MASTERARBEIT | MASTER'S THESIS

Titel | Title

The AITUAM

verfasst von | submitted by

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angestrebter akademischer Grad | in partial fulfilment of the requirements for the degree of

Master of Science (MSc)

Wien | Vienna, 2024

Studienkennzahl lt. Studienblatt | Degree programme code as it appears on the student record sheet:	UA 066 915
Studienrichtung lt. Studienblatt | Degree programme as it appears on the student record sheet:	Masterstudium Betriebswirtschaft
Betreut von | Supervisor:	Univ.-Prof. Mag. Dr. Bernhard Kittel

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Abstract:

Um die Akzeptanz von Human Resource Managern bezüglich des Einsatzes von Künstlicher Intelligenz im Bewerbungsprozess zu bestimmen, wurde in dieser Masterarbeit ein theoretisches Akzeptanzmodell (Artificial Intelligence Technology User Acceptance (AITUAM)) entwickelt und empirisch getestet. Das AITUAM basiert auf dem Technology Acceptance Model von Davis (1989). Um die Anwendungsabsicht (Intention to Use) von HR-Manager zu bestimmen, umfasst das Modell folgende Variablen: angenommene Nützlichkeit (Perceived Usefulness), erwartete Leichtigkeit der Verwendung (Perceived Ease of Use), das Vertrauen in die durch die KI gelieferten Ergebnisse (Trust) sowie Angst vor der KI-Technologie (AI-Anxiety). Um die Aussagekraft des Modells zu erhöhen, wurden zudem Alter, Geschlecht sowie Erfahrung mit KI als Kontrollvariablen in das Modell integriert. Anhand von Daten, die durch eine Online-Umfrage mit HR-Managern gewonnen wurden, wurde das AITUAM getestet und evaluiert. Die empirischen Ergebnisse verdeutlichen, dass für die Individuen der Stichprobe, Perceived Usefulness sowie Perceived Ease of Use einen direkten positiven Einfluss auf Intention to Use haben, während AI-Anxiety einen direkten negativen Einfluss auf Intention to Use hat. Trust wirkt sich dagegen nur indirekt signifikant auf Intention to Use aus, über den signifikanten positiven direkten Einfluss auf Perceived Usefulness und Perceived Ease of Use. Die Ergebnisse der statistischen Auswertung deuten darauf hin, dass die HR-Manager, welche schon Erfahrungen mit KI-Tools im Bewerbungsprozess gemacht haben, eine höhere Intention to Use aufweisen, als diejenigen die noch keine Erfahrung mit der Technologie gemacht haben. Die Ergebnisse der empirischen Ausarbeitung zeigen zudem, dass Frauen eine höhere Intention to Use haben als Männer. Zudem wurde ein moderierender Effekt von Alter gefunden. Je älter das Individuum ist, desto stärker ist der negative Einfluss AI-Anxiety auf Intention to Use. Die Ergebnisse dieser Masterarbeit heben hervor, dass die AI-Anxiety, einer der wesentlichen Faktoren ist, um die Anwendung von KI-Tools im Bewerbungsprozess zu ermitteln.

Abstract:

This Master thesis develops and empirically tests a theoretical model of Artificial Intelligence User Acceptance (AITUAM) which intends to determine HR manager's acceptance of Artificial Intelligence tools used in the application process. The proposed model is based on the TAM from Davis (1989) and includes the variables perceived usefulness, perceived ease of use, trust in the generated output of the AI (Trust), and anxiety about AI (AI-Anxiety) to determine the intention to use AI tools in the application process. To further increase the explainability of the AITUAM, age, gender, and prior experience with AI tools are included in the AITUAM as control variables. Utilizing data collected from HR managers in the DACH region via an online survey, the AITUAM is evaluated. The empirical results indicate that, for the used sample, perceived usefulness and perceived ease of use are positively related to intention to use, while AI-Anxiety is negatively related to intention to use. Trust has an indirect, significant positive effect on intention to use through its impact on perceived usefulness and perceived ease of use. Further findings are that the HR managers who already had experience using AI tools in the application process have a higher intention to use these tools than their inexperienced counterparts, and that female HR managers are more inclined to use them than male HR managers. For Age, a moderating effect on the relationship between AI-Anxiety and Intention to Use has been found. The older the HR manager, the stronger the negative impact AI-Anxiety has on Intention to Use. The results of this Master's thesis show that AI-Anxiety is important to be recognized as a factor that decreases the behavioral intention to use AI tools in the application process.

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1: Introduction

The rise of Artificial Intelligence (AI) and its ability to generate output indistinguishable from human-created output raises the question of to what extent AI is going to change the labor market. Companies implement AI to achieve labor cost savings and increase productivity. A recent report from Goldman Sachs found that two-thirds of current jobs are being exposed to some degree of AI automatization and that generative AI could substitute up to one-third of current job tasks (Briggs et al., 2023), while other reports estimate that 400 to 800 million workers are going to be replaced by AI by 2023 (McKinsey, 2022). AI and its introduction in the labor market have the potential to drastically change how companies and organizations interact with the labor force. Fundamental changes in the labor market create opportunities as well as challenges for employers and employees. Using AI in the recruitment process might fundamentally transform the employment landscape. A recent study by the Pew Research Center found that there is a range of views about the use of AI by employers. While the use of AI in making final hiring decisions is opposed by around 90% of the respondents, around 50% believe that AI would do a better job than humans in evaluating job applicants (Rainie, 2023). Another important finding of that survey is that 66% of the respondents stated that they would not want to apply for a job with an employer that uses AI to help make hiring decisions (Rainie, 2023). These results, compared with the results of a survey by ResumeBuilder.com, which surveyed more than 1000 American employees involved in the hiring process, found that 43% of companies plan to adopt AI interviews by 2024, and 15% of companies will use AI to make decisions on candidates without any human input. While the results reflect current trends in the American employment market and not the employment market of the DACH region, these results do not only indicate the existence of the contrary views employers and employees share about the usage of AI in the application process, but also that AI is increasingly being implemented in the application process. This trend shows that, in the foreseeable future, AI will replace jobs that are currently being done by humans in the recruitment process. According to the WEF Future of Jobs report from 2020, Human Resource Specialists are among the top 20 job roles with decreasing demand across industries (WEF, 2020). A study by the Fraunhofer Institute in Austria found that only 9% of companies currently use AI. An important finding of this study is that almost all companies with more than 2000 employees use AI at least in a test phase, while one-third of these companies are currently using AI in their operational environment. In contrast, companies with fewer than 250 employees do not see the relevance of AI or have no concrete plan for the introduction of AI (Frauenhofer Austria, 2020). Currently, the implementation of AI is a very expensive investment. Thus, companies need to make sure that the implementation runs as smoothly as possible. One of the challenges to implementing innovative technology into an organization is the resistance of the workforce. Thus, it is important to determine the acceptance of the workforce for this technology Davis & Venkatesh (2004). If the innovation is met with acceptance from the workers, one of the implementation challenges is overcome Davis (1989). This leads to the question of how to determine employee acceptance of AI introductions. One of the most commonly used models for determining acceptance is the TAM from Davies (1989). The TAM was successfully used to evaluate the acceptance of various IT applications (Venkatesh & Davis, 2000). This Master Thesis intends to develop an extension to the TAM from Davies (1989) which is designed to determine AI tools in the application process. The TAM's variables (perceived usefulness, perceived ease of use, and intention to use) build the foundation of the model. As an extension to the TAM, two aspects that might influence the acceptance of AI tools are also included in the model. The first aspect is trust in the generated output of the AI (Trust). The second aspect is the individual's anxiety about AI and the use of AI in the application process (AI-Anxiety). Both aspects are included in the model to assess if they influence the acceptance of AI tools in the application process. The extended model is called the Artificial Intelligence Technology User Acceptance Model (AITUAM). The goal of this Thesis is to determine the general acceptance of Human Resource (HR) managers regarding the implementation of AI tools in the application process. This Master Thesis is structured as follows: in the beginning, a short introduction to AI is given; afterward, the application process with its different phases is described; and then, the various AI tools that are currently being used in the application process are specified. Since this Thesis intends to develop a model able to determine the acceptance of AI tools in the application process, multiple acceptance models are being introduced. Parts of these models are used to develop the AITUAM. Afterward, the AITUAM is being hypothesized. The AITUAM is being evaluated using PLS-SEM on data gained through an online survey conducted on Human Resource Managers in the DACH region.

1.1: Artificial Intelligence

According to Sage (2023), in order to determine the acceptance of AI in any form, AI needs to be defined. The lack of a clear definition for AI hinders understanding if people accept real AI or their imagination of what AI seems to be Sage (2023). Defining AI is not a simple task. AI is an umbrella term that includes a variety of different highly complex mathematical models like machine learning, natural language processing, computer vision, audio processing, and many more. This variety leads to a multitude of different definitions (Samioili, 2020). This thesis uses the definition of AI from an independent High-Level Expert Group on Artificial Intelligence set up by the European Comission (HLGE), which states: "Artificial intelligence (AI) systems are software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information derived from this data, and deciding the best action(s) to take to achieve the given goal. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behavior by analyzing how the environment is affected by their previous actions."(HLEG, 2019). This definition encompasses the various core domains of AI. The core domains of AI include reasoning, planning, learning, communication as well as perception (Samoili, 2020). AI reasoning describes the process through which AI uses the given data to generate knowledge, which allows the AI to provide and present solutions to its given task (Samoili, 2020). The domain of planning allows the AI to design and execute strategies that are needed to solve compound tasks that require complex solutions (Samoili, 2020) (Hendler, 1990). The domain of learning includes various algorithmic approaches that are grouped under the umbrella term Machine Learning like reinforcement-, supervised- or unsupervised learning. This allows the AI to learn, predict, decide, adapt as well as react. Thus, the AI can solve a specific task without needing to be explicitly programmed to do so (Mahesh, 2020) (Samoili, 2020). The communication domain contains various Natural Language Processing systems that allow the AI to understand input or generate output in written and or spoken language (Nadkarni, 2011). The perception domain refers to the AI´s ability to become aware of the environment, either through computer vision or audio processing. Computer vision is divided into image patterns: recognition and machine vision. Image pattern recognition allows object-class detection for specific tasks, while machine vision allows for example face and/or body recognition and video content recognition (Wiley, 2018) (Samoili, 2020).

Audio processing enables the AI to perceive or generate audio signals (Samoili, 2020). The different domains and the various examples show how broad the umbrella term AI is. The implications this technology has on society and the possible innovations resulting from the implementation of AI in the labor market are uncertain. The implementation of AI might fundamentally transform society since it is the software engine that drives the Fourth Industrial Revolution (WEF, 2020). The Fourth Industrial Revolution is described by Davies (2016) as the arrival of cyber-physical systems that evolve entirely new capabilities for people and machines. In comparison to the third Industrial revolution, which included electronics, IT as well as automated production, the fourth industrial revolution represents new ways in which technology becomes embedded within society. Individual and collective choices to adopt and employ innovative technologies in their daily life have led over the course of time to all industrial revolutions Davis (2016). Thus, the choices of a few to implement AI might affect many. A gap in the perception of the usage of AI can be seen when it comes to its implementation in the application process. The term "AI recruitment" is used to describe the process in which organizations attempt to restructure their Human Resource (HR) department by applying AI to achieve higher levels of efficiency (Ochmann, 2020). If this development continues, there might be fundamental changes to the traditional application process.

1.2: The application process

The traditional application process is divided into three phases. The first phase of the application process is called the outreach phase (Black, 2020) (Tambe, 2019). The goal of this phase is to reach the best possible candidates while minimizing costs. The traditional approaches to recruiting, for example, writing newspaper ads to find employees, are inefficient and time-consuming (Chen, 2023). Productivity gains can be generated in this phase by increasing the number of targeted candidates while maintaining costs. It is estimated that the number of passive candidates is about three times larger than the number of active candidates, who interact with the company independently, depending on the profession and industry (Chen, 2023). Thus, the objective of the outreach phase is to get as many of the passive candidates as possible to become active candidates and apply for the open position. There are two ways to target possible candidates: "active sourcing" and the "post & pray" strategy. In the active sourcing strategy, the candidates are directly contacted. In the "post & pray" strategy, job offers are being posted, and the candidates apply actively to them (Stefan Thalmann, 2021). Using the "post & pray" strategy can result in numerous applicants applying for the advertised position. Many companies, especially famous ones, receive a multitude of applications, depending on the advertised position (Black, 2020). This corresponds to an immense amount of work for the company's HR managers, who must evaluate each applicant based on their provided documents and determine the individual's given skill set and qualifications related to the advertised position. The evaluation of the applicant's provided documents is called screening and is the second phase of the application process (Black, 2020) (Tambe, 2019). After the provided documents of the applicants have been evaluated, the final phase (the assessment phase) of the application process begins. In the assessment phase, the recruiters determine which one of the applicants is the best match for the advertised position (Black, 2020) (Tambe, 2019). This assessment can include several rounds and different means of evaluation, such as interviews or assessment tests. The goal in this phase is to find the best possible candidates and offer them a working contract (Black, 2020). Another important aspect of the application process is the communication between the company and the applicant, which must be maintained through all the phases of the application process.

1.3: AI tools in the application process[1]

Depending on the phase of the application process, different tasks need to be fulfilled, for which different AI tools can be used by HR managers. The following parts give an overview of different AI tools that can be used by HR managers in the application process.

1.3.1: Use of AI in the outreach phase

Depending on the required tasks in the outreach phase, multiple AI tools with different beneficial prospects can be implemented. In the outreach phase, the company targets possible candidates, either through “active sourcing” or the “post & pray” strategy. Active sourcing is the process in which potential applicants are contacted directly by the company. AI tools used for active sourcing enable efficiency gains. When conducting Active Soucing, the success rate of AI tools is lower than the one of a human recruiter. (Eubanks, 2022). However, the speed at which these AI tools conduct active sourcing is not comparable to the one of a human recruiter. The average processing time for active sourcing when conducted by an AI tool is 3.2 seconds, while human recruiters need between 4 and 25 hours (Eubanks, 2022). This increase in efficiency can save costs for active

[1] This part is a revised version of the seminar paper: “Künstliche Intelligenz im Bewerbungsprozess “from the course “Arbeitsmarktsoziologie” at the University Vienna, which was written by the author of this Thesis.

sourcing in both the outreach and screening phases (Wilke, 2022). Another way companies can use AI in the outreach phase is "multi-database candidate sourcing." These AI tools increase the applicant pool by reaching out to passive candidates and former employees. The AI tool scans through multiple relevant databases as well as profiles on social media platforms faster and more accurately than a human recruiter (Albert, 2019). The AI tool uses social media profiles, like LinkedIn or Xing, to compare candidates for their suitability for the advertised position and approach them (Campbell, 2020) (Pillai & Sivathanu, 2020). This leads to an increase in the candidate sourcing rate (Albert, 2019). The advantages of using “multi-database candidate sourcing” AI tools are that it enables the company to use a more qualified candidate pool as well as shorten the entire hiring process, consequently saving resources (Black, 2020). AI tools can also be successfully implemented in the "Post&Pray" strategy, which relies on applicants sending a digital resume or filling out an online application form. Once the applicants send the required documents, the AI tool screens and assesses the applicants. These so-called "targeted job advertising optimization" tools are designed to prevent addressing the wrong target groups or using the wrong channels, thus preventing the waste of resources. Furthermore, the AI Tool improves the candidate approach and maximizes the chances of candidate engagement while minimizing advertising spend (Albert, 2019). AI "job description optimization software" provides recommendations for optimizing job descriptions and adjusting language to be appealing to diverse candidates. This AI tool prevents complex and boring language in job descriptions and indirect discrimination. A job description that is not inclusive can have a negative impact on applicant diversity, reduce the number of applicants, and damage employer branding (Albert, 2019). The advantage for a company implementing this AI tool is the increase in the number and diversity of applicants since it reduces the risk of indirect discrimination from the company (Albert, 2019) (Chen, 2023).

The benefit of implementing AI tools in the outreach phase is reducing costs and indirect discrimination. Additionally, AI tools in the outreach phase help reduce the time that HR managers need to spend on repetitive and non-essential tasks and enable the company to use a more qualified candidate pool (Pillai & Sivathanu, 2020).

1.3.2: Use of AI in the screening phase

Once applicants have applied for the vacant positions, human resource managers use the data submitted by the candidates to determine which ones of them are best suited for the open position. The best-fit applicants then move forward in the application process. In the screening phase of the application process, AI tools can be used particularly well, as large amounts of data must be processed. Unfortunately, not all applicants are truthful in their documents, so the data submitted by the applicants must be verified to be true. Using an "AI-powered background checking" tool to perform background checks on the applicants, the company can verify the truthfulness of the submitted documents (Albert, 2019).

Screening resumes is an important step in selecting applicants, as it can be used to draw conclusions about the applicant's skills, abilities, and motivation (Aydın & Turan, 2023). However, this is also one of the most difficult and time-consuming tasks in the entire recruitment process (Wilfred, 2018). Since screening CVs is time-consuming and costly, and human errors increase the higher the number of CVs, companies can use so-called "CV screening software". This AI tool screens the applicants' CVs and determines the best ones (Albert, 2019) (Laurim, 2021). This reduces bias and problems that occur due to human fatigue while improving diversity. It is important to note that this CV screening software AI tool only supports recruiters. The CVs of the best applicants are then again evaluated by the recruiters, who make the actual hiring decision (Laurim, 2021). The goal of using "CV screening software" is to decrease the workload for the recruiters, which makes the application process more efficient and thus reduces costs (Albert, 2019) (Laurim, 2021).

1.3.3: Use of AI in the assessment phase

After screening the documents of the applicants in the screening phase, recruiters must determine which candidate is the best fit for the vacant position. This phase of the application process is the Assessment Phase. In the assessment phase, AI tools can be used to evaluate applicants. Hiring tests can be provided by AI through "AI-Powered Psychometric Testing.". This AI tool allows the evaluation of candidates and improves the ratio between the number of applicants and hiring. The use of this AI tool leads to an improvement in the applicant experience since outdated, boring, and uninteresting hiring tests can have a negative impact on employer branding (Albert, 2019). For example, hiring tests based on AI, use assessment games to determine the candidate's performance. The applicant's performance in the game is then evaluated by the AI, and the data obtained is used to determine how likely that applicant is to succeed in the advertised position. Those applicants who meet the requirements in this evaluation game are then considered for an interview (Wilke, 2022).

Another form of candidate assessment using AI can be done with the help of chatbots. Chatbots offer the possibility of conducting job interviews. The chatbot asks the applicant various interactive questions and then matches the applicant's answer with the answers of the best-performing employees (Meyer von Wolff, 2020) (Thalmann, 2021). This form of interviewing is particularly helpful for organizations that place great importance on the attitudes and beliefs of their employees (Arslan, 2022).

AI can evaluate video interviews of applicants. The “video screening AI” tool determines the applicant's personality traits and skills based on the video interview (Martínez & Fernández, 2019). (Albert, 2019). The AI determines the characteristics of the candidate by assessing his or her spoken language, eye movement, and facial expressions (Martínez& Fernández, 2019). Consequently, based on these specific characteristics, it chooses the candidate that best fits into the team (Martínez& Fernández, 2019). The AI tool uses interviews to evaluate the person-job fit for the company while preventing bias and discrimination, which can unconsciously be practiced by HR managers. The AI tool is able to capture signs of the personality traits of applicants and manufacture a personality profile based on the candidate's response behavior. Since pre-screening for interviews is very costly and time-consuming, these AI tools enable significant cost savings. Other benefits for the company are the reduction of the time needed for the selection process and the creation of a fairer application process for minorities (Albert, 2019) (Chen, 2023) (Laurim, 2021).

1.3.4: Communication during the application process

In addition to the three phases of the application process, the recruiter and the applicant need to communicate throughout the recruitment process. Chatbots can be used during the application process to answer simple questions regarding salary ranges, vacation opportunities, or other incentives. With the help of chatbots, parts of HR work can be automated. These AI-based candidate engagement Chatbots offer a 24-hour service for applicants. The tools are used to engage candidates quickly and directly and to answer questions throughout the recruitment process that arise for applicants (Albert, 2019). Throughout the application process, appointments need to be scheduled with the applicants. With the help of "Automated scheduling AI" the time needed for administrating tasks can be reduced. The AI tool schedules appointments and automatically performs administrative tasks. Since scheduling calls, hiring tests, and interviews are very time-consuming, these AI tools allow recruiters to focus on more important tasks (Albert, 2019).

1.4: Advantages and disadvantages of using AI in the application process

The use of AI tools in the application process has many advantages. Especially for time-consuming and repetitive tasks, AI tools are more efficient and effective than humans (Black, 2020) (Singh & et al., 2020). The use of AI tools can improve corporate branding and lead to cost reduction, thus facilitating competitive advantages (Aydın & Turan, 2023). One example of how AI increased the efficiency of the application process is the Hilton hotel chain. After introducing AI in their application process, the average hiring time was reduced from 42 days to 5 days (McLaren, 2018). Unilever provides another example. Before implementing AI, Unilever invested large amounts of money and time to recruit graduates from 840 universities on campus. By using AI-based recruitment tools on social media platforms, Unilever was able to expand its applicant pool while reducing costs (Feloni, 2017). The AI-based recruitment tool improved the speed of the recruitment process and the quality of the candidates. The best candidates were then interviewed by the HR managers.

It is important to train AIs with data that is representative of the overall population, to prevent inaccuracy of the technology. AIs that have been trained with biased datasets, can exhibit gender and race bias (Martínez& Fernández, 2019). The use of AI tools in the application process intends to make the application process fairer (Albert, 2019) (Laurim, 2021) (Chen, 2023). An example that shows the exact opposite is Amazon. Amazon developed an AI that reviews applicants' resumes with the goal of making the application process more efficient. However, the company found that the AI used to evaluate applicants for software development jobs and other technical jobs disadvantaged women. The reason for this was that the AI was mainly trained with data from men (Dastin, 2018).

Thus, it can be concluded that there are both positive and negative examples of the implementation of AI in the application process of companies (Feloni, 2017) (Dastin, 2018). The use of AI also raises ethical and legal concerns as aspects of humanity are removed from the application process (Martínez& Fernández, 2019). Ethical aspects need to be considered when implementing and using AI tools in the application process (HLEG, 2019). While the ethical use of AI is important, it will not be further addressed in this Thesis. Another aspect that is important to be considered when implementing AI tools in the application process is the impact this has on recruiters. If the recruiters are unwilling to use these tools, companies could face great costs for the development or implementation of these AI tools without achieving the intended results because the recruiters are unwilling to use them (Davis, 1989). To determine if the recruiters are willing to use AI tools in the application process, acceptance models can be used.

2: Theory on Acceptance

Organizations need to create the required conditions in order to successfully implement a system that is going to be accepted by the various individuals inside the organization. If the system is rejected, the costly implementation project has failed (Davis & Venkatesh, 2004). The larger and more complex a system is, the more difficult it is to implement, and therefore the higher is the failure rate (Davis & Venkatesh, 2004). The "productivity paradox" is a phenomenon associated with significant investments in IT software, which led to little observed productivity increase between the 1970s and the early 1990s (Sichel, 2001). Currently, we are experiencing major investments in AI software, which has an uncertain influence on the productivity of organizations. One of the reasons why the increase in productivity of companies is not fulfilling its potential, after the implementation of an innovative system, is the low usage of the system (Davis, 1989). To be able to prevent low usage of newly installed AI software, theoretic models used to explain technology acceptance can be used. Technology acceptance models provide insights on which factors are important in generating behavioral intention to use and lead to an increase in actual system usage (Davis, et al., 1989). There is a wide variety of different Acceptance Models. To determine the acceptance of AI tools used in the Application process, two types of acceptance are relevant. User acceptance is required for a successful implementation of a technology (Davis, 1989). Therefore, the acceptance of AI tools should be evaluated before implementing this tool. The acceptance of the applicants should not be ignored, since people might have negative views about applying to a company which uses AI tools in the application process (Rainie, 2023). Since this Master Thesis concentrates on developing a user acceptance model (AITUAM), only the acceptance of the H&R managers will be considered. Yet, it is still important for companies not only to evaluate the benefits AI implementation has to them but also how this implication might affect the view applicants have of the company.

2.1: The different theoretical acceptance models

To determine user acceptance, many different theoretical acceptance models have been developed. These theories are rooted in psychology and sociology and are most often used to explain IT system acceptance. While there are different research streams, this Thesis concentrates on the stream of research that determines individual technology acceptance by using the behavioral intention to use or actual use as the dependent variable to determine technology acceptance (Davies, 1989) (Venkatesh, 2003).

