy to use?
- Is technology adoption easier for people with engineering backgrounds?
- Technology adoption, technical departments vs non-technical departments?
- How does organizational culture differ between technical and non technical departments?
- Differences in organizational culture across departments?
- How does innovation culture differ between technical and non technical departments?
- Which departments are the most innovative?

- Which departments have the most innovative culture?
- Which departments are the most innovative and value learning?
- Which organisational departments are the most innovative and value learning?
- Which organisational departments tend to be the most innovative?
- Are R&D departments more innovative than other departments?
- Do R&D departments drive more innovation than others?
- Which organisational department has the most learning culture?
- Which organisational function has the most learning culture?
- Types of innovation in different organisational functions?
- Types of innovation in different organisational departments?
- In which department is product innovation most common?
- How do technical skills vary across organisational departments?
- Which departments require the most technical skills?
- Demographic comparison technical vs non-technical fields?
- Age difference r&d vs marketing department?
- Average age difference r&d vs marketing department?
- Hur ser åldersfördelningen ut svensk industri?
- What is PLS-SEM?