The ground theory that was used to develop the various technology acceptance models that are introduced in this part of the Thesis is called the theory of reasoned action. The theory of reasoned action (TRA) (Ajzen & Fishbein, 1969) is drawn from social psychology and is according to Venkatesh (2004) one of the most fundamental and influential theories of behavior. According to the TRA, intention is the strongest indicator of how hard a person is willing to try and how much effort the person is going to give in order to conduct the behavior. Ajzen & Fishbein (1969) introduced the variable "Behavioral Intention" to measure the strength of an individual's intention to perform a specific task. According to the TRA, an individual's behavioral intention is determined by two variables. These variables are "attitude towards the behavior" (Attitude) and "subjective norm" (Ajzen & Fishbein, 1969). The variable Attitude determines how favorable or unfavorable the individual thinks the intended behavior is. The more favorable the individual evaluates the behavior, the higher the behavioral intention, and therefore the higher the chance that the individual will conduct this behavior (Fishbein, 1974). The variable subjective norm determines the social pressure the individuals feel about performing or not performing the behavior. The higher the social pressure to perform the behavior, the higher the behavioral intention, and thus the higher the chance that the individual performs the behavior (Ajzen, 1980). The AITAUM tries to determine the intention of using AI tools in the application process. While the variables Attitude and subjective norm are not included in the AITUAM, Behavioral intention is the foundation for the dependent variable Intention to Use in the model. The higher the behavioral intention to use AI tools in the application process, the more likely it is that the AI tools in the application process are being used. Figure 1 visualizes the variables and the relationships of the TRA (Ajzen & Fishbein, 1969)

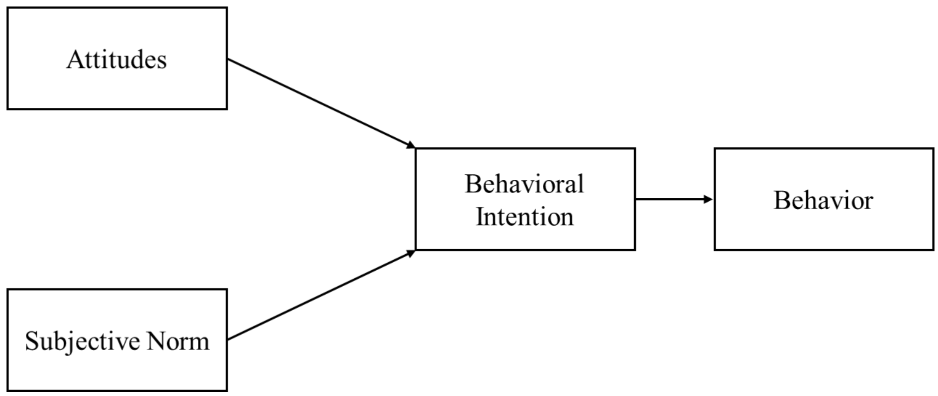

Figure 1 visualization of the TRA from Ajzen & Fishbein (1969).

The following part introduces four different theoretical acceptance models, parts of which were used to develop the AITUAM. The following technology acceptance models are used to determine AI acceptance (Sohn, 2020).

2.1.1 The TAM

The “Technology Acceptance Model” by Davis (1989) is based on the theory of reasoned action and was developed to predict individual adoption and use of new information technology systems. Similar to the theory of reasoned action, the TAM uses behavioral intention to use technology as a direct determinant of actual usage of this technology. According to Davis (1989), an individual’s intention to use a technology depends on two factors: the perceived usefulness and the perceived ease of use of that technology. Perceived usefulness refers to the individual's perception that using this technology will enhance their productivity, performance, and effectiveness. Thus, the more useful a technology is perceived, the higher the behavioral intention to use it. Perceived ease of use refers to the extent to which an individual believes that using this technology will be effortless and easy to learn (Davis, 1989). Thus, the less effort a technology requires to be used and the easier it is to learn this technology, the higher the individual’s intention to use this technology. The higher the intention to use the system, the higher the actual system use (Ajzen & Fishbein, 1969). Thus, determining the behavioral intention to use the system allows us to determine its actual use. If a technology achieves a high level of behavioral intention to use and, subsequently, a high level of actual system use, this technology is accepted by its users Davies (1989). The TAM from Davies (1989) is the base model of the AITUAM. The AITUAM uses the TAM variable's Perceived Usefulness and Perceived Ease of Use to determine the Intention to Use AI tools in the application process. Figure 2 visualizes the variables and the relationships in the TAM (Davis, 1989).

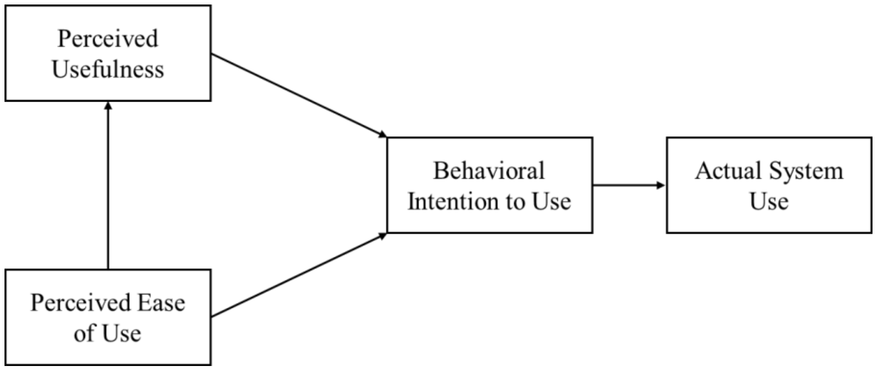

Figure 2 visualization of the TAM from Davis (1989).

2.1.2 The UTAU

Venkatesh (2003) developed a model that synthesizes the contributions made by multiple acceptance models. This model is called the "unified theory of acceptance and use of technology" (UTAU) and was formulated by Venkatesh (2003). According to the UTAUT, performance expectancy, social influence, effort expectancy, and facilitating conditions are predictors of behavioral intentions Venkatesh (2003). The variable performance expectancy is similar to the perceived usefulness of the TAM and is defined as the degree to which a user believes the device will support them in increasing their job performance (Venkatesh, 2003). Social influence measures the individual's perception that others would approve or disapprove of the usage of the system (Venkatesh, 2003). Effort expectancy is similar to perceived ease of use and describes the degree of effort required to use the device (Venkatesh, 2003). The variable facilitating conditions is defined as the availability of support for using the device (Venkatesh, 2003). Further variables that moderate the effects these constructs have on behavior intentions are gender, age, prior experience as well as voluntaries of use (Venkatesh, 2003). In the UTAU gender and age moderate the relationship between performance expectancy and behavioral intention, while gender, age, and prior experience moderate the relationship between effort expectancy and performance expectancy. These variables are very similar to the perceived ease of use and perceived usefulness used in the AITUAM. Behavioral Intention is equal in the UTAU and the TAM, and thus also in the AITUAM. To determine if age, gender, and experience have a moderating effect on the constructs of relationships, age, gender, and experience have been included in the AITUAM as control variables. Since the AITUAM determines the acceptance of AI Tools in the application process for HR managers, voluntariness of use is not included as a control variable since the variable social influence is not included in the AITUAM and the implementation of an AI tool in the application process is decided by the corporate strategy and not by the individual HR manager. The reason why the UTAU is not used as the ground model to determine HR managers' acceptance of AI tools in the application process is due to the increased complexity of the model in comparison to the TAM.

Figure 3 shows the variables and the relationship between the variables as well as the moderators in the UTAU Venkatesh (2003).

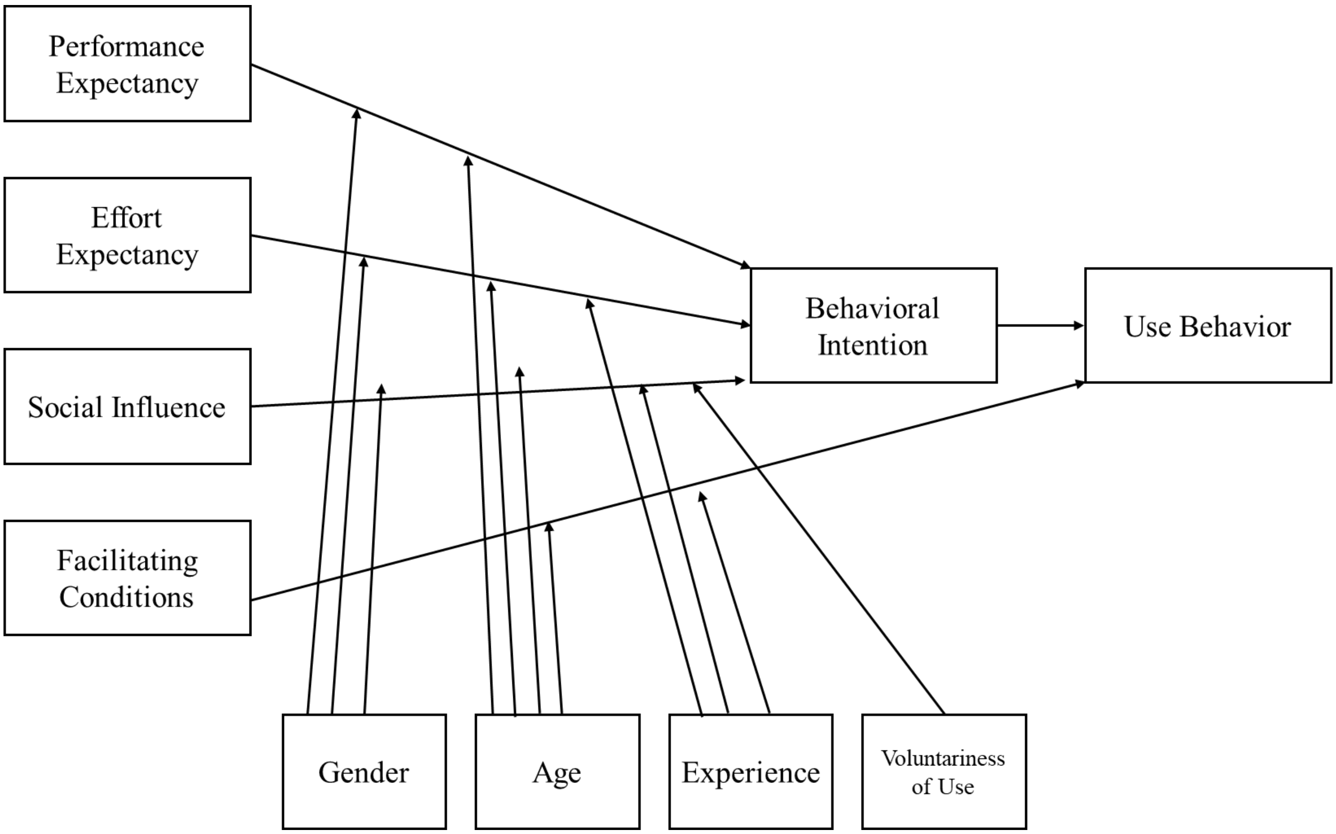

Figure 3 visualization of the UTAU from Venkatesh (2003).

2.1.3 The VAM

According to Kim (2007), the TAM fails to consider many of the effects of exogenous variables in explaining the intention to use new information and communication technologies. Since the TAM explains the adoption of technologies by users in organizational settings, the organization bears the cost of adoption and usage. Thus, the TAM might not be ideal to determine the adoption of technology by customers (Kim, 2007). To solve this problem, the Value-based Adoption Model (VAM) was introduced (Kim, 2007). The VAM was developed to determine the adoption of service consumers and technology users. These users adopt and use the technology for their personal use and bear the cost of adoption and usage themselves. Therefore, these individuals evaluate the specific technology from a cost-benefit perspective and then decide whether to accept that technology or not. Kim (2007) determines the benefit perspective of using technology through the variable perceived benefits, which includes extrinsic and intrinsic motivation. Extrinsic motivation to use a technology refers to the intention to use this technology because it is useful in achieving a specific goal, while intrinsic motivation to use a technology refers to performing an activity for the enjoyment of using this technology. Kim (2007) includes the two types of motivation in his model as the two components for determining perceived benefit. The first component is called usefulness, which is defined as the total value a user perceives from using a specific technology. The second component is called enjoyment and refers to the extent to which the activity of using the technology is perceived to be enjoyable, independent of any anticipated performance consequences. Kim (2007) further determines the cost perspective of using technology through the variable perceived sacrifice. Perceived sacrifice includes the monetary aspect of using this technology by measuring the user's perception of the actual price paid. The non-monetary aspect of perceived sacrifice is the needed time and effort, as well as other unsatisfying factors that occur through the purchase and use of the technology. These two types of costs are included in the VAM as two components for determining perceived sacrifice (Kim, 2007). The first component is called technicality and determines the user’s perception of ease of use, which is directly derived from the TAM. The second component is the perceived fee, which refers to the comparison the customer makes between their internal reference price and the actual price. According to the VAM, perceived benefit and perceived fee directly influence an individual’s perceived value (Kim, 2007). Perceived value refers to the individual’s comparison of the benefits and sacrifices of using the technology. Perceived benefits influence perceived value positively, while perceived sacrifices influence perceived value negatively. After assessing the perceived value of a technology, the individual then decides whether to adopt the technology or not. Perceived value is therefore a direct indicator of adoption intentions (Kim, 2007). The VAM includes unsatisfying factors that occur through the use of the technology and decrease adoption intention (Kim, 2007). The implementation of AI-Anxiety in the AITAUM follows this line of thinking. Anxiety causes people to try to avoid situations that trigger their anxiety (Fagan, 2004). Thus, for individuals with high levels of AI-Anxiety, using an AI tool is an unsatisfying factor that might decrease the usage intention directly, while low levels of anxiety do not increase the usage intention. A thorough explanation of the inclusion of AI-Anxiety in the AITUAM can be found in Part 3.4 (AI-Anxiety) of this Thesis. Since the VAM was specifically developed to determine consumer acceptance of a technology, it is not used as the ground model for the AITUAM, since the AITUAM determines acceptance in an organizational setting. Figure 4 visualizes the variables and the relationships in the VAM (Kim, 2007).

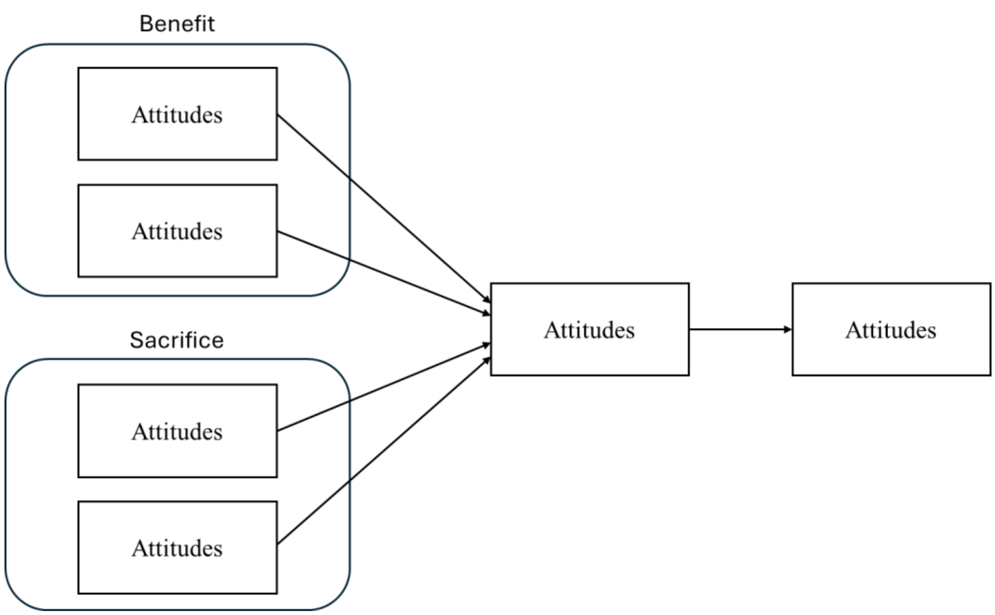

Figure 4 visualization of the VAM by Kim (2007).

2.1.4 The AIDUA

While the prior models have been used to describe technology acceptance for a wide variety of different IT technologies, none of the original models were specifically developed to explain AI. A Technology Acceptance model that was developed to determine AI device acceptance is the AIDUA model (Lu, et al., 2019). The AIDUA is a theoretical model called "artificially intelligent device use acceptance" (AIDUA) that was developed to explain customers' acceptance of AI device use in service encounters. One major difference from the previous acceptance models is that the AIDUA studies determine acceptance as a multistage process. The AIDUA includes three acceptance generation stages: the primary appraisal stage, the secondary appraisal stage, and the outcome stage (Lu, et al., 2019). During the primary appraisal, consumers assess the AI devices based on social influence, hedonic motivation, and anthropomorphism. Social influence is derived from the subjective norm of the TRA (Ajzen & Fishbein, 1969) and measures the individual's perception that others would approve or disapprove of the usage of the AI tool. Hedonic motivation is similar to enjoyment from the VAM (Kim, 2007) and is defined as the perceived pleasure an individual expects to receive from using AI tools (Lu, et al., 2019). Anthropomorphism is the level of an AI's humanlike characteristics, such as human appearance, self-consciousness, and emotion. Anthropomorphism intends to measure the human qualities that the AI device may copy (Lu, et al., 2019). Depending on the appraisal during this stage, the individual will then assess the benefits and costs of using the AI tool in the secondary appraisal stage. Individuals evaluate the costs and benefits of AI tools based on their perceived performance and effort expectations, which are directly derived from the UTAU (Venkatesh & Morris, 2000). According to this evaluation, the individuals form their emotions towards the specific AI tools. If individuals believe that using the AI tool will require too much effort, negative emotions will be generated (Lu, et al., 2019). If individuals believe that the use of these tools will benefit them in their work by enabling higher performance, positive emotions will be generated (Lu, et.al., 2019). These emotions will then determine an individual's willingness to accept the use of the AI tool or lead to an objection to the use of AI tools (Lu, et al., 2019). In the outcome stage, these emotions will then determine an individual's willingness to accept the use of the AI tool or lead to an objection to the use of AI tools (Lu, et al., 2019).

Figure 5 shows the constructs and the relationships in the AIDUA.

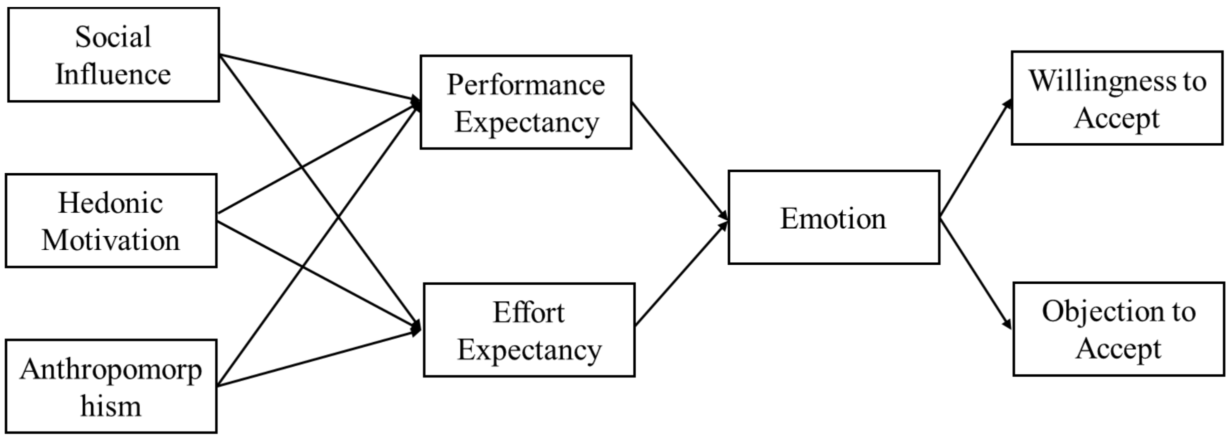

Figure 5 visualization of the AIDUA by Lu, et al. (2019).

The AIDUA includes negative emotions that affect the willingness to accept the use of the AI device (Lu et al., 2019). The AITUAM follows this line of thinking with the inclusion of AI-Anxiety in the model. Since anxiety is a negative emotion, it might directly affect the intention to use AI tools in the application process. A thorough explanation of the inclusion of AI-Anxiety in the AITUAM can be found in Part 3.4 (AI-Anxiety) of this Thesis.

To find a suitable ground model to explain the acceptance of AI tools in the application process, each of these models is evaluated based on their fit for determining the acceptance of AI tools in the application process. All the previously introduced theoretical acceptance models have been used to determine the acceptance of AI (Sohn, 2019). The goal of this Thesis is to develop a model that is able to determine AI tool acceptance in the application process. While the AIDUA was specifically developed to determine AI acceptance, the division into three stages makes this model unsuitable for this Master Thesis, since a three-stage evaluation of HR manager's acceptance, which requires three surveys as well as a steady sample, exceeds the scale and scope of this Thesis. The fact that the VAM was specifically designed to determine consumer acceptance as well as that the monetary aspect of the perceived fee is not relevant to the HR manager's intention to use AI tools in the application process since the company is bearing the costs of implementation makes this model less suitable as a ground model in comparison to the TAM to determine HR managers acceptance of the use of AI tools in the application process. Especially as this thesis intends to include AI-Anxiety as well as Trust as determinants for usage intention, the UTAU is too complex to be used as a ground model. Since the TAM is the most commonly adopted model to measure AI acceptance and has the most predictive success in measuring behavioral intentions (Sage, 2023), this Master Thesis uses an extended version of the TAM to determine HR managers' acceptance of AI tools in the application process.

2.2: The TAM as the foundation of the AITUAM

As of June 2024, Google Scholars listed over 85,000 citations to the journal articles that introduced the TAM (Davis, 1989). According to Davis (1989), user acceptance of a technology is fundamental to the successful implementation of that technology. User acceptance is important to determine if a technology is going to be adopted. If the users do not accept AI tools, this may lead to low user uptake, resulting in a waste of resources. According to Davis (1989), acceptance is a predictive measure that sums up a voluntary action to implement a tool, or acceptance can be an involuntary action, such as when the company strategy decides that an AI tool is going to be implemented and thus has to be used. This means that there are differing agency levels involved in user acceptance Sage (2023). Acceptance is fundamental to understanding which steps are needed to maximize technology uptake in various circumstances Sage (2023). The TAM was originally developed to understand and improve user acceptance of information systems. One of the most common criticisms of the TAM has been the lack of practical suggestions on how to increase technological acceptance (Lee, et.al, 2003).

To further increase the understanding of technology acceptance and to deal with criticism of the traditional TAM, Venkatesh & Davis (2000) introduced the TAM 2. The TAM 2 includes four different types of determinants that influence an individual’s perception of perceived usefulness and perceived ease of use. These determinants are individual differences, system characteristics, social influences, and facilitating conditions (Venkatesh & Davis, 2000). The determinants of individual differences describe the individual’s personality and his or her demographics. The system characteristic determinants are the relevant features of the system that are used to assess favorable or unfavorable opinions about the usefulness and ease of use of the given technology. The social influence type of determinants intends to capture social processes that guide the individual’s perception of the given technology. The last type of determinant that influences an individual’s perception of a given technology is the facilitating conditions, which correspond to the organizational support for using the given technology (Venkatesh & Davis, 2000). In comparison to the original TAM, the TAM2 is more complex. Thus, these four general determinants are not included in the AITUAM to not further increase its complexity. Even though, the TAM is a simple model, it is also a valid and robust model, which can effectively be used to determine the acceptance of various technologies (King, 2006). Besides the general determinants, Venkatesh & Davis (2000) introduce two moderator variables that influence the relationship between perceived usefulness and intention to use. The moderator variables are experience and voluntariness. Venkatesh (2000) suggests that individuals will adjust their perceived ease of use after they gain experience with the new system. The effect of experience on perceived usefulness is that the effect of social influence will weaken over time. To determine if there is a moderating effect of experience, experience is included in the AITUAM as a control variable. Since the AITUAM determines AI tools in the application process, voluntariness is not included as a control variable. The reason for this is that the implementation of AI tools in the application process is decided through the company strategy and using them is an involuntary action for the HR managers. Figure 6 shows the TAM2 from Venkatesh & Davis (2000)

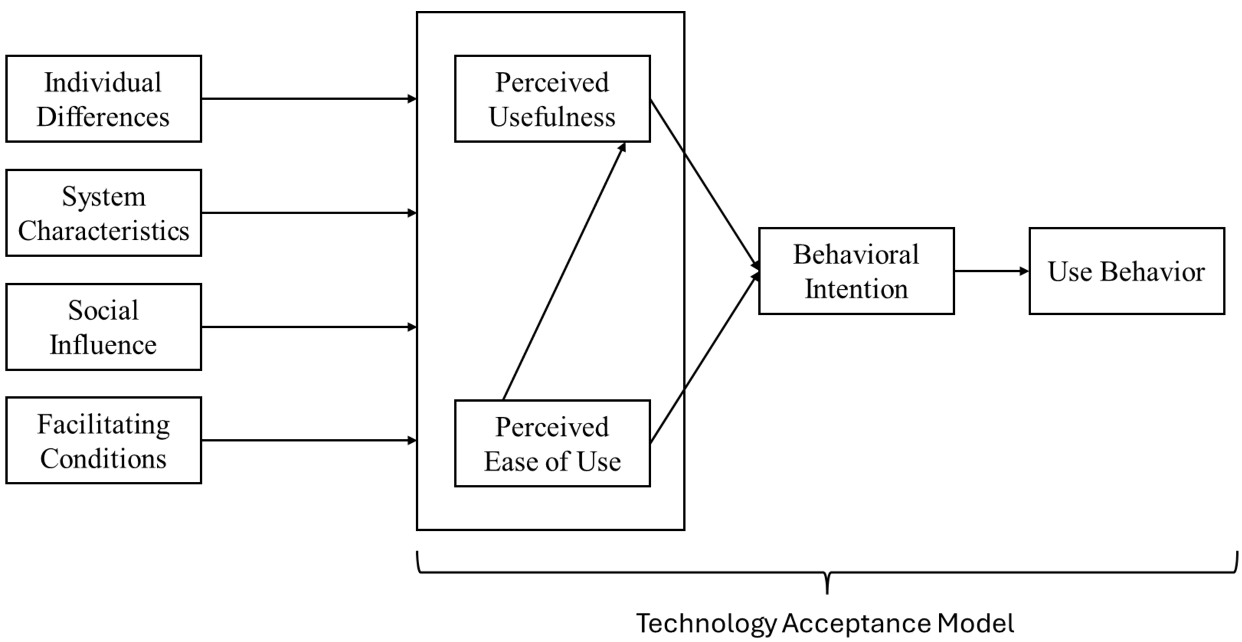

Figure 6 visualization of the TAM2 from Venkatesh & Davis (2000).

To further increase the understanding of technology acceptance, Venkatesh (2000) introduces Anchors to further explain perceived ease of use. These anchors are the general beliefs the individual has regarding computers and computer use. Anchors influence the initial judgment of perceived ease of use. The author states that over time, the individual will adjust their beliefs after getting direct experience with the new system. Venkatesh (2000) introduced six anchors: computer self-efficacy, computer anxiety, computer playfulness, perceptions of external control, perceived enjoyment, and objective useability. While all these Anchors are interesting concepts in determining perceived ease of use, this thesis concentrates on computer anxiety. Computer anxiety is the negative emotional reaction an individual experiences when facing the possibility of using computers (Venkatesh, 2000). One of the consequences of computer anxiety is lower progress expectancies. Individuals with higher levels of computer anxiety have lower expectancies for learning and using new technology in comparison to individuals with lower levels of computer anxiety. Therefore, computer anxiety negatively affects perceived ease of use. According to Venkatesh (2000), computer anxiety is a negative emotional reaction toward computer use. Computer anxiety causes people to avoid using computers since using a computer causes them anxiety. An inverse relationship between computer anxiety and actual computer use exists (Fagan, 2004). Individuals with higher levels of computer anxiety therefore have lower usage intentions for IT applications than individuals with lower levels of computer anxiety. Venkatesh (2000) argues that the higher the experience with a system, the less the effect of computer anxiety on perceived ease of use, and that over time, this effect should diminish. AI-Anxiety as a concept might be similar to Computer anxiety. Computer anxiety resulted from the introduction of computers and IT systems. AI-Anxiety also results from the introduction of AI in the labor market and is reinforced by public figures expressing concern that AI might affect humans and society in disastrous ways (Johnson, 2017). Since AI itself is an innovative technology that is currently in its early stages of implementation, there is a chance of determining the influence of AI-Anxiety on ease of use and behavioral intention to use. AI-Anxiety has already been included in some extended TAMs that intend to determine AI acceptance (Ayanwale, 2022) (Zhang, 2023). Since the TAM variables are used as a foundation for the AITUAM, the AITUAM is considered an extended TAM. To be able to determine if the TAM is able to determine the acceptance of AI tools in the application process, a literature review about the use of extended TAMs to determine AI acceptance has been conducted.

2.3: Literature review

The flowing part of this Thesis gives an overview of different extended TAM models that were used to determine AI acceptance. The results of the literature review can be found in Figure 13-16 in the appendix. The literature review was conducted using Google Scholar as well as usearch.univie.ac.at. The keywords in the search for this review were: “TAM, AI”; “Technology Acceptance Model, AI”, “TAM, Artificial Intelligence”, “Technology Acceptance Model, Artificial Intelligence”. This literature review found 15 different papers with 16 different studies (Choung (2023) conducted 2 different studies with different variables and samples in his paper). In these 16 studies, the TAM has been used to determine acceptance for various AI applications in different industries. The TAM was used to determine acceptance for AI in healthcare, teaching, HRM, accounting, manufacturing, and E-commerce. While the TAM was developed to determine acceptance in an organizational setting (Kim, 2007), 9 out of 16 studies used it to determine consumer acceptance. While in all the examined papers, behavioral intention to use or an equivalent (decision/intention to adopt) has been assessed, only in 4 of these papers is the actual use being determined. The most commonly used determinants of behavioral intention are perceived usefulness, perceived ease of use, trust, and attitude. These findings are in line with the results of Sage (2023). In the 16 different extended TAM models, the following determinants were included: perceived usefulness 15 times, ease of use 13 times, attitude 7 times, and trust 7 times. 14 times perceived usefulness influenced intention to use directly and 1 time indirectly; perceived ease of use influenced intention to use 9 times directly and 2 times indirectly; Trust influenced intention to use 4 times directly and 2 times indirectly; attitude influenced intention to use 3 times directly. It further shows that the TAM is able to determine AI technology acceptance with varying degrees of success. While not all the papers used in this literature review provided their results for the explained variance in determining intention to use, the results from the papers that did show a range for R^2 between 31.92% Damerji (2021) and 66.4% Liu (2021). Trust was used in 7 out of these 16 studies and was 6 out of 7 times either directly or indirectly significant on behavioral intention to use. These results show the importance of trust as a variable in determining behavioral intention, and that trust is an important extension of the original TAM in determining AI acceptance. The only variables for which there seems to be inconsistency in the way these studies determine the effect age and gender have on AI acceptance. These are the only variables that are being evaluated for having a direct effect on behavioral intention or a moderating effect on the relationship between the variables in the model. Sage (2020) found that age and gender do not have a significant direct effect on behavioral intention. Liu (2021) found that gender has a positive moderating effect on the relationship between trust and intention to use. Hmoud (2020) found no moderating effect for age and gender. Also, for experience, mixed findings have been made; according to Liu (2021) experience moderates the relationship between trust and perceived usefulness. Hmoud (2020) found that experience has no moderating effect on trust and behavioral intention. Sage (2020) found that, depending on the industry, experience is significant in determining behavioral intention. These mixed findings indicate the importance of evaluating if the variables age, gender, and experience have a direct effect on intention to use or if they have a moderating effect on the relationships between the variables in the model.

3: The AITUAM

To determine the acceptance of AI tools in the application process, the variables perceived usefulness (PU) and perceived ease of use (EoU), trust, AI-Anxiety, and behavioral intention to use (IoU) have been used in the AITUAM.

3.1: Perceived Ease of Use

Perceived ease of use in this Master Thesis follows the definition from Davis (1989) as "The degree to which a person believes that using a particular system would be free of effort". According to Davis, perceived ease of use is a determinant of intention to use and a determinant of perceived usefulness. In TAM1, ease of use and perceived usefulness are parallel, direct determinants of the usage intention (Davis, 1989). Perceived ease of use is a direct determinant of perceived usefulness (Venkatesh & Davis, 2000). The reason for this is that users are driven to adopt a technology primarily because of its function and, secondarily, of how easy it is to learn and use it for solving its intended task. Users are often willing to cope with a difficult system if it can provide them with the needed functionality. Yet, the difficulty of use can hinder the adoption of an otherwise useful system (Davis et al., 1989). However, no amount of ease of use can compensate for a system perceived as not useful (Davis et al., 1989). To conclude, the less difficult a system is to learn and to use, the more useful it is perceived to be. AI tools that are perceived to be easier to use than others are more likely to be accepted by users. To determine one's perceived ease of use, it is not rudimentary to know the specific AI tool, since a user can have a sense of his or her ability to use technology in general (Venkatesh, 2000). This general ability to use technology provides an anchor for judging an innovative technology. Even if a user has little or no knowledge of the ease of use of a new system, he or she may certainly have a well-formed sense of his or her abilities to use technology in general (Venkatesh, 2000). The impact of perceived ease of use on perceived usefulness, as well as the influence of these variables on intention to use, has extensive empirical evidence for a vast variety of technologies (Venkatesh & Davis, 2000). The literature review showed that perceived ease of use is an essential determinant for the use of AI technologies, with mixed findings regarding its effect on behavioral intention. Thus, **Hypothesis 1 states: Perceived Ease of Use of an AI tool positively influences a) Perceived Usefulness and b) Intention to Use**.

3.2: Perceived Usefulness

Perceived usefulness is defined according to Davis (1989) as "the degree to which a person believes that using a particular system would enhance his or her job performance." The performance expectancy of a technology is fundamental in determining its acceptance (Davis et al., 1989). As in the previously described acceptance models, perceived usefulness is determined by the individual's perception of how the use of this technology will increase their productivity, performance, and effectiveness when doing their job (Davis, 1989). A system high in perceived usefulness is one in which the individual believes in the existence of a positive use-performance relationship. Users tend to accept or reject a technology depending on whether they believe that it will assist them in performing better at their jobs (Davis et al., 1989). Davis (2004) showed that to determine the perceived usefulness of a technology, the user does not need experience with the technology. The user only needs to be informed about the intended functionality of the system to determine its perceived usefulness. Across the many empirical tests of TAM, perceived usefulness has consistently been a strong determinant of usage intentions for non-AI technology (Venkatesh & Davis, 2000). The literature review for using the TAM to determine AI acceptance showed that perceived usefulness is the strongest and most essential determinant for the use of AI technologies. This leads to the formulation of **Hypothesis 2: Perceived Usefulness of an AI technology positively influences Intention to Use**.

3.3: Trust

As an extension of the original technology acceptance models, Trust is included in the AITUAM. Trust is the subjective attitude that allows a person to make a vulnerable decision; thus, Trust in technology allows users to believe that using this technology will achieve the desired goal (Sage et al., 2023). Trust is crucial for new technologies, where perceptions of risk must first be overcome to create the willingness to use the technology (McKnight, 2002). Developing trust in innovative technology is a fundamental step in determining its acceptance. According to Hengstler (2016), the concept of trust provides a valid foundation for describing the relationship between humans and AI. Trust, as a variable in the Thesis, is defined as the extent to which the individual believes he or she can trust the AI-generated output. Since AI tools automate whole tasks in the application process, trust might be a crucial factor in determining the HR manager's behavioral intention to use these tools. Trust is a central aspect of many economic transactions because humans need to identify when, why, and how other social actors behave (Gefen, et al., 2003) (Gefen, 2008). Developing trust in a Technology, or trust formation, is a dynamic process. Trust is a relational attribute based on experience. The level and characteristics of trust vary over time (Pavlou, 2003). According to Hengstler (2016), in the early phases of technology implementation, trust is mainly driven by the predictability of the technology, which is defined as the degree to which future behavior can be anticipated (Hengstler, 2016). Initial Trust is not based on any kind of prior experience. McKnight (2011) defines three dimensions of trust in technology: functionality, reliability, and helpfulness, which are related to human trust. Functionality is defined as the capability of the technology; reliability is defined as the consistency of the operation; and helpfulness is defined as whether the specific technology helps the user achieve his or her goal or not. These variables determine the level of cognitive trust in AI (Glikson & Woolley, 2020). Since the functionality aspect of trust is conceptually similar to perceived usefulness, it may be that trust and perceived usefulness share some variance in predicting behavioral intentions (Sage, 2022). According to the HLEG trust in AI is a prerequisite for individuals to use AI (HLGE, 2019). In some TAM models, which determine non-AI acceptance, trust is a significant direct determinant of intention to use (Ghazizadeh, 2012) (Who, 2011) (Gefen, 2003). In the context of determining the acceptance of AI-based technology, Trust is one of the most commonly used constructs besides perceived usefulness and perceived ease of use (Sage, et al. 2023). The literature review part of using the TAM to determine AI acceptance showed mixed findings on the effect of trust. Trust is directly significant (4/7) as a determinant of intention to use, indirectly significant on intention to use (2/7), or insignificant in determining intention to use. The indirect effect of trust on behavioral intention comes through its influence on the variable's perceived ease of use and perceived usefulness. Higher levels of Trust are associated with increased perceived usefulness, which in turn increases usage intention (Choung 2023). The higher the trust in the AI, the higher the ease of use, which also increases perceived usefulness, and thus the higher the usage intention (Choung, 2023). Therefore, **Hypothesis 3 states that Trust perception positively influences a) Perceived Usefulness b) Ease of Use c) Behavior intention.**

3.4: Ai-Anxiety

With the development and implementation of AI, individuals started to express anxiety concerning AI. This anxiety is reinforced by professional opinions as well as multiple studies that point out possible adverse effects AI could have on society or the workforce through its introduction into the labor market (Li, 2020). The possible adverse effects are tremendous changes in the labor market which would then result in a huge increase in permanent unemployment and poverty for a large proportion of the population (Vicsek, 2021). These opinion leaders and their warnings about the possible negative impacts on society increase AI-Anxiety (Li, 2020). While AI-Anxiety is a novel concept, only a few studies have researched its impact on acceptance. Liang (2017) studied the sociological fear of AI and found that individuals who are more concerned about job displacements caused by AI exhibit a higher level of fear of AI. VU (2021) studied which factors influence public attitudes towards the use of AI and found that an individual's level of fear of AI taking existing jobs negatively influences acceptance of AI. Their results show that AI-Anxiety can decrease AI acceptance and thus might play an important role in determining the acceptance of AI tools in the application process. Sánchez-Prieto (2019) proposes a theoretical model based on the TAM that includes AI-Anxiety as a construct directly adopted from Venkatesh's computer anxiety (Venkatesh, 2000). While computer anxiety has been researched in the context of the TAM (Venkatesh, 2000), Artificial Intelligence anxiety has been researched very little. While there are clear differences between computer anxiety and AI anxiety, both types of anxiety might have a similar influence on users. Computer anxiety is largely due to the fact that beginners feel out of control during their early experiences with computers (Venkatesh, 2000). There might be many beginners who have had their first experiences with AI and who also feel out of control while using this technology. Venkatesh (2000) states that computer anxiety serves as an anchor in determining an individual’s ease of use of technology. This means that before actual behavioral experience, individuals rely on general information about the technology that serves as an anchor. Prior to direct experience with the target system, individuals anchor their perceived ease of use to reflect their interaction with the system (Venkatesh , 2000). This might be the reason why people who score high on AI-Anxiety might have a low perceived ease of use in comparison to individuals scoring low on AI-Anxiety. Thus, Hypothesis 4A states that AI-Anxiety negatively influences perceived Ease of Use.

Since anxiety causes people to avoid situations that trigger their anxiety, individuals with computer anxiety experience an unpleasant emotional reaction when using computers. Thus, computer anxiety negatively affects the intention to use computers as well as actual computer use (Fagan, 2004). This could also be the case for Ai-Anxiety. Individuals with high levels of AI-Anxiety or even the fear of AI will avoid using AI since using it might trigger their anxiety. Thus, HR managers who score higher on AI-Anxiety might exhibit a lower intention to use AI tools in the application process. Thus, **Hypothesis 4 states that AI-Anxiety negatively influences a) perceived Ease of Use and b) Intention to Use.**

3.5: Control variables

To further increase the explainability of the AITUAM, three control variables have been included in the model. Since Venkatesh (2000) found that age and gender moderate the relationships in the UTAU, and the literature review of TAM for AI applications showed mixed findings regarding age and gender, these variables are included in the AITUAM as control variables. Control variables are included in the AITUAM to rule out alternative explanations for the results of the empirical evaluation and to increase its statistical power (De Battisti, 2019). The effect of the control variables is estimated in the empirical evaluation by statistical control (De Battisti, 2019). The statistical control is conducted by measuring if these control variables have a relationship with either the dependent or the independent variables. If the control variables have a significant relationship with any of the used variables, they should be included in the subsequent analysis (De Battisti, 2019). This allows us to determine if the control variable distorts the relationship between the variables in the model (Bernerth, 2016). Bernerth (2016) further states that it is of great importance to offer a clear justification for the control variables implemented. For statistical controls, it's especially important to justify the inclusion of the control variables based on a theoretical foundation. If the result of the empirical evaluation of the statistical control has an empirically established relationship with the variable of interest, this inclusion provides an incremental step or removal of alternative explanations of the results. The following part justifies the inclusion of the control variables Age, Gender, and Experience in the AITUAM:

3.5.1: Gender

To further improve the understanding of how individual technology acceptance is generated, it is important to recognize existing gender differences (Venkatesh, et al., 2000). Gender in this Thesis is defined as biological sex. The moderating effect of gender in the TAM was first determined by Venkatesh & Davis (2000) who stated that an individual's demographics influence perceived usefulness and perceived ease of use. Venkatesh, et al. (2000) found that perceived usefulness is more relevant for men, while perceived ease of use is more relevant for women. The reason for this is that men are primarily affected by the functionality aspect of technology, while for females, the individual’s confidence in her ability to use the technology is more important (Venkatesh et al., 2000). Thus, it is possible that for female HR managers the relationship between perceived usefulness and behavioral intention to use is weaker than for male HR managers, as well as for female HR managers, the strength of the relationship between perceived ease of use and intention to use is higher than for male HR managers. The relationship between perceived ease of use and trust is moderated by gender. Gender also affects Trust, Choung (2023) found that for females, ease of use was a significant predictor of trust but not for males. Thus, for female HR managers, the relationship between trust and perceived ease of use might be higher than for male HR managers. Further findings regarding the impact gender has on the relationship between trust and intention to use come from Liu (2021) who found that trust in the output of AI is more important for female users than for males. This might be similar for HR managers, for female HR managers, the relationship between trust and intention to use might be stronger than for male HR managers. Gilroy and Desai (1986) state that women are more prone than men to computer anxiety. Since AI-Anxiety is based on computer anxiety, gender might also affect AI-Anxiety, Lian (2017) found that females exhibit a higher level of fear regarding AI. Thus, female HR managers might exhibit higher AI-Anxiety than their male counterparts. The theory of reasoned action provides a theoretical explanation of why female HR managers might have a stronger behavioral intention to use AI tools in the application process than their male counterparts. Women are more strongly affected by subjective norms than men (Venkatesh, et al., 2000). The subjective norm is the individual's perceived social pressure to perform the behavior. In an organizational setting, social pressure comes from superiors and peers, especially in the early implementation stage of technology (Venkatesh & Morris, 2000). Thus, female HR managers might have a higher behavioral intention to use AI tools in the application process than their male counterparts. To determine if gender has a moderating effect on the relationships between variables in the model or a direct effect on the variables, the empirical evaluation will determine the possible effects, and if significant effects have been found, gender will be included in the AITUAM as a single item construct to further increase the explainability of the AITUAM.

3.5.2: Age

Technophobia is the fear or dislike of new technologies and is an umbrella term that also includes computer anxiety. Older adults are more technophobic than their younger counterparts (Faloye, 2022). For people who have high levels of technophobia, using technology creates negative emotions and anxiety, which constrains their ability to use this technology (Lythreatis, 2022). Findings regarding the impact age has on computer anxiety come from Laguna (1997), who found that older adults had higher computer anxiety than their younger counterparts. Since AI anxiety is based on computer anxiety, the older the HR managers are, the higher their overall AI anxiety level might be. An increase in Age could also impact the relationship that AI anxiety has with perceived ease of use as well as the behavioral intention to use AI tools in the application process. Thus, Age is included as a control variable to determine if age has a direct effect on AI anxiety or a moderating effect on the relationships between AI anxiety and perceived ease of use, as well as on the relationship between AI anxiety and behavioral intention. If significant effects are found, Age will be included in the AITUAM as a single-item construct to further increase the explainability of the AITUAM.

3.5.3: Experience

Experience in the AITUAM is defined as whether the individual HR manager has already used AI tools in the application process or not. Thus, it divides the sample into first-time users and sustained users. Experience plays an important role in determining acceptance, especially in the earliest stages of technology introduction. Users are making an “acceptance” decision, which is different from “sustained usage” decisions, which are a result of increases in experience with the technology (Davis & Venkatesh, 2004). Regarding AI acceptance, this plays a vital role. Sage (2020) suggests that individuals without any experience in AI might accept only their imagination of what AI seems to be, while experienced individuals instead accept AI for what AI really is. Experience might have a significant direct effect on the intention to use AI in the application process, since depending on experience, either an “acceptance” decision or a “sustained usage” decision is being made.

Individuals without experience with technology use their pre-implementation beliefs to determine the perceived ease of use of a technology, which is based on the belief of how able the individual is to use technology in general (Venkatesh, 1996). Thus, inexperienced HR managers evaluate perceived ease of use according to their beliefs on how able they are to use technology in general, while experienced managers have different beliefs since they already have knowledge of how easy it is for them to learn and use AI tools. Over time, with the accumulation of experience, ease of use becomes non-significant in determining behavioral intention to use (Szanja, 1996). Therefore, experience might have a direct negative effect on the perceived ease of use of AI tools in the application process.

Experience has a direct impact on trust, since trust is an attribute based on experience (Hengstler, 2016). Gefen (2000) states that trust develops through lifelong socialization, and as soon as an interaction with the trusted party occurs, this disposition is mitigated. Depending on the outcome of the interaction the individual makes with the trusted party, the individual then reevaluates their trust in the trusted party. If the outcome is negative, trust in the trusted party decreases, and if the outcome is positive, trust in the trusted party increases. Thus, there might be differences between experienced and inexperienced HR managers, since initial trust is not based on any kind of prior experience.

Venkatesh (2000) uses computer anxiety as an anchor to determine perceived ease of use. Individuals without direct experience rely on general information that serves as an anchor. Prior to direct experience with the target system, individuals anchor their perceived ease of use to reflect their interaction with the system (Venkatesh, 2000). Computer anxiety exerts a negative influence on the perceived ease of use of a new system. The development of computer anxiety is due to beginners feeling out of control during their early experiences with computers; over time, this effect diminishes. With an increase in experience, computer anxiety decreases. Similar to computer anxiety, AI-Anxiety might also decrease with an increase in experience. Thus, experience might have a direct impact on AI-Anxiety. Experienced HR managers might exhibit lower levels of AI anxiety than their inexperienced counterparts.

The inverse relationship between computer anxiety and perceived ease of use results from beginners feeling out of control during their early experiences with the system (Venkatesh, 2000).

With an increase in experience with the system, the individual then reevaluates the ease of use of the system. The effect of computer anxiety decreases with increasing experience (Venkatesh, 2000). Since AI-Anxiety is based on computer anxiety, inexperienced HR managers with AI Tools in the application process could have a weaker relationship between AI-Anxiety and perceived ease of use than their experienced counterparts.

The more experience an individual gets with the technology, the less important perceived ease of use has on behavioral intention, which is then primarily formed on the perception of usefulness (Szanja, 1996). Experience therefore has a moderating effect on the relationship between ease of use and behavioral intention. For inexperienced HR managers, the relationship between perceived ease of use and intention to use might be stronger than for experienced ones.

Before direct experience with a technology, an individual's perceived usefulness is affected by how other individuals with whom they are in contact perceive the given technology (Venkatesh, 2000). Thus, even though the individual perceives the technology as favorable, they will have a lower/higher intention to use it because others have a negative/positive view of this technology. With an increase in direct experience with the technology, this effect diminishes. Thus, with enough experience, an individual is no longer affected by what others think about this technology. This moderating effect of experience on the relationship between perceived usefulness and intention to use was first discovered by Venkatesh (2000). This is an important aspect in determining the acceptance of AI in the application process. For inexperienced HR managers, their perception of the usefulness of AI tools in the application process might depend on what others think about the implementation of AI in the application process, which affects the strength of the relationship between perceived usefulness and intention to use. Thus, the strength of the relationship between perceived usefulness and intention to use might differ depending on experience. To be able to control for the possible direct impact that experience has on the constructs in the AITUAM as well as the relationships between the constructs, experience is included in the AITUAM as a control variable. If the significant effects of experience are found, the experience will be included in the AITUAM as a single-item construct to further increase the explainability of the model.

3.6: The AITUAM

The model that was created and used in this Master Thesis is called the Artificial Intelligence Tool User Acceptance Model (AITUAM). The AITUAM is an extension of the original TAM and includes Trust and Anxiety as well as the TAM variables Perceived Usefulness, Ease of Use, and Intention to Use. To be able to determine AI tool acceptance in a simple Model, the AITUAM was created. The AITUAM includes perceived usefulness, ease of use, and trust in AI as variables that determine the behavior intention of AI tools. For an AI tool to generate the behavioral intention to use it, the user needs to perceive the tool as useful and easy to learn and use and needs to have confidence in the results (Choung, 2023). The confidence in the AI tools results aspect is included in the AITUAM as trust. Since higher levels of anxiety about AI might negatively impact perceived ease of use and the intention to use AI tools, AI anxiety is included in the model.

A visualization of the AITUAM can be found in Figure 7

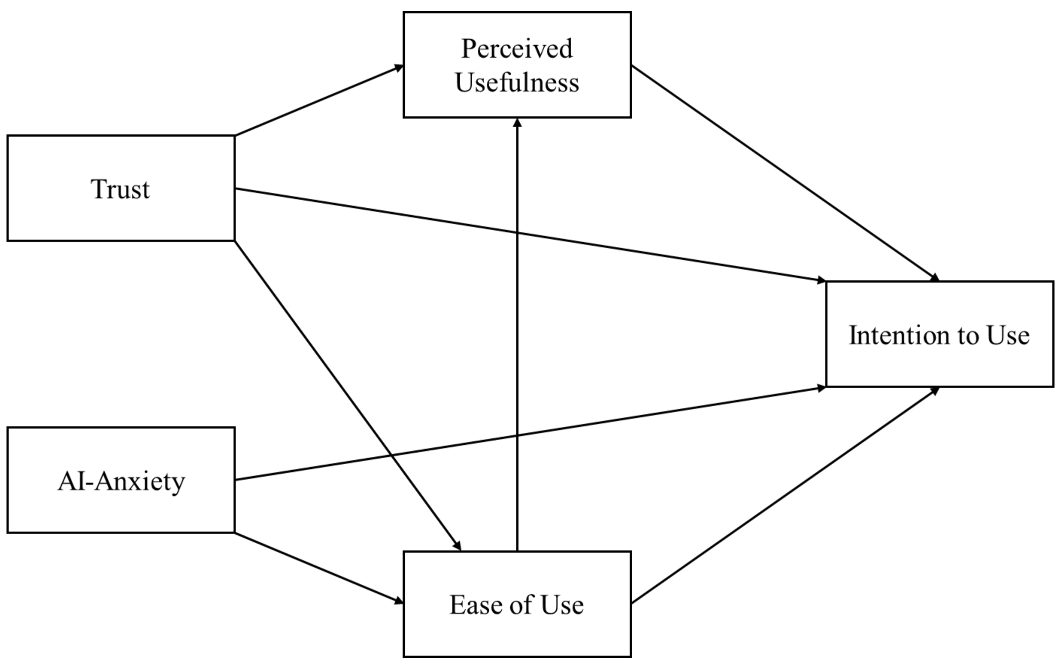

Figure 7 The AITUAM.

Figure 7 shows the variables and the relationships of the variables used in the AITUAM. To further increase the explainability of the AITUAM, the control variables Age, Gender, and Experience are included in the model.

4: Research Method

To determine the acceptance of AI tools in the application process, human resource managers were surveyed via an online survey regarding their intention to use AI tools in the application process. This thesis intends to determine the general acceptance of HR managers for the implementation of AI tools used in the application process. Therefore, the individuals in the sample were asked to give their individual views about the general use of AI tools in the application process. It is important to consider that there might be differences regarding the acceptance of specific tools that are used for the various tasks in the different phases of the application process. Over 3 Months, 86 individuals took part in the online survey; all participants were living in the DACH region. For the empirical evaluation, 62 observations were used. To prevent any language barriers, the questionnaire was written in the German language. Overall, there were 38 female participants (61%) and 24 male participants (39%). All participants were between 20 and 64 years old, and most of the participants were in the age group 25–29 years old. 26 (42%) of the participants have had prior experience with AI, while 36 (58%) had no prior experience with AI or did not know if they had prior experience with AI tools in the application process.

Figure 8 visualizes the sample distribution.

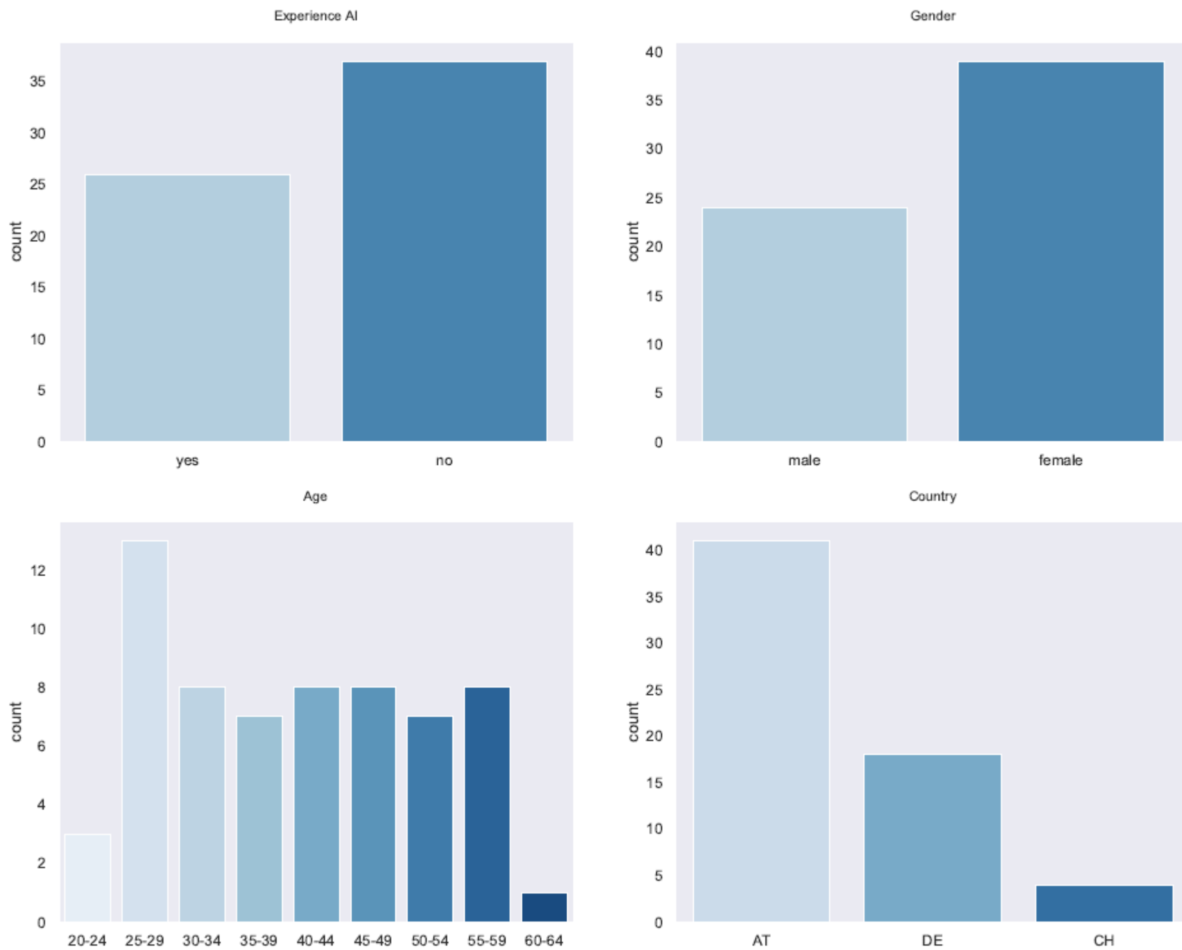

Figure 8 the used sample

To determine the effect experience with AI Tools has on the variables in the AITAUM, the experience was added as a control variable in the questionnaire. The participants were asked if they had prior experience with AI tools in the application process if they had no prior experience with AI tools in the application process, or if they were uncertain. Depending on this answer, the individuals were given two separate questionnaires, which differed only by the wording of the given questions. Individuals who were uncertain whether or not they had experience with AI were included in the inexperienced group. The variables Perceived Usefulness (PU), Perceived Ease of Use (EoU), Trust, and AI-Anxiety (AIA) were measured using a 5-point Likert scale. For each variable, between 3 and 5 questions were used to determine the individual's perception. To determine the HR manager's behavioral intention to use AI tools in the application process, the variable Intention to Use (IoU) was determined via 3 questions and evaluated using a 5-point Likert scale. The questions for perceived usefulness as well as perceived ease of use directly follow the original questionnaire used by Davies (1989). The questions to determine the Variable Trust follow the guidelines used in Choung (2023) to determine functionality trust in AI. The questions to determine AI-Anxiety follow the guidelines used to evaluate computer anxiety in Venkatesh (2008), as well as an additional question that determines the level of anxiety the individual has that the implementation of AI tools in the application process will lead to job loss. The questionnaire can be found in Figures 12 and 13 in the appendix. The empirical evaluation of the survey results was conducted using partial least squares-structural equation modeling (PLS-SEM).

5: Analysis

At the beginning of this part, an overview of the techniques used and the program in which the PLS-SEM was conducted is given. Afterward, the PLS-SEM is conducted, which follows the direct guidelines of (Sarstedt, et al., 2021) on how to conduct PLS-SEM.

5.1: Structural equation modeling

Structural equation modeling (SEM) is used for path-analytic modeling with latent variables. In SEM, the model uses latent variables, which are derived from multiple observed measures (Chin, 1998). According to Chin (1998), SEM allows for the determination of both attitudinal and behavioral outcomes and applies to nominal, ordinal, and single-item measures. The survey used a Likert scale with 5 options to determine the variables Perceived Usefulness, Ease of Use, Trust, AI-Anxiety, and Intention to Use. Thus, these variables are ordinal. Only 49 HR managers fully completed the survey by answering every given question on the Likert scale. 14 HR managers answered some questions with the possibility “I don’t know,” which resulted in a missing value in the data frame. The mean value for each of the questions used to determine the opinion of the managers was then used to replace the missing values in the data. Since the questionnaires of experienced and inexperienced HR-Managers differed in wording, the mean values of the experienced HR-Managers were used to fill out the missing value for the experienced HR-Manager, while the mean values of the inexperienced HR-Managers were used to fill out the missing value for the inexperienced HR-Manager. These mean values are metrical. To be able to use these mean values in the empirical evaluation, the ordinal data was treated as metric data. According to Liddel, et al. (2018), who conducted a literature review on articles mentioning the term “Likert” in high-ranking psychology journal articles, 100% of these papers treated the ordinal data as if they were metric. The Authors found that this leads to Type 1 errors (detecting effects where they do not exist) and Type 2 errors (failing to detect effects), as well as systematic inversion of effects. This needs to be considered when evaluating the results. To test the theorized relationships in the hypotheses part of this Thesis, structural equation modeling (SEM) is used.

5.2: PLS-SEM

In SEM, the structural model establishes the links between the latent variables (constructs) that are used. When applying SEM, it is important to differentiate between reflective and formative indicators. Reflective indicators are affected by the same underlying concept, which means that the latent variable affects the indicator. Formative indicators are the cause of the creation or change in the latent variables (Chin, 1998). In the AITUAM, the indicators are reflective. According to Chin (1998), it is recommended to model reflective indicators using the component-based approach of partial least squares (PLS). PLS path modeling does not rely on assumptions about the population or the scale of measurement, making it suitable for non-normally distributed data and small sample sizes (Henseler, 2013). According to Sarstedt, et al. (2021), the minimum required sample size in PLS is 10 times the largest number of formative indicators or 10 times the largest number of structural paths directed at a construct in the structural model. The largest number of formative indicators in the AITUAM is 5, while the largest number of structural paths directed at a construct is 6 for Intention to Use (Figure 1). Thus, the sample size of 63 is sufficient for conducting a partial least squares structural equation modeling analysis (PLS-SEM). PLS-SEM analysis enables the development of a theoretical model that accounts for all covariances among the measured items and captures direct as well as indirect (mediated) and interaction (moderator) effects (Ringle, et al. 2020). The goal of PLS-SEM is to predict and explain the key target construct (Intention to Use) as well as to identify which of the predecessor constructs are relevant in determining this construct. PLS-SEM is often used to identify key success factors of competitive advantage for key constructs such as behavioral intentions and usage behavior (Venkatesh, et al. 2003). Therefore, PLS-SEM is commonly used to determine HRM practices (Ringle, et al., 2020). These are the reasons why PLS-SEM is used for the empirical evaluation. The critique of PLS-SEM is that it lacks goodness-of-fit measures and can produce biased estimates (Rönkkö, et al. 2016). Sarstedt, et al. (2021) state that while validation using goodness-of-fit values is relevant for PLS-SEM, researchers should primarily focus on the predictive performance of the model. To conduct the PLS-SEM analysis, the tool SmartPLS4 has been used (SmartPLS4, 2024).

5.2.1: SmartPLS4

The path model (Figure 1) visualizes the hypotheses and constructs relationships, which are estimated in the SEM analysis. The constructs represent the conceptual variables that were defined in the theoretical part of this Thesis (Sarstedt, et al., 2021). In SmartPLS4, the blue circles represent the constructs. The relationships between the constructs are visualized by single-headed arrows. The yellow squares are the indicators, each indicator represents a question (item) from the questionnaire, Tables 18 and 19 in the appendix show which indicator represents which item (SmartPLS4, 2024). Single-item constructs can be included in PLS-SEM (Sarstedt, et al., 2021).

Since construct and indicator are the same for single-item constructs, the relationship is represented by a line instead of an arrow (SmartPLS4, 2024). SmartPLS4 allows us to determine the moderating effects of a construct on the relationship between two constructs. The moderating effect is visualized as a dotted arrow pointing away from the construct towards the causal-predictive relationship. The strength of the relationship between the constructs is represented by the path coefficients, which are the result of each construct on their appointed counterpart (Becker, 2023). The first step in conducting PLS-SEM in SmartPLS4 is to calculate the PLS-SEM results. SmartPLS4 shows the results of the calculations for the indicator loadings, path coefficients, moderating effects, and R2 values of the dependent variables. The evaluation of the PLS-SEM results is a two-stage process. In the first stage, the measurement theory is examined, while the second stage determines the significance of the constructed relationships that represent the hypothesis (Sarstedt, et al., 2021). To examine the measurement theory used, the internal reliability of the used constructs is being determined.

5.2.2: Internal consistency reliability

The first stage of evaluating a PLS-SEM result is to determine if the measurement theory used for a reflexive model is acceptable. In order to do so, indicator reliability, internal consistency reliability, convergent validity, and discriminant validity are being assessed (Sarstedt, et al., 2021). An essential step when conducting PLS-SEM is to determine if the questions associated with the latent variable are understood by the participants of the survey in the same way as they were intended by the questionnaire (Kock, 2014). This step is called internal consistency and reliability testing. The first step in internal reliability testing is to examine the strength of the indicator loadings in the so-called composite reliability test. Indicators with loadings lower than 0.4 should always be deleted (Hair, 2019). Indicator loadings between 0.40 and 0.70 should only be removed if deleting this indicator leads to an increase in composite reliability above the suggested threshold value (Hair, 2019). Since multicollinearity poses a great problem in PLS-SEM, the variance inflation factor (VIF)for the indicators needs to be examined. Ringel, et al. (2015) recommend that the indicator VIF values should have a maximum of 5 and indicators with higher VIF scores should be deleted. VIF values below 3.3 are considered good.

The Composite reliability test determines if all items of the construct consistently measure the construct. Composite reliability controls for undesirable response patterns such as answering all questions with the same answer or if the survey questions are too identical and thus redundant

(Sarstedt, et al., 2021) (Diamantopoulos, et al., 2012). The higher the values of the composite reliability coefficient (rho_a), and the consistent reliability coefficient (rho_c) the higher the level of reliability of the construct. Values below the threshold of 0.7 indicate low reliability, while values above the threshold of 0.95 indicate that the used items are too identical and thus redundant (Sarstedt, et al., 2021). According to (Sarstedt, et al., 2021) indicator loadings above 0.708 indicate the construct explains more than 50% of its variance, thus ensuring internal consistency and reliability. After this, convergent validity needs to be ensured. Convergent validity assesses how well the indicators explain an item's variance. This assessment is conducted using the average variance extracted (AVE). To ensure convergent validity, the threshold for AVE is higher than 0.5 Hair (2019). If the AVE is above 0.5 the construct explains an average of at least 50 % of the item's variance (Ringle, 2020). While three indicators are statistically adequate, Chin (1998) recommends at least 4 indicators to adequately test convergent validity. After concluding that convergent validity is given, the last evaluation criterion is Cronbach´s alpha, which measures if the indicators are not correlated and do not exhibit high internal consistency. Cronbach's alpha should be 0.7 or higher (Sarstedt, et al., 2021). If all these values are higher than their recommended thresholds, the internal consistency and reliability of a construct are given (Sarstedt, et al., 2021).

The next step in conducting PLS-SEM is the assessment of the discriminant's validity. Discriminant validity assessment verifies that a construct exhibits stronger relationships with its own indicators than with the indicators of any other construct in the PLS path model (Sarstedt, et al., 2021). Thus, it shows the extent to which a construct is empirically distinct from other constructs. The discriminant validity assessment determines how much the constructs are correlated and how distinctly the indicators represent a single construct (Sarstedt, et al., 2021). This assessment is a prerequisite for analyzing the relationships between the measured constructs. Discriminant validity is assessed using the Heterotrait-Monotrait ratio of correlations (HTMT). The HTMT criterion is defined as the mean value of the indicator correlations across constructs relative to the geometric mean of the average correlations of the indicators measuring the same construct (Ringle, 2020). High HTMT values indicate that the construct exhibits strong relationships with the indicators of another construct. Henseler et al. (2015) suggest that the HTMT threshold value be smaller than 0.9 for conceptually similar constructs, while for more conceptually distinct constructs, a threshold value of 0.85 is suggested. If internal consistency, reliability, and discriminant validity are given for each construct, an empirical evaluation of the model can be conducted (Sarstedt, et al., 2021).

5.2.3: The structural model evaluation

If internal reliability and discriminant validity have been assessed, the second stage of the PLS-SEM evaluation can be conducted. To determine the statistical significance of the relationships in PLS-SEM, a nonparametric procedure called bootstrapping is being used. The reason for using bootstrapping is that PLS-SEM is being applied to data that is not normally distributed. Significance tests that are applied in regression analysis for non-normally distributed data are unable to test the significance of the path coefficients (Becker, 2023). To determine the significance of the estimated path coefficients, bootstrapping creates subsamples with randomly drawn observations from the original data set. This process is repeated until a large number of subsamples are drawn Becker (2023). According to Streukens and Leroi-Werelds (2016), 500 bootstrap samples are sufficient for an initial assessment. The final model analysis should be drawn on at least 5000 bootstrap samples. In general, the more subsamples, the more precise the estimated parameter distribution, which increases the testing precision (Sarstedt, et al., 2021). With 10.000 subsamples, the random variations in the estimates are leveled out (Sarstedt, et al., 2021).

The estimates for the outer loadings and path coefficients, which are obtained from the created subsamples, are used to determine the 95% confidence intervals that are used for the significance testing. The PLS-SEM results are significant if they are outside the 95% confidence interval (Becker, 2023). According to Sarstedt, et al. (2021), it is not only important to consider if the results are significant, but also if they are substantial. This is conducted by examining the F^2 coefficients. F^2 values from 0.02 to 0.15 indicate a weak effect, and from 0.15 to 0.35 medium effect, while an F^2 value above 0.35 indicates a strong effect (Sarstedt, et al., 2021). Bootstrapping also provides standard errors for the estimates as well as the t-values, which are used to assess the significance of the estimates. To evaluate the total effects on the constructs, the direct and indirect relationships on this construct are used. To determine the model's in-sample predictive powers, the R^2 values of all the dependent constructs should be examined by Ringel, et al. (2020). The final step in conducting a PLS-SEM is to determine the goodness of fit (GoF). In PLS-SEM, GoF is determined by comparing the observed values of the dependent variables with the values predicted by the model (saturated model). A poor model fit is indicated if the used model exhibits a great difference between the Chi-square value of the saturated model and the estimated model (Hensler, 2013). Henseler and Sarstedt (2013) show that for PLS, GoF is not suitable for model validation, but it is useful in group comparison since it shows how well different subsets of the data can be explained by the particular model (Henseler and Sarstedt, 2013) (Sarstedt, et al. 2011).

5.3: The empirical evaluation

The conceptual model based on the Hypothesis serves as a foundation for determining HR managers acceptance of AI tools and is shown in Figure 17 in the appendix. This model allows for the explanation of 57.7% of the variance in Intention to Use. The goal of this thesis is to determine the acceptance of HR managers in the application process. The variables Age, Gender, and Experience might influence the AITUAM variables or the relationships between the variables used in the model. Therefore, the conceptual model was used to statistically test the impact of these control variables.

To determine if the control variable Gender is significant in influencing the AITUAM variables, the models visualized in Figures 20 and 21 in the appendix were used. The analysis of Figure 20 revealed that Gender is significant on Intention to Use at the 5% level but not significant on the other TAM variables. Figure 21 shows the significance of the moderating effect of Gender. The results of the bootstrapping method show that Gender has no significant moderating effect on the relationships in the AITUAM. Thus, no moderating effect on Gender was included in the AITUAM. Therefore, Gender was included as a single-item construct directly influencing Intention to Use to the AITUAM.

To determine if the control variable Age has a significant effect on the variables in the AITUAM, Figure 22 in the appendix was used. Figure 22 shows that Age has no significant direct effect on any of the TAM variables. Thus, Age was not included as a direct determinant of the AITUAM variables. Figure 23 was used to determine if Age has a moderating effect on the relationships in the AITUAM. Age has a significant moderating effect on the relationship between AI-Anxiety and Intention to Use at the 5 % level. This is the reason why Age was included in the AITUAM as a moderator.

To test if Experience has a significant direct effect on the TAM variables, Figure 18 in the appendix was used. The results show that Experience is significant for Ease of Use and Intention to Use at the 1% level. To determine if experience moderates the relationships in the AITUAM, Figure 19 in the appendix was used. The results show that Experience does not moderate the relationships in the AITUAM. Therefore, experience as a single-item construct that directly influences Ease of Use and Intention to Use was included in the AITUAM.

Becker (2023) states that when hypothesizing a direct main-effect relationship between two constructs, the effect should be estimated without the inclusion of the moderator. Since any testing of the direct effect is dependent on the moderator and thus differs from the formulated hypothesis, Becker (2023) recommends first establishing a base model without the moderator to test the direct effect's significance and then including the moderator to assess its impact. The base model was established and empirically tested in the "The AITUAM without Age as a moderator" part of the appendix. The results show that the direct effect of AI-Anxiety is significant on Intention to Use. Thus, the following part of this Thesis shows the empirical evaluation of the AITUAM with the inclusion of Age as a moderator.

5.3.1: The AITUAM with Age as a moderator

In this part of the Thesis, the empirical evaluation of the AITUAM is being conducted. The structural model determines Intention to Use (IoU) depending on Ease of Use (EoU), Perceived Usefulness (PU), Trust, AI-Anxiety (AI-Anx), Experience (Exp), Gender and Age as moderators. The model consists of two independent variables: Trust and AI-Anxiety as well as two dependent variables: Perceived Usefulness and Ease of Use as well as two control variables: Experience and Gender and one moderator variable, Age.

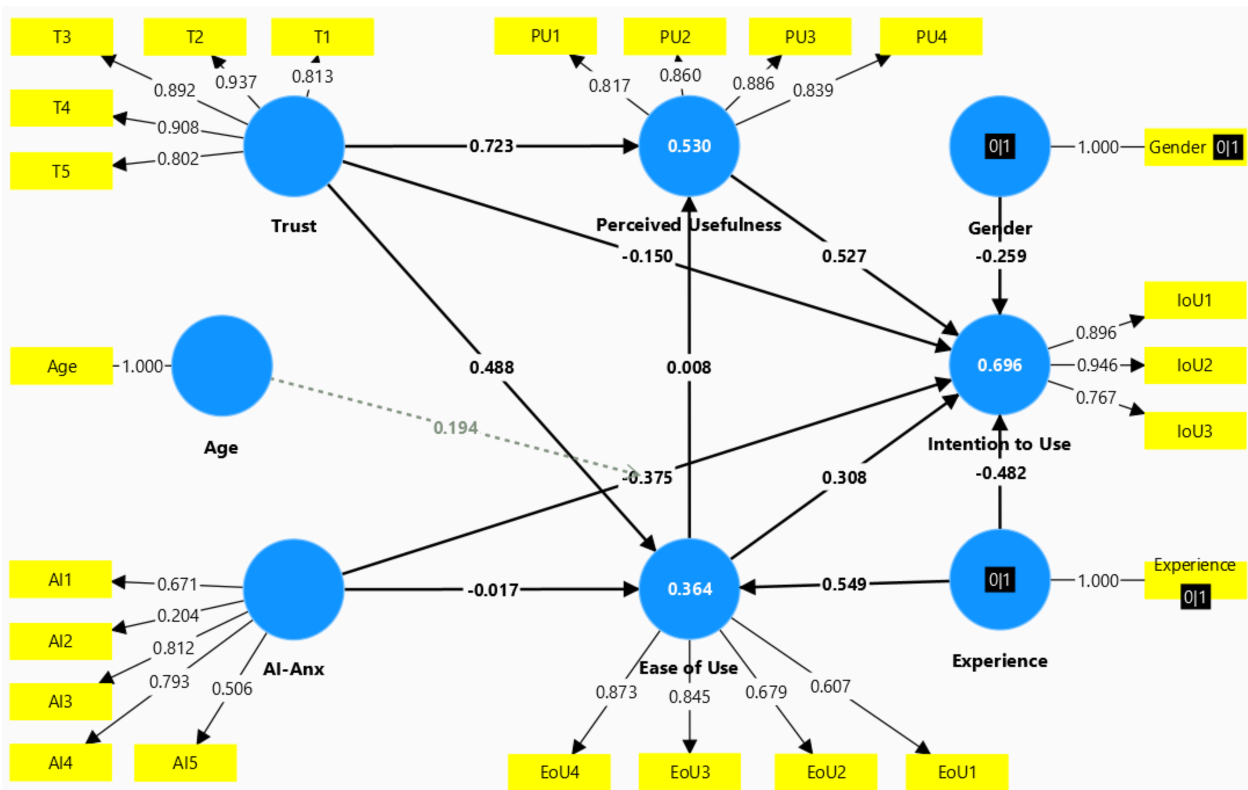

Figure 9 the PLS-SEM results for the AITUAM.

To determine if the measurement theory used is acceptable, indicator reliability, internal consistency reliability, and convergent validity were assessed. Figure 1 and Table 1 indicate key issues regarding the internal consistency, reliability, and indicator loadings for the constructs AI-Anxiety and Ease of Use.

Table 2 shows the results for the construct reliability and validity testing for the ground model in Figure 1.

Table 1 the results for the construct reliability and validity testing.

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE
AI-Anxiety	0.620	0.697	0.750	0.407
Ease of Use	0.774	0.853	0.842	0.576
Intention to Use	0.842	0.876	0.905	0.762
Perceived Usefulness	0.873	0.874	0.913	0.724
Trust	0.921	0.927	0.941	0.761

For AI-Anxiety, AVE is below 0.5 (0.407) and Cronbach´s alpha is below 0.7 (0.620), and therefore below the recommended thresholds (Sarstedt, et al. 2021) (Hair, 2019). The indicator loading for AI2 (0.204) is lower than 0.4 and should be removed, according to Hair (2019). After removing AI 2 from the model (see Figure 27 in the appendix), the indicator loadings for AI5 (0.506) and AI1 (0.671) are still below the recommended threshold of 0.7, and Cronbach´s alpha is below 0.7. Thus, AI5 is also being removed from the model. Table 2 shows that after removing the indicators AI 2 and AI 5 internal reliability is given for AI-Anxiety. Deleting these indicators pushed all key figures above the recommended threshold. Thus, there is no need to delete AI1 from the model, since indicators with loadings below 0.7 should only be removed if deleting this indicator leads to an increase in composite reliability above the suggested threshold value (Hair, 2019). The indicator AI2 represents the survey question, "I am afraid that the implementation of AI tools in the application process will lead to job loss". The indicator AI5 represents the survey question, "I am afraid that learning to use AI tools in the application process will be overwhelming for me.". Deleting these indicators reduces the scope of the construct AI-Anxiety is able to explain. AI2 was included as an extension since the higher levels of fear that AI is replacing existing jobs negatively influence AI acceptance (Vu, 2021). AI5 is intended to measure the fear of being unable to learn how to use AI tools in the application process. As can be seen in Tables 4 and 5 in the Appendix, AI-Anxiety as a construct affects the general level of fear of AI (A1), the fear that using AI tools in the application process creates possible problems (A3), and the fear that AI tools in the application process can malfunction (A4).

For Ease of Use, the indicator loadings for EoU1 (0.607) and EoU2 (0.679) are below 0.7. Table 1 shows that for Ease of Use, the key figures are all above the recommended threshold. Therefore, there is no need to exclude the indicators EoU1 and EoU2. The examination of variance inflation factor (VIF) scores, which can be found in Table 7 in the appendix, reveals high values for the indicator T3 (5.034), surpassing the threshold of 5 recommended by Ringel, et al. (2015). Consequently, indicator T3 is removed from the model to prevent multicollinearity issues. The adjustments made to solve the internal reliability issues aim to enhance the overall robustness and validity of the AITUAM (Figure 2). Excluding the indicators AI2, AI5, and T3 contributes to ensuring the reliability and accuracy of the AITUAM´s findings in measuring the construct relationships. The PLS-SEM results for the adjusted model can be found in Figure 2.

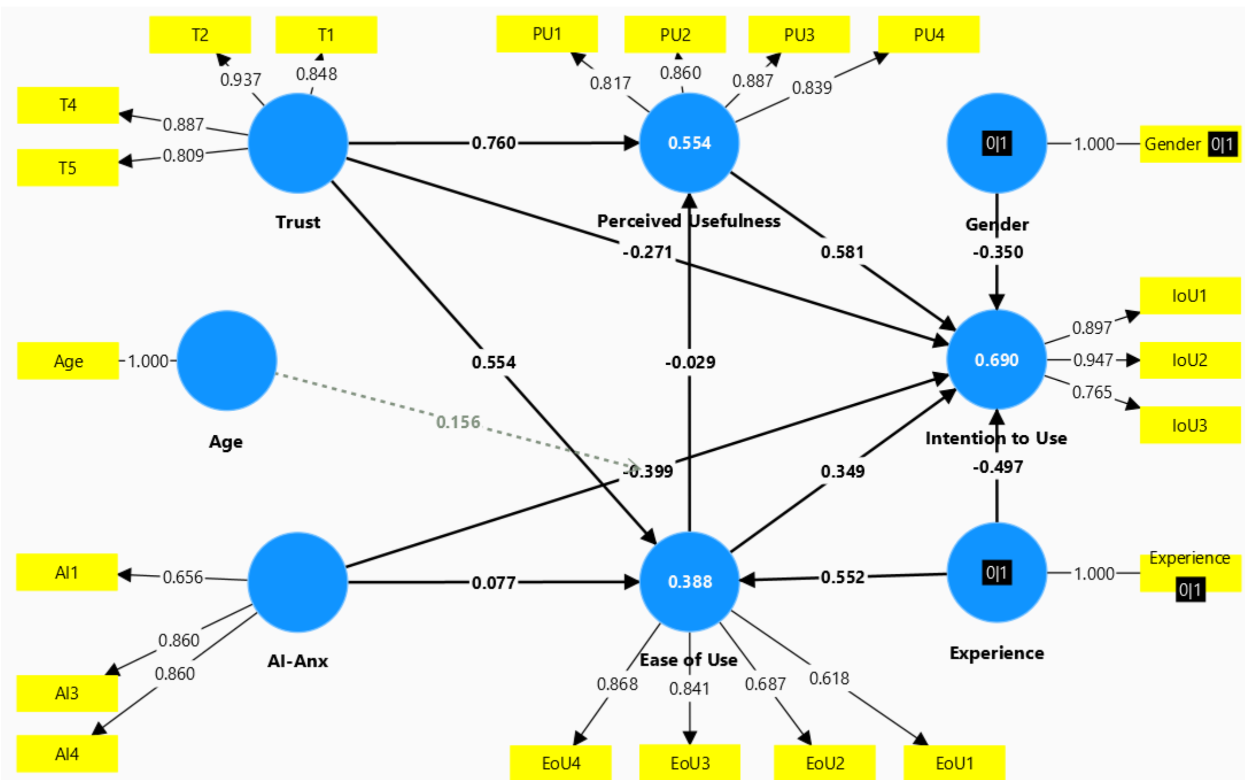

Figure 10 The PLS-SEM results for the AITUAM.

While the indicators EoU1, EoU2, and AI1 are still below 0.7, the results for the construct reliability and validity tests (Table 2) show no further problems with internal reliability (Sarstedt, et al., 2021) (Ramayah, et al. 2016) (Hair, 2019). For all the constructs, Cronbach´s alpha values are above 0.7, composite reliability values are higher than 0.7, and the AVE values are all higher than 0.5.

Table 2 the results for the internal reliability testing.

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE
AI-Anxiety	0.718	0.771	0.838	0.637
Ease of Use	0.774	0.845	0.844	0.579
Intention to Use	0.842	0.879	0.905	0.762
Perceived Usefulness	0.873	0.874	0.913	0.724
Trust	0.894	0.902	0.926	0.759

After establishing internal reliability for the constructs following the exclusion of the problematic indicators (AI2, AI5, T3), discriminant validity has to be assessed, to ensure that the constructs are distinct from one another. The results from the HTMT matrix, which determines discriminant validity, can be found in Table 3.

Table 3 shows the HTMT matrix.

The HTMT Matrix	AI-Anx	Age	EoU	Gender	IoU	PU	Exp	Age x AI-Anx
AI-Anxiety								
Age	0.346							
Ease of Use	0.238	0.212						
Gender	0.291	0.280	0.133					
Intention to Use	0.599	0.076	0.439	0.176				
Perceived Usefulness	0.417	0.107	0.393	0.131	0.785			
Trust	0.576	0.246	0.613	0.080	0.576	0.840		
Experience	0.100	0.107	0.398	0.004	0.201	0.129	0.163	
Age x AI-Anx	0.097	0.110	0.268	0.053	0.199	0.146	0.089	0.272

All HTMT values are lower than 0.85, therefore, discriminant validity has been established for all constructs. This indicates that the constructs are sufficiently distinct from each other. However, it's important to note that the HTMT value of 0.840 between Trust and Perceived Usefulness is very close to 0.85, which is the recommended threshold by Henseler, et al. (2015). This indicates that the construct of Trust exhibits strong relationships with the indicators of the construct's Perceived Usefulness (Henseler, et al., 2015). The findings from the HTMT matrix allow us to come to the conclusion, that discriminant validity has been successfully established for all used constructs. Each of the constructs used in the AITUAM demonstrates stronger associations with its own indicators than with the indicators of other constructs.

Figure 2 shows the strength of the path coefficients as well as the R^2 values of the dependent variables. AI-Anxiety has a negative influence on Intention to Use (-0.399) and a minor positive impact on Ease of Use (0.077). That AI-Anxiety has a minor positive impact on Ease of Use is contrary to the theory, thus for the HR managers who took part in the survey, higher levels of AI-Anxiety do not decrease the perception of how easy it is to learn or use AI tools in the application process. Trust exhibits a strong positive influence on Ease of Use (0.554) and a very strong positive influence on Perceived Usefulness (0.760) while having a negative influence on Intention to Use (-0.271). The negative effect trust has on Intention to Use is contrary to the theory and is counterintuitive since this means that the more trustful the generated output of the AI tools is, the lower the intention to use them. Ease of Use has a positive influence on Intention to Use (0.349) and has a negligible negative effect on Perceived Usefulness (-0.029). The fact that Ease of Use has a negligible negative effect on Perceived Usefulness is contrary to the theory and indicates that the perception of how easy it is to learn and use an AI tool has a negligible effect on how useful it is being perceived. Perceived Usefulness has a strong positive influence on Intention to Use (0.581). Gender negatively affects Intention to Use (-0.350). Experience positively affects Ease of Use (0.552) and negatively affects Intention to Use (-0.497).

The R^2 values as well as the adjusted R^2 values for the dependent variables can be found in Table 18 in the appendix. The R^2 values indicate that the AITUAM can explain 38.8 % of the variances for Ease of Use, 55.4% for Perceived Usefulness, and 69% of the variance in Intention to Use, which is a fundamental increase in explainability in comparison to the conceptual model, which was based on the Hypotheses. The adjusted R^2 values for Ease of Use is (0.356), Perceived Usefulness (0.539), and Intention to Use (0.634), further validating the model's explanatory power. The F^2 values that can be found in Table 9 in the appendix show that Trust has a strong effect on Ease of Use (0.370) and a fundamental effect on Perceived Usefulness (0.892). Perceived Usefulness has the strongest effect of all the constructs on Intention to Use (0.462). AI-Anxiety has a rather strong effect on Intention to Use (0.342). Experience has a moderate effect on Intention to Use (0.159). Ease of Use has a moderate effect on Intention to Use (0.217). However, despite the strengths of the model, the model fit assessment indicates poor goodness-of-fit (GoF). The results for the model fit can be found in Table 10 in the appendix and show a great difference between the Chi-squared values of the saturated model and the estimated model. Hensler and Sarstedt (2013) showed that the GoF is not suitable for model validation. Thus, the poor GoF is not a reason to discard the AITUAM. To determine the significance of the relationships in the AITUAM an empirical evaluation using the bootstrapping method was conducted.

The results of the Bootstrapping method:

A percentile bootstrapping method, as recommended by Becker, et al. (2023), with 10.000 bootstrapping samples was used to determine the significance of the relationships in the AITUAM. A fixed seed was used for the random number generator to allow consistency and reproducibility of the results (Sarstedt, et al., 2021). To determine the significance of the path model, a two-tailed significance test at the 5% level was conducted.

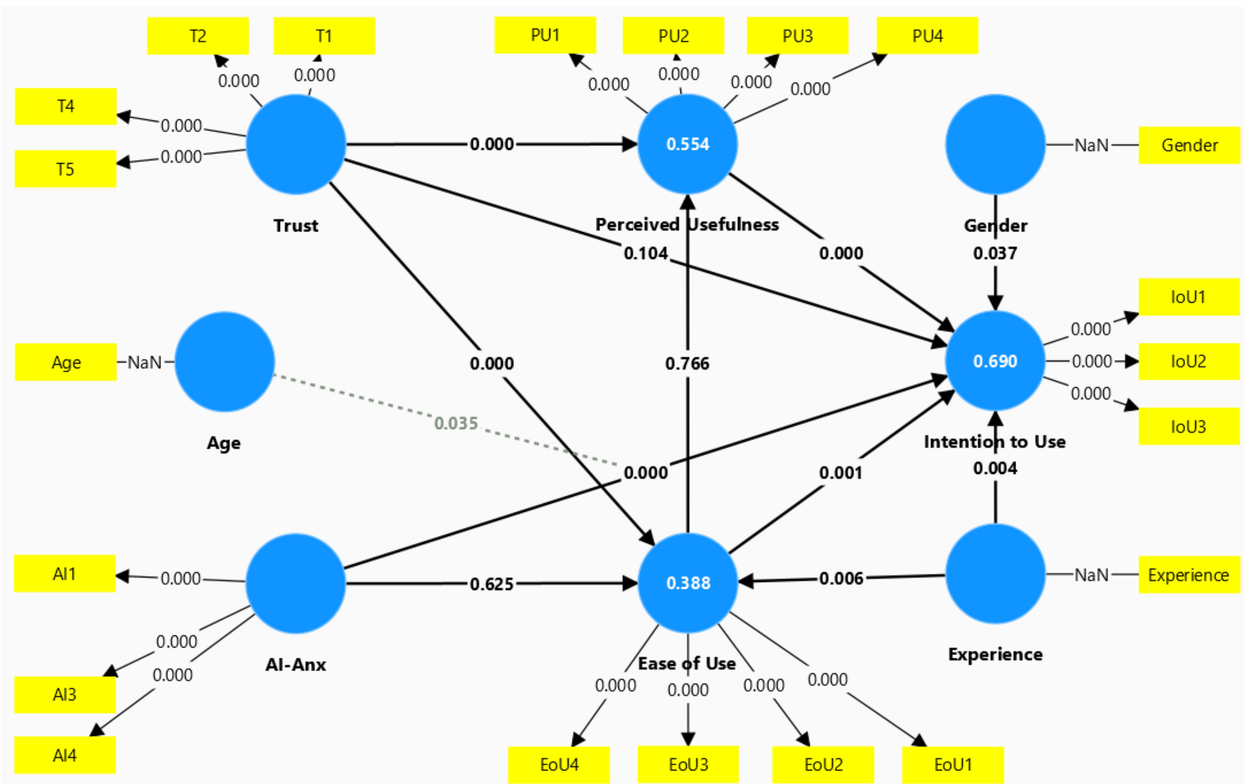

Figure 11 the result of the bootstrapping method.

The result of the bootstrapping method (Figure 3) shows that all the indicator loadings are statistically significant at the 1% level, confirming the reliability of the measurement model. The results for the construct relationships show that Trust is statistically significant at the 1% level on Ease of Use (0.000) as well as Perceived Usefulness (0.000), but not statistically significant on Intention to Use (0.104). Ease of Use is not statistically significant on Perceived Usefulness (0.766) but is significant at the 5% level on Intention to Use (0.001). Perceived Usefulness is statistically significant at the 1% level for Intention to Use (0.000). Experience is statistically significant at the 1% level on Ease of Use (0.006) and on Intention to Use (0.004). Gender is significant for Intention to Use at the 5% level (0.037). AI-Anxiety is not statistically significant on Ease of Use (0.625), but is statistically significant on Intention to Use, at the 1% level (0.000). Since the relationship's strength between AI-Anxiety and Ease of Use as well as AI-Anxiety and Intention to Use is moderated by Age, this estimate is subject to heterogeneity (Becker, 2023). Age has a significant moderating effect on AI-Anxiety at the 5% level. The only construct with a significant indirect effect at the 1% level on Intention to Use is Trust (0.000). The indirect effects of the other variables can be found in Figure 11 in the appendix. The total effect matrix can be found in the appendix in Table 12. The total effect shows that through its influence on Perceived Usefulness and Ease of Use Trust has a significant total effect on Intention to Use at the 1 % level (0.001). Any result about the direct effect AI-Anxiety has on Intention to Use is dependent on the moderator's Age. Age has a significant moderating effect on the 5 % level of the relationship between AI-Anxiety and Intention to Use (0.035). The results of the F^2 test can be found in Table 15 in the appendix and show a weak strength (0.011) of the moderating effect. These results allow the conclusion that Age as a moderator only has a minor impact on the relationships between the constructs and does not change their significance. The total effects after the inclusion of Age as a moderator can be found in Table 17 in the appendix.

5.3.2: Testing the Hypotheses

The result of the empirical evaluation provides important insights into the hypothesized relationships within the AITUAM. Hypothesis 1 states that the perceived ease of using AI tools positively influences a) Perceived Usefulness and b) Intention to Use. Ease of Use has a minor negative influence on Perceived Usefulness (-0.029) and is not significant in determining Perceived Usefulness at the 5% level (0.766). Therefore, **Hypothesis 1a) is rejected**. The perception of how easy AI tools in the application process are to use does not positively influence how useful they are being perceived by the HR managers in the sample used. Ease of Use has a positive influence on Intention to Use (0.349) and is statistically significant in determining Intention to Use at the 1% level (0.001). Thus, **Hypothesis 1 b) is accepted**. The perception of how easy AI tools in the application process are to use increases the intention of the HR managers who took part in the survey to use them.

Hypothesis 2 states that the perceived usefulness of AI tools does positively influence the intention to use AI tools. Perceived Usefulness has a strong positive influence on Intention to Use (0.581) and is statistically significant on Intention to Use at the 1% level (0.000). According to these results, **Hypothesis 2 is being accepted**. The more useful the HR managers perceived the AI tools in the application, the higher their intention to use them.

Hypothesis 3 states that trust in the outcome of AI tools does positively influence the perceived usefulness a), the perceived ease of use b), as well as the intention of using AI tools c). Trust has a very strong positive influence on Perceived Usefulness (0.760). Trust is statistically significant at the 1% level on Perceived Usefulness (0.000). Thus, **Hypothesis 3a) is accepted**. The higher the HR managers in the used sample had trust in the output of AI tools is a fundamental and significant determinant of how useful these AI tools are being perceived. Trust has a strong positive influence on Ease of Use (0.554). Trust is statistically significant at the 1% level on Ease of Use (0.000). Thus, **Hypothesis 3b) is accepted**. For the individuals who took part in the survey, trust in the output of AI tools is a strong and significant determinant of how easily AI tools are perceived to be learned and used. Trust has a direct negative influence on Intention to Use (-0.271) and is not significant at the 5% level (0.104). **Hypothesis 3 c) is therefore being rejected**. While Trust does not have a significant direct effect on Intention to Use, it still has a positive (0.354) and significant total effect on Intention to Use (0.000) through its direct positive influence on Perceived Usefulness and Ease of Use. The positive total effect trust has on Intention to Use is the sum of the direct and indirect effects. The indirect effects on Perceived Usefulness and Ease of Use compensate for the weak direct effect on Intention to Use, which leads to a significant positive total effect. Thus, the results of the empirical evaluation allow us to come to the conclusion that Trust while not having a direct effect on Intention to Use is an important aspect in determining the intention to use AI tools in the application process for the HR managers who took part in the survey.

Hypothesis 4a) states that AI-Anxiety negatively influences AI tool's perceived Ease of Use. AI-Anxiety has a minor positive influence on Ease of Use (0.077). Since AI-Anxiety is not statistically significant at the 5% level (0.625) on Ease of Use, **Hypothesis 4a) is being rejected**. AI-Anxiety is not a significant determinant of the perceived Ease of Use of AI tools in the application process used by HR managers. Hypothesis 4b) states that Ai-Anxiety negatively influences the Intention to Use. The results of this evaluation show that AI-Anxiety has a negative direct influence on Intention to Use (-0.390) which is significant on the 1% level (0.000). Therefore, **Hypothesis 4b) is accepted**. The relationship between AI-Anxiety and Intention to Use is moderated by Age. The empirical evaluation of the AITUAM without the inclusion of Age as a moderator can be found in the appendix under “The AITUAM without Age as a Moderator.”. With the inclusion of Age as a moderator, AI-Anxiety has a stronger negative influence on Intention to Use (-0.399) which is significant at the 1% level. Thus, for the HR managers who took part in the survey, higher levels of anxiety about AI resulted in a decrease in the intention to use these tools in the application process, even more so for older individuals.

6: Discussion

The results of the empirical evaluation show that the AITUAM can explain the acceptance of HR managers in the application process. The result from the literature review about the use of the TAM to determine AI acceptance showed that the range for R^2 is between 31.92% Damerji (2021) and 66.4% Liu (2021). Without the inclusion of the control variables (Figure 17 in the appendix), the AITUAM is able to explain 55.7% of the variance in Intention to Use, making it a solid model in comparison to the other models. Some of the results of the empirical evaluation are contrary to the theory. Perceived Ease of Use was not a significant determinant of Perceived Usefulness. Thus, for the HR managers who took part in the survey, it was not relevant how difficult a system is to learn and use, to perceive the AI tools as useful. Trust was hypothesized to have a positive direct impact on intention to use. In the used sample, trust had a negative, insignificant direct effect on Intention to Use but a significant positive total effect on it through its influence on perceived usefulness and perceived ease of use. Even though Trust has no significant direct impact on Intention to Use, trust in the generated output still plays an important role in determining acceptance of AI tools in the application process. The high F^2 value (0.892) for Trust and Perceived Usefulness indicates that the individual's level of trust in the generated output is a fundamental determinant of how useful these tools are being perceived. Since Perceived Usefulness has the strongest impact on Intention to Use, Trust is an important factor when evaluating the HR managers' acceptance of using AI tools in the application process. While AI-Anxiety was based on computer anxiety from Venkatesh (2000), the findings of this thesis indicate that AI-Anxiety differs from computer anxiety. Computer anxiety is an anchor for perceived ease of use. Before direct experience with the technology, the anchor determines perceptions about the ease of use of a new system (Venkatesh, 2000). Independent of having prior experience or not, AI-Anxiety is not significant in determining perceived ease of use in the sample used. According to Venkatesh (2000) Computer anxiety is largely due to the fact that beginners feel out of control during their early experiences with computers. Thus, individuals with higher levels of computer anxiety have a lower perceived ease of use than those with lower levels of computer anxiety. If individuals fear that the implementation of AI will lead to job loss, they have a decreased intention to use these tools (Liang, 2017). This aspect of AI-Anxiety was included as indicator A2 in the AITUAM. A2 was not used in the final evaluation since including it violated the internal consistency AI-Anxiety. Figure 28 in the appendix shows that A2 itself has no significant effect on Intention to Use.

Thus, for the HR managers who took part in the survey, the fear that the implementation of AI tools in the application process is not a significant determinant of the intention to use AI tools in the application process. Still, AI-Anxiety is a strong negative determinant of intention to use. The HR managers who scored higher on AI-Anxiety had a lower intention to use AI tools in the application process than the managers who scored lower on AI-Anxiety. The results of the F^2 test show that AI-Anxiety has the second-strongest effect of all the constructs used in the AITUAM on Intention to Use (0.311). These results show the importance of including AI-Anxiety in determining usage intentions for AI tools in the application process. It is important to note that this relationship is being moderated by Age. The older the HR managers are, the stronger the negative impact of AI-Anxiety on Intention to Use is. While the strength of the moderating effect of Age is weak, this is still an interesting finding.

The inclusion of the control variables Age, Gender, and Experience in the AITUAM increased the explainability of Intention to Use. Gender is a significant determinant for Intention to Use on the 5% level (0.037). The PLS-Sem results show that Gender has a negative influence on Intention to Use (-0.350). The fact that Gender is coded with 1 for male and 0 for female indicates that the female HR managers who took part in the survey have a higher Intention to AI than their male counterparts. Experience is a significant determinant of Intention to Use (0.004) as well as Ease of Use (0.006). The PLS-SEM results show that Experience influences negatively Intention to Use (-0.497) and positive Ease of Use (0.552). Experience is coded with 0 for experience and 1 for inexperience. In the sample, the inexperienced HR managers perceive AI tools in the application process as easier to use and learn than their experienced counterparts. These individuals also have a higher intention to use AI tools in the application process than their inexperienced counterparts. According to Davis & Venkatesh (2004) there are differences depending on experience, since inexperienced individuals have to make an “acceptance” decision while experienced individuals make a “sustained usage” decision. The results of the empirical evaluation show that depending on experience, differences in usage intention also exist for the HR managers who took part in the survey.

6.1: Conclusion

This Thesis aimed to determine the acceptance of HR managers for using AI tools in the application process. To be able to achieve this, an overview of the different types of technologies that are included in the umbrella term AI was given, as well as a summary of the tasks and goals during the different phases of the traditional application process. After this, different types of AI tools that are currently being used in the application process were introduced. AI tools are best suited to conduct time-consuming and repetitive tasks. They enable the company to make the application process more time-efficient, as they take over more insignificant tasks or tasks that are very time-consuming. Thus, AI tools enable the company to make the entire recruitment process more efficient and can improve corporate branding while achieving cost reduction (Aydin & Truan, 2023) (Wilke, 2022) (Verhoeven, 2020). While the implementation of AI tools in the application process has many advantages, it is crucial to recognize the disadvantages. An AI tool trained with a biased database can lead to unintended discrimination (Dastin, 2018). It is also important to recognize that potential candidates might have strong negative feelings about the use of AI tools during the application process (Rainie, 2023). As suspected of an innovative technology in its early development and implementation phase, the majority of HR managers who took part in the survey lack experience with AI tools. This suggests that the implementation of AI tools in the application process is not yet an inherent part of the application process in the DACH region.

To prevent low usage of newly implemented AI tools in the application process, the acceptance of the HR manager who uses these tools needs to be considered. To determine the acceptance of AI tools in the application process, the AITUAM has been developed. The AITUAM is based on the TAM from Davies (1989) and determines the behavioral intention to use AI tools in the application process. The AITUAM uses the variables perceived ease of use and perceived usefulness, as well as Trust and AI-Anxiety, to determine HR managers' intention to use AI tools in the application process. Three control variables (Age, Gender, and Experience) are included in the AITUAM to further increase the explainability of the model. Perceived Ease of Use, Perceived Usefulness, and AI-Anxiety are all direct significant determinants of Intention to Use. While Trust is not directly significant, it has a significant positive direct effect on Intention to Use through its significant influence on Perceived Usefulness and Perceived Ease of Use. The results of the empirical evaluation show that the most important factor that influences the intention to use AI tools in the application process is perceived usefulness. The more useful AI tools are perceived, the higher the intention to use them. Another interesting finding is that inexperienced HR managers with AI tools have a higher perceived ease of use and a lower intention to use these tools than their experienced counterparts. AI-Anxiety was included in the AITUAM to recognize the fact that negative emotions about AI in general and the use of AI tools in the application process decrease the intention to use AI tools. Ai-Anxiety was based on Venkatesh's (2000) computer anxiety. Computer anxiety is an anchor that determines the initial evaluation of an individual's perception of the ease of use of an IT application. One important contribution of this paper is that, for the HR managers who took part in the survey, AI-Anxiety is not a significant determinant of perceived Ease of Use but is a significant direct determinant of Intention to Use. The fact that AI-Anxiety has a strong negative effect on Intention to Use indicates its relevance in determining the acceptance of AI tools in the application process. The AITUAM without the inclusion of the control variables, is able to explain 57.7 % of the variance in Intention to Use, whereas with the inclusion of the control variables, it is able to explain 69% of the variance in Intention to Use. This allows us to conclude that the AITUAM is able to determine HR managers' acceptance of AI tools in the application process. The results of the empirical evaluation allow us to give the practical implication that it is rudimentary to implement AI tools in whose output the HR managers have trust. Trust in the output is the strongest determinant of perceived usefulness. Thus, an AI tool that is unable to generate trust in the quality and correctness of its output will be perceived as less useful and thus have a lower behavioral intention to use. While the scale and scope of the survey do not allow us to come to a general conclusion about AI, this still is an aspect worth recognizing when developing AI tools. Google's AI Tool "AI overview" generated untruths and errors, which undermined trust in Google's search engine. This led to a drop in the market value of the company by approximately $100 billion (Grant,2024). Another practical implication is that companies should try to reduce AI-Anxiety for their employees when planning to implement AI tools in the application process to further improve the behavioral intention to use this tool.

6.2: Limitations and further research

The empirical evaluation yielded significant results in determining variables that increase or decrease the usage intention of AI tools in the application process. Yet, it is crucial to recognize the limitations of this Master Thesis. One aspect that needs to be considered is that the survey questioned HR managers about their general opinion about AI tools in the application process. Thus, the response behavior of the subjects for their usage intention of a specific AI tool might differ. In a broader sense, the focus of this Master Thesis on the human resource field does not cover all dimensions of the TAM adoption of AI tools, but only the general acceptance of AI tools used by HR managers in the application process. Since the sample is not representative, all results gained in this Thesis only represent the sample and not the population of HR Managers in the DACH region. Despite this limitation, this Thesis makes an important contribution to determining that AI-Anxiety has a significant negative impact on behavioral intention to use. It is also important to recognize that in this Master Thesis, intention to use was the dependent variable, which is a direct determinant of actual system use and thus acceptance (Davis, 1989). As the results of the literature review about the TAM for AI show, most research on AI acceptance only determines behavioral intention to use and not actual system use. Another important limitation that has to be considered is that the AITUAM entails linear relationships. There might be non-linear relationships in the AITUAM, for trust, perceived usefulness, and perceived ease of use (Choung,2023). Further research might use a model that entails non-linear relationships for these variables or use a variable that entails these variables as an umbrella term since usefulness, ease of use, and trust in the output are all functional aspects of an AI tool. Further research should also aim at targeting specific AI tools, to allow for a more isolated insight into how the variables of the AITUAM can determine AI tool acceptance. To be able to determine AI tool acceptance, a broader time frame should be considered, ideally using a consistent sample of HR managers who have no experience in AI, who then, over time, gain experience and, after the introduction of AI tools, are surveyed on their acceptance of this tool in their day-to-day work. Thus, at least a three-step survey ranging over a longer timeframe should be used in determining the acceptance of AI tools.

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Appendix

Autor	Titel	Journal	Examined AI	Variables	Survey	Significant on Behavioral Intention	Summary of the paper
Choung (2023) 1	Trust in AI and Its Role in the Acceptance of AI Technologies	International Journal of Human–Computer Interaction	AI voice assistants	perceived ease of use, perveived usefulness,trust, attitude, intention to use	312 undergraduate students	perceived ease of use, perveived usefulness directly, trust indirectly	Choung (2023) uses an extended TAM model to determine the acceptance of AI voice assistants. They research the role of trust as a construct for the TAM and examine the relationship between Trust on the determinants of acceptance of AI technologies. Choung (2023) argues that since trust is required to build mutuality and interdependences between parties, and that trust has been examined as a key factor in the acceptance of emerging technologies (K.Wu et al. 2011), it is a relevant determinant for AI acceptance. the Authors offer a twofold conceptualization of trust, first the trust that is given to AI because of its human-like aspects, the human-like trust in AI, and second the trust in the functionality of AI, which refers to its ability, reliability, and safety, the functionality trust in AI. Choung determined the acceptance of AI voice assistant usage, which is influenced by perceived ease of use, trust, perceived usefulness, and attitude. An online survey targeting undergraduate students was conducted and overall 312 responses were considered in the empirical evaluation. The results suggest that perceived ease of use and perceived usefulness significantly affect attitude and intention to use AI voice assistants. They find that trust directly influences perceived usefulness and attitude and that trust is influenced by perceived ease of use. Trust does not directly affect intention to use but has an indirect effect on intention to use through its influence on perceived usefulness and attitude.
Choung (2023) 2	Trust in AI and Its Role in the Acceptance of AI Technologies	International Journal of Human–Computer Interaction	AI voice assistants	perceived ease of use, perveived usefulness,human-like trust, functionality trust, attitude, intention to use	survey using a representative panel with 640 responses	perceived ease of use, human-like trust, functionality trust, perceived usefulness, and attitude.	The authors used the perceived ease of use, perceived usefulness, attitude as well as trust to determine the intention to use AI smart technologies. The items to measure trust differed from the first study and were divided into human-like trust in AI and functionality trust in AI. The authors then used two path models to examine human-like trust and functionality trust in AI. The results indicate that perceived ease of use significantly influences perceived usefulness, both types of trust, attitude, and usage intention. Perceived usefulness significantly influenced attitude and usage intention. Human-like Trust and functionality trust in AI had significant indirect effects on the intention to use AI smart technologies trough the influence on perceived usefulness and attitude. Their results further showed no clear difference between human-like trust in AI and functionality trust in AI.
Seo & Lee (2021)	The emergence of service robots at restaurants: Integrating trust, perceived risk, and satisfaction	Sustainability (Switzerland)	Service Robots	perceived usefulness, perceived ease of use , trust, perceived risk, satisfaction, behavioral intention, revisit intention	scenario-based online survey with 338 respondents	perceived usefulness directly, ease of use and trust indirectly	Seo (2021) uses an extended TAM model to determine the acceptance of service robots in a restaurant setting. Besides the original TAM constructs, perceived usefulness, perceived ease of use, and behavioral intention the authors integrated trust, perceived risk, satisfaction and revisit intention into the model. They performed a scenario-based online survey and had 338 respondents. Their results show that perceived usefulness had a significant effect on behavioral intention, while perceived ease of use had no significant effect on behavioral intention. Perceived ease of use had a direct impact on perceived usefulness, thus EoU indirectly affects behavioral intention. Trust had a significant positive influence on the Tam variables PU and EoU towards a service robot as well it positively influenced satisfaction and revisit intention while also decreasing perceived risk. From all the variables used to extend the TAM, trust had the strongest impact on PU followed by its impact on EoU. According to the authors, the result of their study confirms trust as a crucial predecessor variable of the TAM.

Figure 12 Papers used in the Literature review (1/5).

Autor	Titel	Journal	Examined AI	Variables	Survey	Significant on Behavioral Intention	Summary of the paper
Sandra et al. (2021)	Exploring acceptance of artificial intelligence amongst healthcare personnel: a case in a private medical centre	International Journal of Advanced Engineering and Managagement	AI in healthcare	perceived ease of use, perceived usefulness, subjective norm, attitude and intention to use AI.	96 individuals working as hospital personell	attitude directly ; usefulness and subjective norm indirectly	Sandra et al. (2021) study the acceptance of AI among health care professionals. This study examines the effect of perceived ease of use, perceived usefulness, subjective norm, and attitude on the intention to use AI. The empirical evaluation was conducted using 96 answers to a questionnaire given to hospital personnel. The results show that ease of use is not significant on attitude, usefulness is significant on attitude, and subjective norm is significant on attitude. Through attitude, ease of use is not significant on intention to use, usefulness is significant on intention of use through attitude, and subjective norm is significant on intention to use through attitude.
Liu (2021)	The roles of trust, personalization, loss of privacy, and anthropomorphism in public acceptance of smart healthcare services	Computers in Human Behavior	smart healthcare services	perceived usefulness, perceived ease of use, trust, personalization, loss of privacy, anthropomorphism, gender, age on usage experience and intention to use	769 survey samples	perceived usefulness, trust and personalization directly;	The authors conducted a PLS-SEM to determine their structural model. According to the authors, the results of their study provided strong support for the validity of their acceptance model, as it explained 66.4% of the variance in behavioral intention. Their results show that perceived usefulness, trust, and personalization influence behavior intention directly, while perceived ease of use has no significant direct effect on behavioral intention. Trust mediated the effects of perceived usefulness, perceived ease of use, personalization, loss of privacy, and anthropomorphism on acceptance behavior. They found that perceived usefulness and perceived ease of use are fundamental determinants of trust in smart healthcare services. The result of their multi-group analyses found that gender, age, and usage experience were moderator variables. Gender has a positive moderating effect on the relationship between trust and intention to use, the path coefficient was significantly larger for females than for men. Gender also moderated the relationship between perceived ease of use and perceived usefulness and was stronger for males than for females. Perceived ease of use was a significant determinant of trust for females but not for males. Age moderated the relationship between anthropomorphism and trust, there were significant differences between younger and middle-aged adults. Usage experience moderated the effect of perceived usefulness and trust. Only for the inexperienced group, perceived usefulness was a significant predictor of Trust, while for experienced users perceived ease of use was a significant predictor of trust. Overall, no significant group differences were found.
Chatterjee (2021)	Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model	Technological Forecasting and Social Change	AI adoption in manufacturing and production firms	perceived usefulness , perceived ease of use,organizational culture, organizational support, participation of the company,intention to adopt	391 responses of Top- and middle-level IT professionals	perceived usefulness, ease of use directly	Chatterjee (2021) determined AI adoption in manufacturing and production firms in India by using a TAM-TOE Model. This Model included the TAM Variables' Perceived Usefulness and Perceived ease of Use as direct determinants in determining the Intention to Adopt. They validated a quantitative study by conducting surveys with 391 responses from Top- and middle-level professionals of IT and other companies where AI is contemplated to be adopted or is being adopted. They used a partial least square (PLS) based structural equation modeling (SEM) to analyze the data and found that the determinants of the TAM Perceived Usefulness and Perceived ease of Use are statistically significant at least at the 5% level in predicting Intention to adopt and that perceived ease of use statistically significant impacts perceived usefulness. It's important to consider that in India the adoption of AI in organizations is in its preliminary stage and the responses have been gathered from nonadopters, as well as that an integrated model has been researched. Yet these findings show that the determinants of the TAM are significant variables in determining behavioral intention for AI adoption in manufacturing and production firms.

Figure 13 Papers used in the Literature review (2/5).

Autor	Titel	Journal	Examined AI	Variables	Survey	Significant on Behavioral Intention	Summary of the paper
Alhashmi (2019)	Critical success factors for implementing artificial intelligence (AI) projects in Dubai Government United Arab Emirates (UAE) health sector: applying the extended technology acceptance model (TAM).	International conference on advanced intelligent systems and informatics.	AI in the health sector	Perceived Ease of Use, Perceived Usefulness, Attitude towards use and Behavioral intention to use	53 employees working in the health and IT sector	perceived usefulness, ease of use, attitude	The authors use an extended model of the TAM using the factors perceived ease of use, perceived usefulness, and attitude towards use in determining behavioral intention to Use. The data was collected through surveys from employees working in the health and IT sector in the United Arabic Emirates with a total of 53 participants. The authors found that perceived usefulness and Perceived Ease of Use are significant on attitude towards use as well as behavioral intention to use which is a direct determinant of Actual System Use. The Author also found that Perceived Ease of Use significantly influences Perceived Usefulness. The results show that the TAM can determine actual system use for employees in the health and IT sector for implementing Artificial Intelligence.
Alshurideh (2021)	Factors affecting the use of smart mobile examination platforms by universities' postgraduate students during the COVID-19 pandemic: An empirical study	Informatics	smart mobile examination platforms	perceived ease of use, percevied usefulness, content quality, service quality, information quality, and system quality , intention to use	566 students	perceive ease of use, perceive usefulness	The Authors use an extended version of the Technology Acceptance Model to determine the intention to use smart mobile examination platforms for students in the United Arabic Emirates. They included content quality, service quality, information quality, and system quality as determinants of the TAM Variables. They used a self-survey method to obtain the data. In total 566 students participated in the survey. Their results show that Perceived Ease of Use significantly influences Perceived Usefulness and Intention to Use Smart Mobile Exam Platforms and that Perceived Usefulness significantly influences Intention to Use Smart Mobile Exam Platforms.
Na et al. (2022)	Acceptance model of artificial intelligence (AI)-based technologies in construction firms: Applying the Technology Acceptance Model (TAM) in combination with the Technology–Organisation–Environment (TOE) framework	Buildings	AI in construction	perceived usefulness, perceived ease of use, attitude, intention to use, organizational culture, organizational support, participation of the company	241 construction company workers	perceived ease of use, perceived usefulness	The authors explore influencing factors on intentions to use and acceptance of AI-based technology in construction companies. They use an expanded technology acceptance model by combining the TAM with the technology-organization-environment (TOE) framework. The results show that the organizational factors of culture, support, and participation of the company as a whole are important factors for AI-based technology implementation. They conducted a survey on construction company workers and used 241 samples for the empirical evaluation. Their results show that end-users' perceived usefulness had a positive influence on the perceived ease of use and the attitude toward AI. Perceived usefulness had the most important influence on acceptance. Both variables perceived ease of use as well as perceived usefulness had a positive impact on usage intention for AI-based technologies in construction firms.

Figure 14 Papers used in the Literature review (3/5).

Singh (2020)	Technology Acceptance Model to Assess Employee's Perception and Intention of Integration of Artificial Intelligence and Human Resource Management in IT Industry.	Technology	AI for Human Resource Management in the IT Industry	perceived ease of use, perceived innovativeness, employee perception and employees adoption intentions	115 HR officials	perceived innovativeness and employee perception directly, perceived ease of use indirectly	Singh (2020) examines the willingness of employees to adopt AI-enabled technologies for HR managers in the IT sector in India. They use a new model designed after the technology acceptance model by using perceived ease of use, perceived innovativeness, and employee perception in determining employee adoption intentions. They surveyed 115 HR officials who participated in the survey. Their results show that while perceived ease of use is not statistically significant in determining employee adoption intention, perceived ease of use does positively influence employee perception which directly influences employee intention to adopt AI. Thus, ease of use has an indirect impact on adoption intention. They also found that perceived innovativeness positively affects the intention to adopt. Another interesting finding is that when a company has more innovative employees, the AI adoption ratio will increase and an increasing application of AI improves HR activity performance.
Kim (2020)	My teacher is a machine: understanding students' perceptions of AI teaching assistants in online education	Int. J. Human-Comp. Inter.	AI teaching assistants in online education	perceived usefulness, attitude towards AI, attitude towards new technologies, perceived ease of communication and intention to adopt	312 students	perceived usefulness, ease of communication	Kim 2020 investigates student perception of AI teaching assistants in higher education. The authors used an extended TAM to determine the adoption of AI teaching assistant-based education. Besides the traditional TAM determinants Perceived Usefulness Intention to adopt, the authors include attitude towards AI, attitude towards new technologies as well as perceived ease of communication with an AI teaching assistant. Perceived ease of communication was determined using the items from perceived ease of use from Davis (1989). They used an online survey and the final sample consisted of 312 participants. The results show that perceived usefulness and perceived ease of communication positively influence attitudes towards using an AI teaching assistant, which leads to a stronger intention to adopt. Perceived usefulness and ease of communication directly predict the intention to adopt AI teaching assistants
Damerji (2021)	Mediating effect of use perceptions on technology readiness and adoption of artificial intelligence in accounting	Acc. Educ.	AI in accounting	perceived ease of use, perceive usefulness, technological readiness, decision to adopt, technology acceptance	101 accounting students	perceived usefulness, perceived ease of use	Damerji (2021) uses the TAM to determine the decision to adopt AI in accounting by examining perceived ease of use, perceived usefulness as well and technological readiness to determine the decision to adopt AI. The purpose of the study was to examine whether perceived usefulness and perceived ease of use mediate the relationship between technology readiness and technology adoption of AI by accounting students. The survey was conducted in two universities by a questionnaire, and 101 responses were used in the empirical evaluation. The results show that perceived usefulness and perceived ease of use statistically significantly predict technology acceptance when controlling for technological readiness. Further results are that Pu and PeoU have a mediating effect on the relationship technological readiness has with the technology adoption of AI. By applying the extended model, the researcher including perceived usefulness and perceived ease of use as well as technological readiness combined explained around 32% of the total variance of technology adoption of AI by accounting students (R^2 =31.92%). These results suggest that other factors help determine AI acceptance, the TAM variables PU and PEOU increase the decision adoption of AI technology by accounting students.
Vărzaru (2022)	Assessing artificial intelligence technology acceptance in managerial accounting.	Electronics	AI in managerial accounting	perceived usefulness, perceived ease of use, behavioral intention, user satisfaction, actual use	396 specialists in managerial accounting	perceived ease of use, perceived usefulness	Vărzaru (2022) researches the acceptance of AI technology among accountants in Romanian organizations. They used the TAM variable's perceived usefulness, and perceived ease of use to determine behavioral intention which then was used together with user satisfaction in determining the actual use of the AI. The author conducted a survey based on a questionnaire. For the final empirical evaluation, the answers of 396 specialists in managerial accounting from Romanian organizations were used. The results show that perceived ease of use and perceived usefulness significantly influence behavioral intention. User satisfaction influenced behavioral intentions and positively influenced the actual use of AI in managerial accounting. The results also show that behavioral intention significantly positively influences the actual use of AI technology.

Figure 15 Papers used in the Literature review (4/5).

Autor	Titel	Journal	Examined AI	Variables	Survey	Significant on Behavioral Intention	Summary of the paper
Hmoud (2020)	Artificial intelligence in human resources information systems: Investigating its trust and adoption determinants	International Journal of Engineering and Management Sciences	AI based information system in human resource management	facilitating conditions, technological readiness, performance expectancy , trust, behavioral intention	185 HR managers	trust, performance expectancy (synonim for perceived usefulness)	The authors determine the acceptance for AI based information system in human resource management. and use an extended version of the TAM to determine behavioral intention. They use facilitating conditions, technological readiness, performance expectancy and Trust as direct determinants of behavioral intention. According to the authors, performance expectancy is considered a synonym of perceived usefulness from the original TAM. They also determine if age and experience have a moderating effect on the relationship between trust and behavioral intention as well as performance expectancy on behavioral intention. They conducted an online survey and used the answers of 185 HR managers for their empirical evaluation. They conducted a PLS-SEM to evaluate their path model. Their results show that trust and performance expectancy have a significant positive influence on HR-professionals behavioral intention to use AI based information systems, as well as that age and experience do not have a moderating effect on the relation ship between trust and behavioral intention nor on performance expectancy and behavioral intention.
Sage (2022)	A multi-industry analysis of the future use of AI chatbots	Human Behavior and Emerging Technologies	AI chatbots in mental health care, online shopping and online banking.	used perceived usefulness, perceived ease of use, privacy concerns, trust, pre-exisiting knowledge, age, gender, behavioral intention	360 participants from an university population	perceived usefulness,trust for metal health care and online banking; pre-exisiting knowledge, perceived usefulness, privacy concerns and trust for online shopping	This study determines the behavioral intention to use AI chatbots for mental health care, online shopping, and online banking. They used perceived usefulness, perceived ease of use, privacy concerns, trust, pre-existing knowledge, age, and gender as direct determinants of behavioral intention. For their empirical evaluation, they used the results of an online survey which included 360 participants, who belong to the university population of the Queensland University of Technology. Their results for the mental health care industry show that perceived usefulness and trust are significant predictors for behavioral intention to use AI chatbots while the other determinants were insignificant. The adjusted R^2 for the mental health care industry was 0.697. For the online shopping industry, pre-existing knowledge, perceived usefulness, privacy concerns, and trust are significant determinants for behavioral intention to use. The model's adjusted R^2 was 0.774 for the online shopping industry. For the online banking industry, perceived usefulness and trust were significant determinants of behavioral intention, the adjusted R^2 was 0.751. Thus, the results show that an identical model allows to explain the variance in behavioral intention depending on the industry the AI chatbot is used, as well as that depending on the industry different determinants are significant.
Wang (2023)	An empirical evaluation of technology acceptance model for Artificial Intelligence in E-commerce	Heliyon	AI technology in E-commerce	perceived usefulness, perceived ease of use, attitude, trust, subjective norm, behavioral intention, actual use	220 purchasers of E-commerce	Perceived usefulness	This study determines technology acceptance for AI technology in E-commerce. They use an extended TAM using the constructs of perceived usefulness, perceived ease of use, attitude, trust, and subjective norm as well as behavioral intention to determine the actual use of AI technology in E-commerce. In the structural model, actual use is determined by behavioral intention which is determined by attitude and perceived usefulness. Attitude is determined by perceived usefulness and perceived ease of use. Perceived ease of use is determined by trust and subjective norms. Perceived usefulness is determined by perceived ease of use, trust, and subjective norm. They surveyed 220 participants who purchased E-commerce. Their results show that behavioral intention is significant in determining active use. Perceived usefulness is significant in behavioral intention. Perceived ease of use is significant on perceived usefulness, and trust is significant on perceived ease of use but not on perceived usefulness. The results for R^2 show that the model allows to explain 42.9 % of the variance in behavioral intention and 39.4 % of active use.

Figure 16 Papers used in the Literature review (5/5).

Survey Questions:

Table 4 the questionnaire for the experienced group.

Questions for the experienced group	
A1	Ich weiß nicht, warum, aber KI macht mir Angst.
A2	Ich befürchte, dass durch den Einsatz von KI-Tools, die im Bewerbungsprozess verwendet werden, Arbeitsplätze gefährden werden könnten.
A3	Ich habe Angst vor möglichen Problemen, die mit KI-Tools, die im Bewerbungsprozess verwendet werden, verbunden seien könnten.
A4	Ich habe das Bedenken, dass KI-Tools, die im Bewerbungsprozess verwendet werden, falsch funktionieren könnten.
A5	Ich habe Angst, dass mich das Erlernen der Nutzung von KI im Bewerbungsprozess überfordern könnte.
T1	Ich vertraue darauf, dass die KI-Tools, die ich im Bewerbungsprozess verwende, mir hilfreich sind.
T2	Ich vertraue darauf, dass die KI-Tools, die ich im Bewerbungsprozess verwende, mir zuverlässige Ergebnisse liefern.
T3	Ich habe Vertrauen darin, dass die KI-Tools, die ich im Bewerbungsprozess verwende, mir richtige Ergebnisse liefern.
T4	Ich vertraue darauf, dass die Entscheidung der KI-Tools, die ich im Bewerbungsprozess verwende, richtig ist.
T5	Ich vertraue darauf, dass das KI-Tool, welches ich im Bewerbungsprozess verwende, mir qualitativ hochwertige Ergebnisse für die gegebene Aufgabe liefert.
EoU1	Mir viel es leicht, die Anwendung von KI-Tools, die ich im Bewerbungsprozess verwende, zu erlernen.
EoU2	Mir fällt es leicht, KI-Tools, die ich im Bewerbungsprozess verwende, zu bedienen.
EoU3	Es fällt mir leicht, KI-Tools, die ich im Bewerbungsprozess verwende, dazu zu bringen, mir das bestmögliche Ergebnis zu liefern.
EoU4	Mir ist es leichtgefallen, geschickt im Umgang mit den KI-Tools zu werden, die ich im Bewerbungsprozess verwende.
PU1	Aufgrund der Implementierung von KI-Tools im Bewerbungsprozess kann ich schneller alle notwendigen Schritte, die ich für die Bearbeitung einer Bewerbung benötige, durchführen.
PU2	Die Implementierung von KI-Tools im Bewerbungsprozess ermöglichte es mir, mich auf die wichtigeren Aufgabenfelder innerhalb des Bewerbungsprozesses zu konzentrieren.
PU3	Der Einsatz von KI-Tools im Bewerbungsprozess macht meine Arbeit in der Bearbeitung von Bewerbungen leichter.
IoU1	Ich verwende gerne KI-Tools im Bewerbungsprozess, wenn die KI-Tools mir bei der Ausübung meiner Arbeit helfen.
IoU2	Ich möchte KI-Tools im Bewerbungsprozess in Zukunft weiterhin nutzen.
IoU3	Ich möchte weiterhin mein Wissen im Umgang mit KI-Tools vertiefen, um diese bestmöglich einzusetzen

Table 5 the questionnaire for the inexperienced group

Questions for the inexperienced group	
A1	Ich weiß nicht, warum, aber KI macht mir Angst.
A2	Ich befürchte, dass durch den Einsatz von KI-Tools, die im Bewerbungsprozess verwendet werden, Arbeitsplätze gefährden werden könnten.
A3	Ich habe Angst vor möglichen Problemen, die mit KI-Tools, die im Bewerbungsprozess verwendet werden, verbunden seien könnten.
A4	Ich habe das Bedenken, dass KI-Tools, die im Bewerbungsprozess verwendet werden, falsch funktionieren könnten.
A5	Ich habe Angst, dass mich das Erlernen der Nutzung von KI im Bewerbungsprozess überfordern könnte.
T1	Ich vertraue darauf, dass KI-Tools, die im Bewerbungsprozess verwendet werden, mir hilfreich seien werden.
T2	Ich vertraue darauf, dass KI-Tools, die im Bewerbungsprozess verwendet werden, mir zuverlässige Ergebnisse liefern werden.
T3	Ich habe Vertrauen darin, dass KI-Tools, die im Bewerbungsprozess verwendet werden, mir richtige Ergebnisse liefern werden.
T4	Ich vertraue darauf, dass die Entscheidung der KI-Tools, die im Bewerbungsprozess verwendet werden, richtig seien werden
T5	Ich vertraue darauf, dass die KI-Tools, die im Bewerbungsprozess verwendet werden qualitativ hochwertige Ergebnisse für die gegebene Aufgabe liefern werden.
EoU1	Ich denke, es würde mir leicht fallen, die Anwendung von KI-Tools, die im Bewerbungsprozess verwendet werden, zu erlernen.
EoU2	Ich denke, mir würde es leicht fallen, KI-Tools, die im Bewerbungsprozess verwendet werden, zu bedienen.
EoU3	Ich denke, es würde mir leicht fallen, ein KI-Tool, welches im Bewerbungsprozess verwendet wird, dazu zu bringen, mir das bestmögliche Ergebnis zu liefern.
EoU4	Ich denke, es würde mir leicht fallen geschickt im Umgang mit KI-Tools zu werden, die im Bewerbungsprozess verwendet werden.
PU1	Ich denke, dass die Implementierung von KI-Tools im Bewerbungsprozess mich schneller alle notwendigen Schritte, die ich für die Bearbeitung von Bewerbungen benötige, durchführen lassen würde.
PU2	Ich denke, dass die Implementierung von KI-Tools im Bewerbungsprozess es mir ermöglichen würde, mich auf die wichtigeren Aufgabenfelder innerhalb des Bewerbungsprozesses zu konzentrieren.
PU3	Ich denke, dass die Implementierung von KI-Tools im Bewerbungsprozess meine Arbeit in der Bearbeitung von Bewerbungen leichter machen würde.
IoU1	Ich denke, dass ich KI-Tools im Bewerbungsprozess gerne verwenden werde, wenn die KI-Tools mir bei der Ausübung meiner Arbeit helfen.
IoU2	Ich möchte KI-Tools im Bewerbungsprozess in Zukunft nutzen.
IoU3	Ich möchte erlernen KI-Tools im Bewerbungsprozess so zu nutzen, dass ich diese bestmöglich einsetzen kann.

The empirical evaluation of the control variables:

In this part of the appendix, the effects the control variables have on the variables and the relationships in the AITUAM are being statistically tested.

The conceptual model:

The hypothesized model without the inclusion of the control variables explains 57.7% of the variance in Intention to Use.

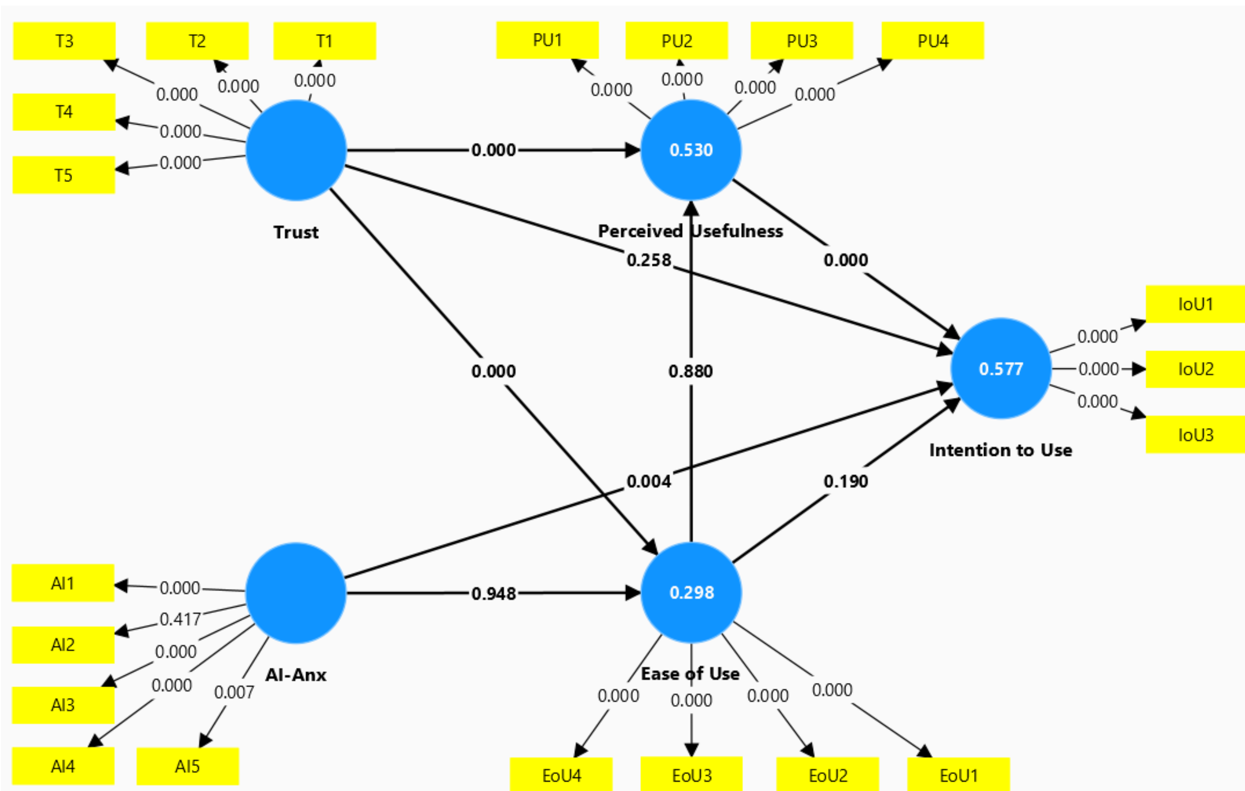

Figure 17 the conceptual model based on the Hypothesis.

Control Variable Experience:

Figure 18 tests the significance Experience has on the AITUAM variables.

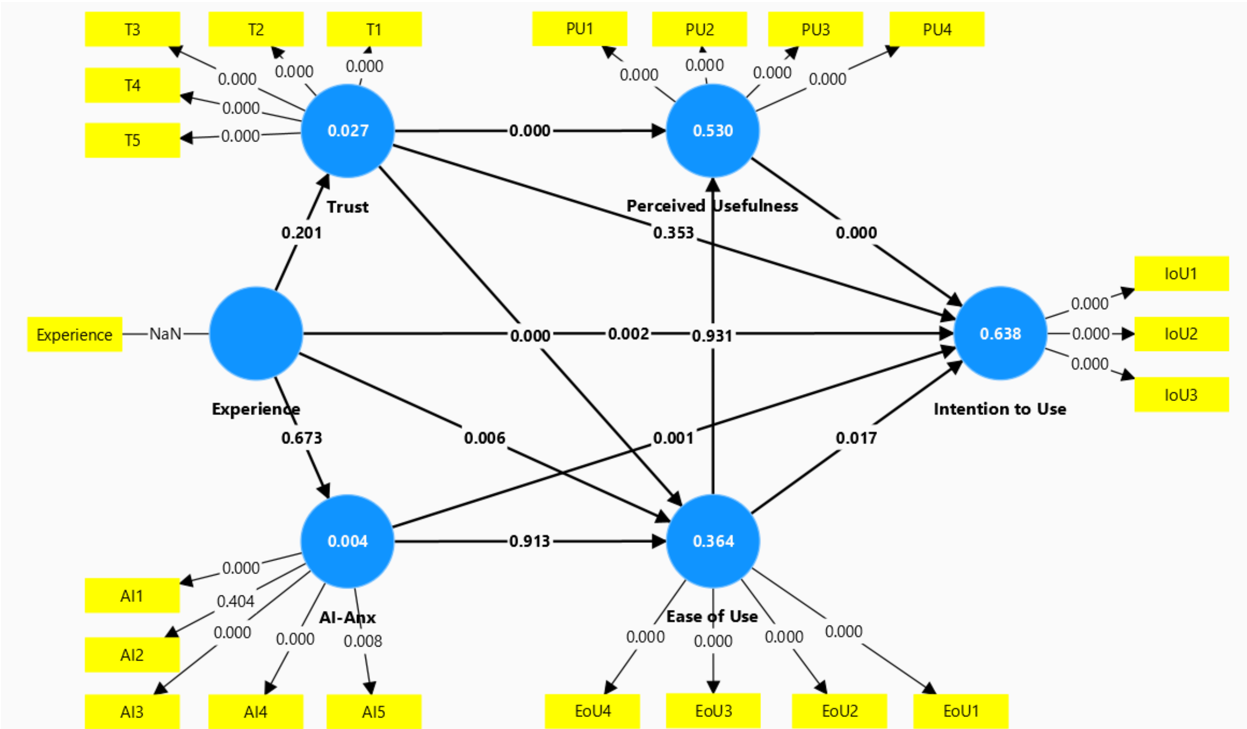

Figure 18 testing the direct effect Experience has on the TAM variables.

Experience has a significant direct effect on Ease of Use (0.006) as well as Intention to Use (0.002). The results of the path coefficient can be found in Table 6

Table 6 the path coefficients for Experience as a Moderator.

Path	Original Sample	Sample Mean	STDEV	T statistics	P values
Exp -> AI-Anx	-0.133	-0.140	0.315	0.422	0.673
Exp -> EoU	0.549	0.540	0.201	2.726	0.006
Exp -> IoU	-0.552	-0.539	0.181	3.051	0.002
Exp -> Trust	0.334	0.331	0.261	1.280	0.201

The moderating effect of Experience on the construct relationships in the AITUAM:

Figure 19 tests the moderating effect of Experience

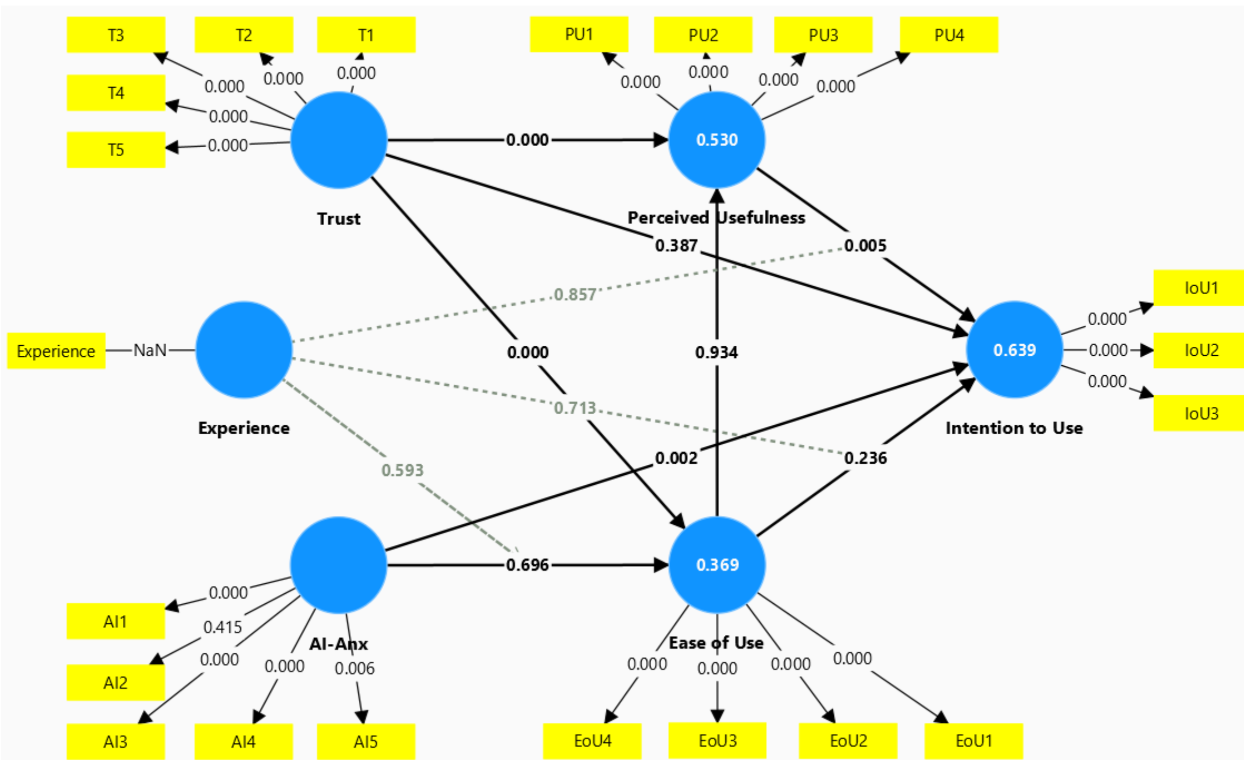

Figure 19 testing the moderating effect of Experience.

The significance of the moderating effect can be found in Table 7. Experience does not moderate any of the relationships at the 10 % significance level.

Experience has no significant moderating effect on any of the construct's relationships in the AITUAM. The results for the path coefficients of Experience as a moderator can be found in Table 7.

Table 7 the results for the moderating effect of Age.

Total effects	Original Sample	Sample Mean	STDEV	T statistics	P values
Exp*Ease of Use -> IoU	0.082	0.101	0.224	0.365	0.715
Exp*PU -> IoU	-0.038	-0.066	0.229	0.166	0.868
Exp*AI-Anx -> EoU	0.137	0.128	0.256	0.535	0.593

Control Variable Gender:

Figure 20 tests if Gender is significant on the TAM variables.

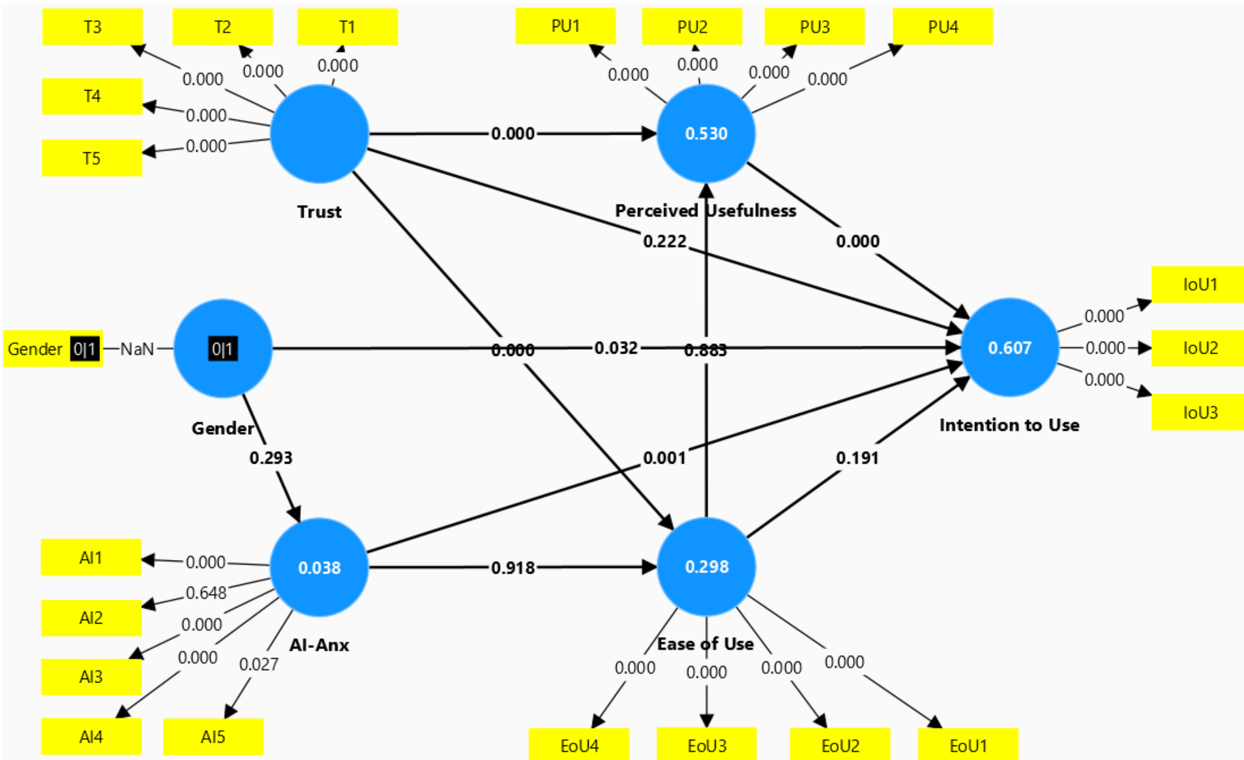

Figure 20 Testing the direct effect Gender has on the TAM variables.

The results show that Gender is statistically significant on Intention to Use (0.032). Thus, Gender is included in the AITUAM as a direct determinant of Intention of Use. This allows to determine the control variable exhibits on Intention of Use.

Table 8 the path coefficients for Gender as a Moderator.

Path	Original Sample	Sample Mean	STDEV	T statistics	P values
Gender-> AI-Anx	-0.400	-0.363	0.380	1.052	0.293
Gender -> IoU	-0.358	-0.365	0.167	2.140	0.032

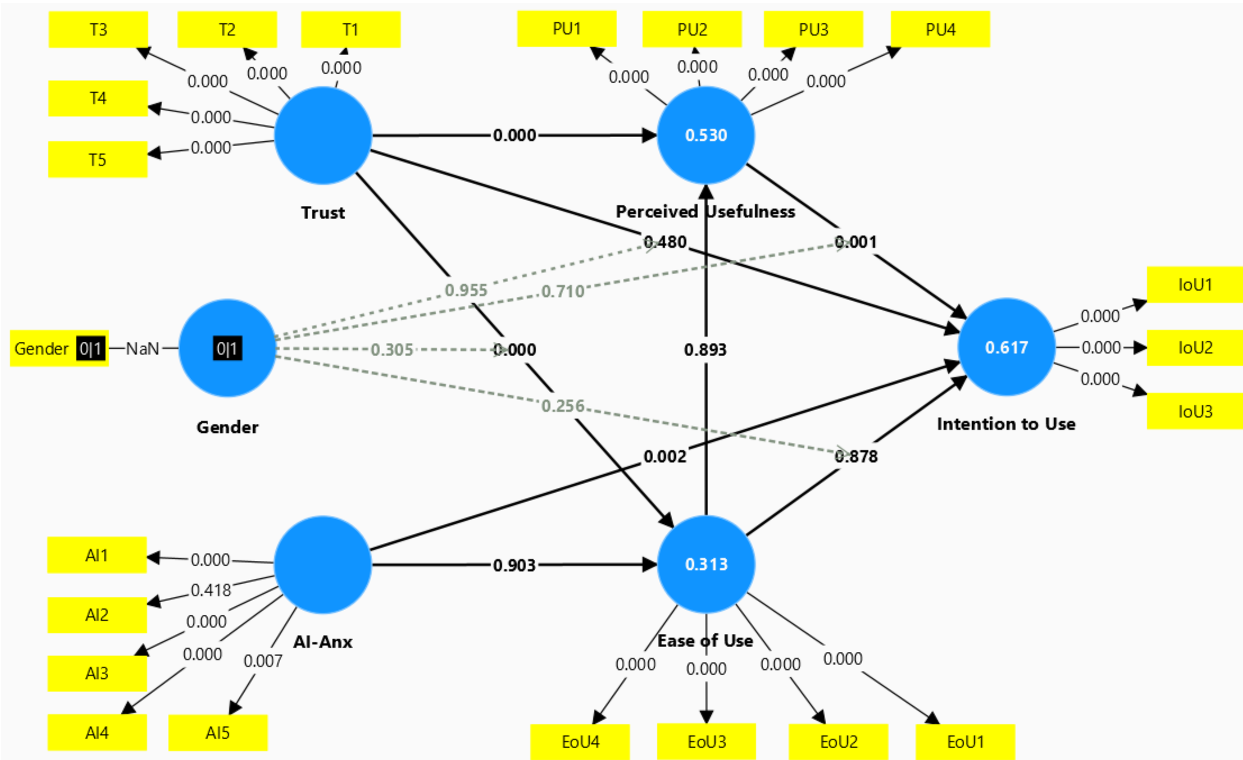

Figure 21 testing the moderating effect of Gender.

Figure 21 shows the results of testing the moderating effect of Gender by conducting a bootstrapping method with 10.000 bootstrapping subsamples.

Gender has no significant moderating effect on the 10% level on any of the construct's relationships in the AITUAM. The results for the path coefficients of Gender as a moderator can be found in Table 9.

Table 9 the path coefficients for Gender as a Moderator.

Path	Original Sample	Sample Mean	STDEV	T statistics	P values
Gender*PU -> IoU	-0.116	-0.132	0.312	0.372	0.710
Gender*Ease of Use -> IoU	0.283	0.272	0.249	1.137	0.256
Gender*Trust-> EoU	0.237	0.199	0.231	1.026	0.305
Gender*Trust -> IoU	-0.021	0.000	0.360	0.057	0.955

Control Variable Age:

Figure 22 tests if Age is significant on the TAM variables.

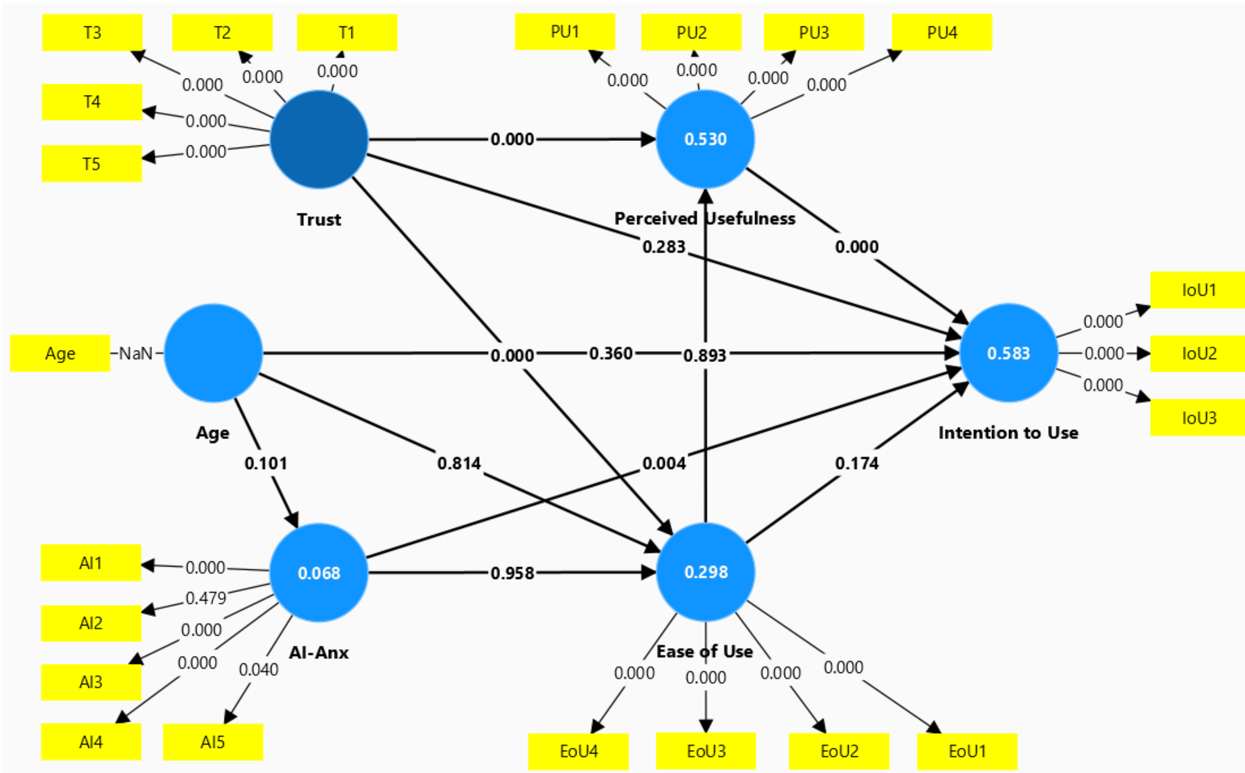

Figure 22 testing the direct effects of Age on the TAM variables.

The results of the bootstrapping method using 10.000 bootstrapping subsamples shows, that Age has no significant direct effect on the constructs in the AITUAM. The path coefficients of Age can be found in Table 10.

Table 10 the results for the moderating effect of Age.

Path	Original Sample	Sample Mean	STDEV	T statistics	P values
Age -> AI-Anx	-0.261	-0.257	0.159	1.639	0.101
Age -> EoU	0.030	0.037	0.128	0.236	0.814
Age -> IoU	-0.085	-0.091	0.093	0.916	0.360

Figure X tests the moderating effect of Age:

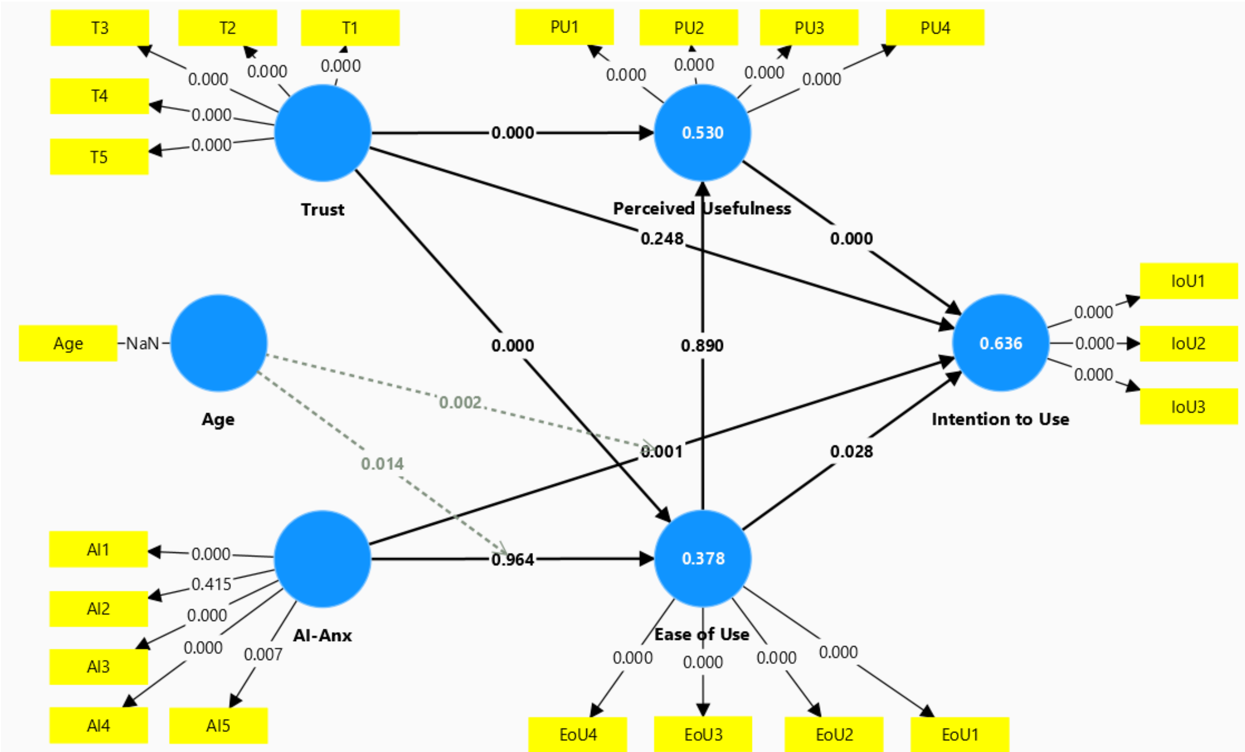

Figure 23 the results for the moderating effect of Age.

Age has a significant moderating effect on the relationship between AI-Anxiety and Ease of Use (0.002) on the 1% level and a not significant moderating effect on the relationship between AI-Anxiety and Intention to Use (0.014). Since the relationship between AI-Anxiety and Ease of Use is not significant, the moderator effect of Age is not considered in the final model. Thus, the final model which is used to evaluate the acceptance of AI tools in the application process. Includes Age as a moderator on the relationship AI-Anxiety and Intention to Use.

Table 11 the results the moderating effect of Age.

Path	Original Sample	Sample Mean	STDEV	T statistics	P values
Age*AI-Anx -> EoU	-0.270	-0.236	0.110	2.455	0.014
Age*AI-Anx -> IoU	0.237	0.210	0.077	3.072	0.002

The AITUAM without Age as a Moderator:

Following the recommendations by Becker (2023), a base model without Age as a moderator was used to assess the significance of the direct effects. The structural model determines Intention to Use depending on Ease of Use, Perceived Usefulness, Trust, AI-Anxiety, Experience, and Gender. The Model consists of three independent variables: Experience, Anxiety, and Trust as well as three dependent variables: Ease of Use, Perceived Usefulness, and Intention to Use. The results of the SEM-PLS analysis are presented in Figure 24.

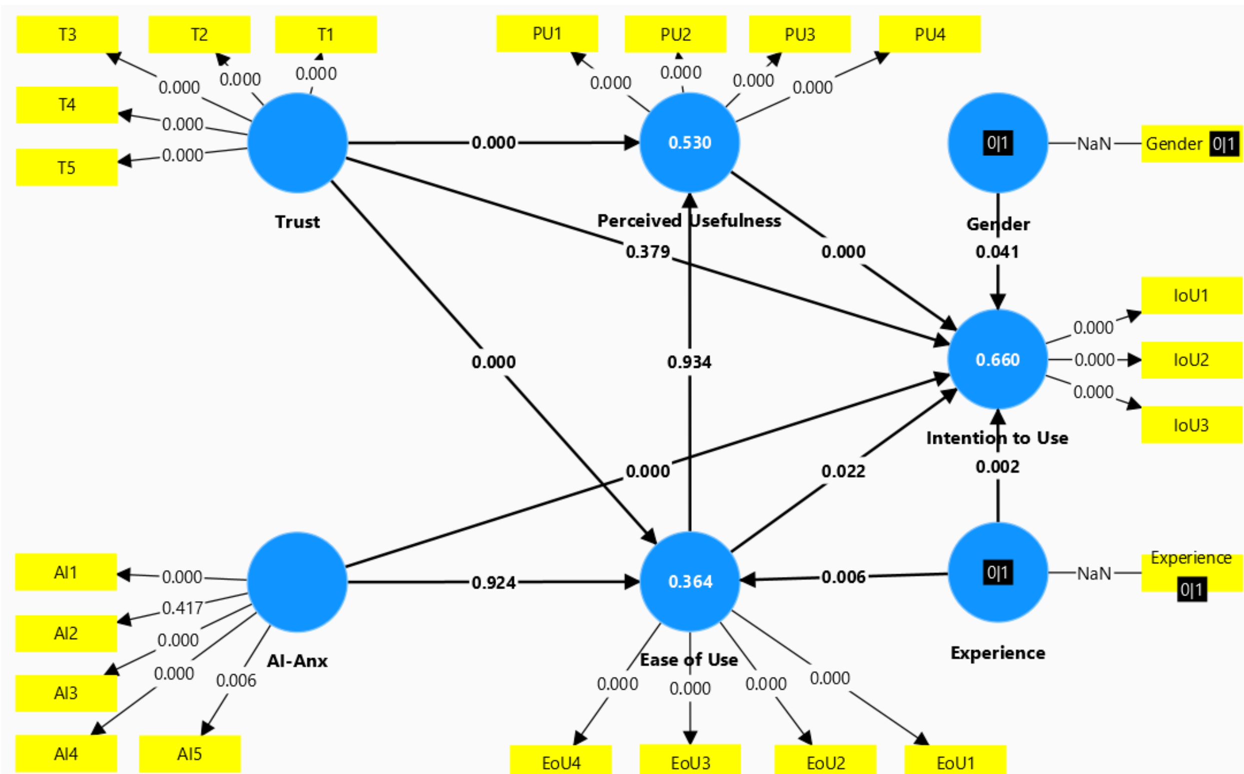

Figure 24 the results of the PLS-SEM analysis.

To determine if the measurement theory used is acceptable, indicator reliability, internal consistency reliability and convergent validity were assessed. Figure 24 and Table 12 indicate key issues regarding the internal consistency, reliability, and indicator loadings for the constructs AI-Anxiety and Ease of Use.

Table 12 shows the results for the construct reliability and validity testing for the ground model in Figure 24.

Table 12 results for the construct reliability and validity testing.

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE
AI-Anxiety	0.620	0.697	0.750	0.407
Ease of Use	0.774	0.853	0.842	0.576
Intention to Use	0.842	0.876	0.905	0.762
Perceived Usefulness	0.873	0.874	0.913	0.724
Trust	0.921	0.927	0.941	0.761

For AI-Anxiety, AVE is below 0.5 (0.408) and Cronbach´s alpha is below 0.7 (0.620), and therefore below the recommended thresholds (Sarstedt et al. 2021) (Ramayah et al. 2016) (Hair 2019). The indicator loading for AI2 (0.216) is lower than 0.4 and should be removed according to Hair (2019). After removing AI 2 from the model indicator loadings for AI5 (0.491) and AI1 (0.669) are still below the recommended threshold of 0.7, and Cronbach´s alpha is below 0.7. Thus, AI5 is being removed from the model. Table 13 shows that after removing the indicators AI 2 and AI 5 internal reliability is given for AI-Anxiety. Deleting these indicators pushed all key figures above the recommended threshold, thus there is no need to delete AI1 from the model, since indicators with loadings below 0.7 should only be removed if deleting this indicator leads to an increase in composite reliability above the suggested threshold value (Hair 2019). The indicator AI2 represents the survey question, "I am afraid that the implementation of AI tools in the application process leads to job loss". The indicator AI5 represents the survey question, "I am afraid that learning to use AI tools in the application process will be overwhelming for me.". Deleting these indicators reduces the scope the construct AI-Anxiety is able to explain. AI2 was included as an extension since the higher levels of fear that AI is replacing existing jobs negatively influence AI acceptance VU (2021). AI5 intended to measure the fear of being unable to learn how to use AI tools in the application process. AI-Anxiety as a construct affects the general level of fear of AI (A1), the fear that using AI tools in the application process creates possible problems (A3) and the fear that AI tools in the application process can malfunction (A4).

For Ease of Use, the indicator loadings for EoU1(0.607) and EoU2(0.679) are below 0.7. Table 12 shows that for Ease of Use, the key figures are all above the recommended threshold. Therefore, there is no need to exclude the indicators EoU1 and EoU2. The examination of variance inflation factor (VIF) scores, which can be found in Table 16 in the appendix, reveals high values for the indicator T3 (5.034), surpassing the threshold of 5 recommended by Ringel et al. (2015). Consequently, indicator T3 is removed from the model to prevent multicollinearity issues.

The adjustments made to solve the internal reliability issues aim to enhance the overall robustness and validity of the AITUAM (Figure 25). Excluding the indicators AI2, AI5, and T3 contribute to ensuring the reliability and accuracy of the AITUAM´s findings in measuring the construct relationships. The PLS-SEM results for the adjusted model can be found in Figure 25.

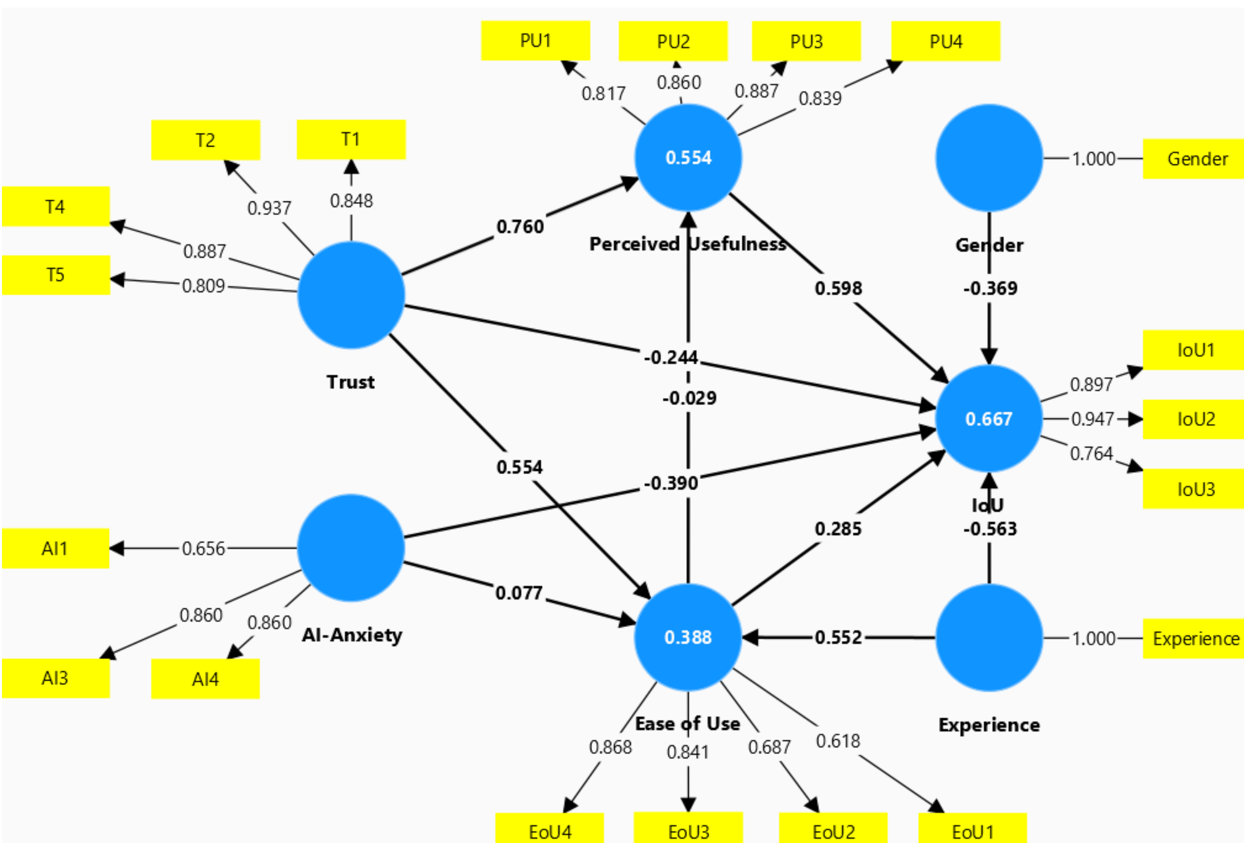

Figure 25 the PLS-SEM results for the AITUAM.

While the indicators EoU1, EoU2, and AI1 are still below 0.7, the results for the construct reliability and validity tests (Table 13) show no further problems with internal reliability (Sarstedt et al. 2021) (Ramayah et al. 2016) (Hair 2019). For all the constructs, Cronbach´s alpha values are above 0.7, composite reliability values are higher than 0.7, and the AVE values are all higher than 0.5.

Table 13 the results for internal reliability testing.

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE
AI-Anxiety	0.718	0.772	0.838	0.637
Ease of Use	0.774	0.845	0.844	0.579
Intention to Use	0.842	0.880	0.905	0.762
Perceived Usefulness	0.873	0.874	0.913	0.724
Trust	0.894	0.902	0.926	0.759

After establishing internal reliability for the constructs following the exclusion of the problematic indicators (AI2, AI5, T3), discriminant validity has to be assessed, to ensure that the constructs are distinct from one another. The results from the HTMT matrix, which determines discriminant validity, can be found in Table 14.

Table 14 the HTMT matrix after the removal of the indicators.

The HTMT Matrix	AI-Anxiety	EoU	Gender	IoU	PU	Trust	Exp
AI-Anxiety							
Ease of Use	0.238						
Gender	0.291	0.133					
Intention to Use	0.599	0.439	0.176				
Perceived Usefulness	0.417	0.393	0.131	0.785			
Trust	0.576	0.613	0.080	0.576	0.840		
Experience	0.100	0.398	0.004	0.201	0.129	0.163	

All HTMT values are lower than 0.85, therefore discriminant validity has been established for all constructs. This indicates that the constructs are sufficiently distinct from each other. However, it's important to note that the HTMT value of 0.84 between Trust and Perceived Usefulness is very close to the limit of the recommended threshold. This indicates that a strong correlation exists between Trust and the Perceived Usefulness of AI tools in the application process. The findings from the HTMT matrix confirm that discriminant validity has been successfully established for all used constructs, this implies that each construct demonstrates stronger associations with its own indicators than with the indicators of other constructs.

Figure 25 shows the strength of the path coefficients as well as the R^2 values of the dependent variables. AI-Anxiety has a negative influence on Intention to Use (-0.390) and a minor positive impact on Ease of Use (0.077). Trust exhibits a strong positive influence on Ease of Use (0.554) and a very strong positive influence on Perceived Usefulness (0.760) while having a negative influence on Intention to Use (-0.244). Ease of Use has a weak positive influence on Intention to Use (0.285) and has a minor negative effect on Perceived Usefulness (-0.029). Perceived Usefulness has a strong positive influence on Intention to Use (0.598). Gender negatively affects Intention to Use (-0.369). Experience positively affects Ease of Use (0.552) and negatively affects Intention to Use (-0.563). The R^2 values as well as the adjusted R^2 values for the dependent variables can be found in Table 8 in the appendix. The R^2 values indicate that the AITUAM can explain 38.3 % of the variances for Ease of Use, 55.4% for Perceived Usefulness, and 66.7% of the variance in Intention to Use, which is a fundamental increase in explainability in comparison to the conceptual model which was based on the Hypotheses. The adjusted R^2 value for Ease of Use is (0.297), Perceived Usefulness (0.539), and Intention to Use (0.630), further validating the model's explanatory power. The F^2 values that can be found in Table 9 in the appendix show that Trust has a strong effect on Ease of Use (0.396) and a fundamental effect on Perceived Usefulness (0.877). Perceived Usefulness has a strong effect on Intention to Use (0.455). AI-Anxiety has a rather strong effect on Intention to Use (0.311). Experience has a medium effect on Intention to Use (0.195) Ease of Use has a weak effect on Intention to Use (0.144).

A percentile bootstrapping method, as recommended by Becker et al. (2023), with 10.000 bootstrapping samples was used to determine the significance of the relationships in the AITUAM. A fixed seed was used for the random number generator to allow consistency and reproducibility of the results (Sarstedt et al. 2021). To determine the significance of the path model, a two-tailed significance test at the 5% level was conducted.

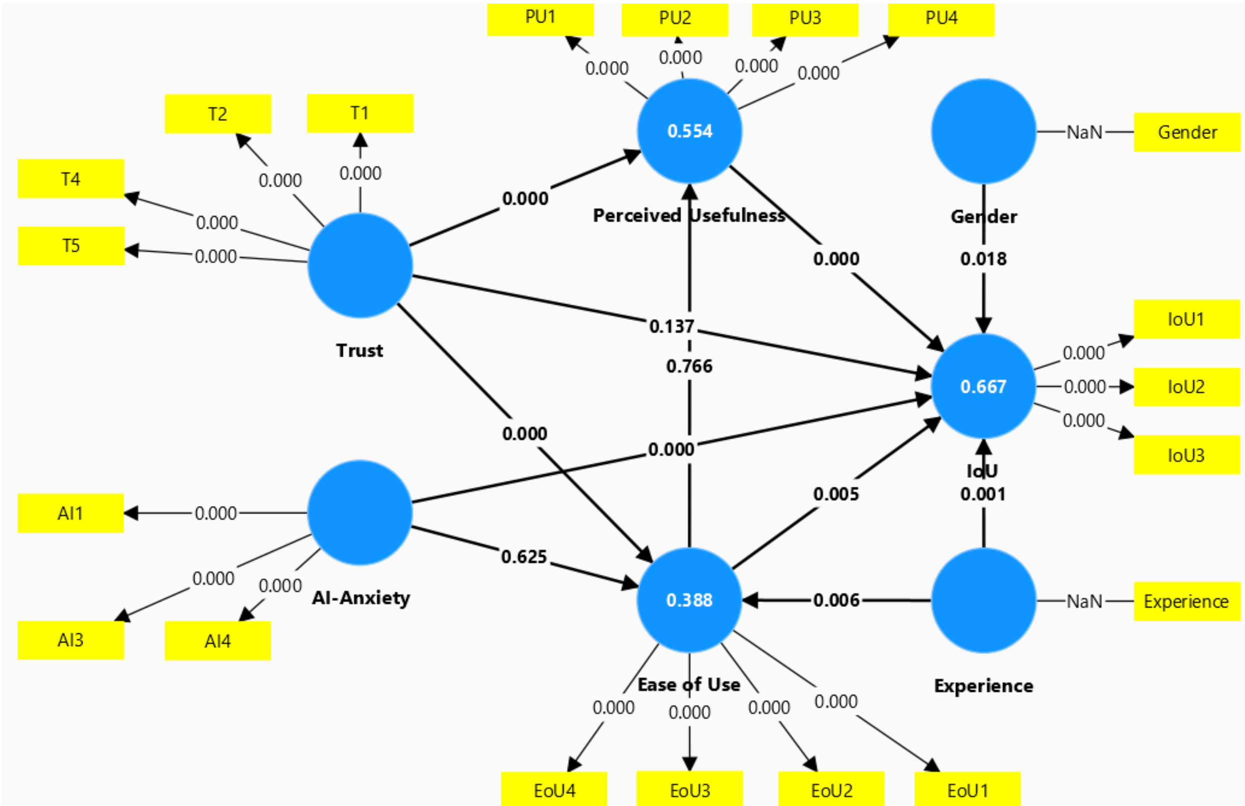

Figure 26 shows the result of the bootstrapping method.

The result of the bootstrapping method (Figure 26) shows that all the indicator loadings are statistically significant on the 1% level, confirming the reliability of the measurement model. The results for the construct relationships show that Trust is statistically significant on the 1% level on Ease of Use (0.000) as well as Perceived Usefulness (0.000) but is not statistically significant on Intention to Use (0.137). Ease of Use is not statistically significant on Perceived Usefulness (0.766) but is significant on the 5% level on Intention to Use (0.005). Perceived Usefulness is statistically significant on the 1% level on Intention to Use (0.000). Experience is statistically significant on the 1% level on Ease of Use (0.006) and on Intention to Use (0.001). Gender is significant on Intention to Use on the 5% level (0.018). AI-Anxiety is not statistically significant on Ease of Use (0.625) but is statistically significant on Intention to Use, at the 1% level (0.000). Since the relationship´s strength between AI-Anxiety and Ease of Use as well as AI-Anxiety and Intention to Use is moderated by Age, this estimate is subject to heterogeneity (Becker, 2023). Any result about the direct effect AI-Anxiety has on Ease of Use and Intention to Use is dependent on the moderator Age. Because the effect AI-Anxiety has on Ease of Use differs from the formulated hypothesis, Becker (2023) recommends establishing a base model without the moderator to test the direct effect's significance and then to include the moderator to assess its impact. Since this evaluation showed a direct significant effect from AI-Anxiety on Intention to Use, Part 5.3.1 in this Thesis determines the AITUAM including Age as a moderator to assess the impact Age has on the relationship between AI-Anxiety and Intention to Use.

Key Figures for the AITUAM with Age as a Moderator:

Figure 27 shows the PLS-SEM results after the removal of AI2.

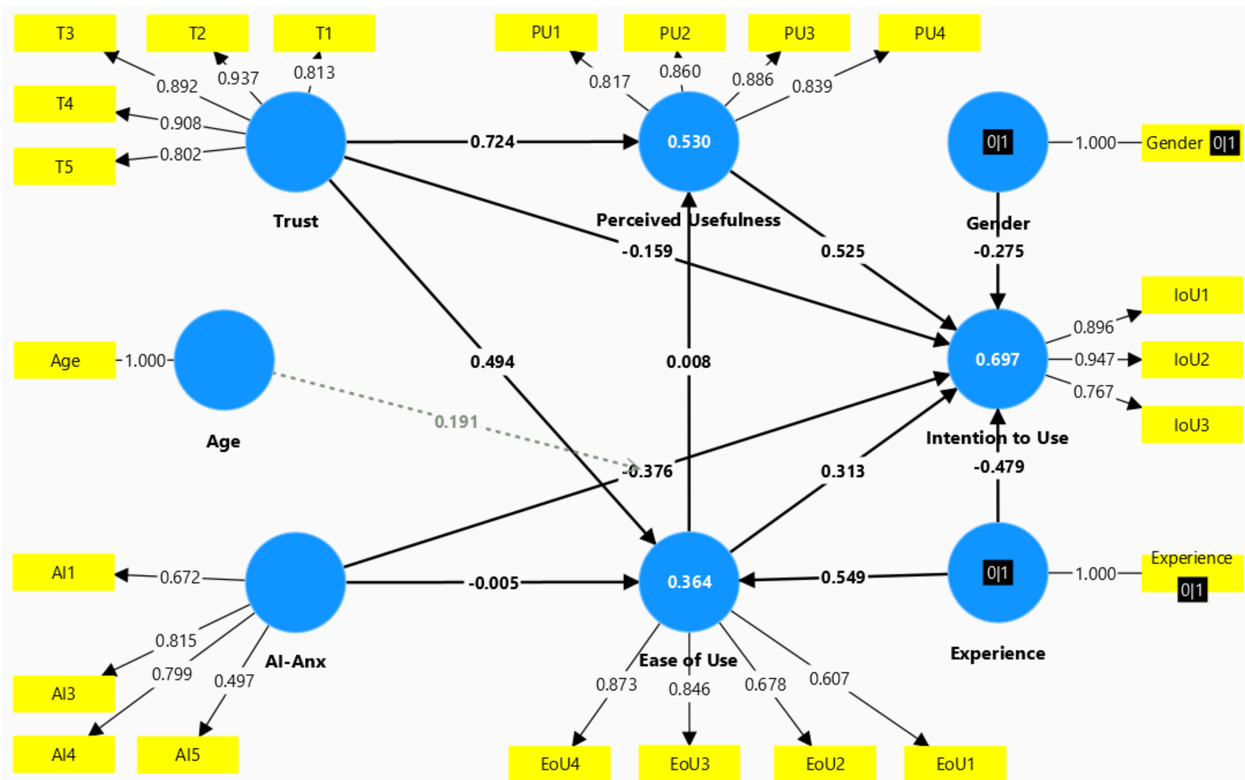

Figure 27 PLS-SEM results after the removal of AI2.

Table 15 shows the results of the internal validity and reliability testing after AI2 has been deleted.

Table 15 results of the internal reliability testing.

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE
AI-Anxiety	0.658	0.690	0.795	0.500
Ease of Use	0.774	0.852	0.842	0.576
Intention to Use	0.842	0.875	0.905	0.762
Perceived Usefulness	0.873	0.874	0.913	0.724
Trust	0.921	0.927	0.941	0.761

Table 16 shows the results of the VIF scores for the indicators. Only T3 has a VIF value above 5 and thus is removed from the AITUAM.

Table 16 The VIF scores of the Indicators in the AITUAM.

Indicator	VIF
AI1	1.360
AI2	1.109
AI3	1.545
AI4	1.630
AI5	1.191
EoU1	1.844
EoU2	2.027
EoU3	1.784
EoU4	1.942
Gender	1.000
IoU1	2.907
IoU2	3.679
IoU3	1.654
PU1	2.035
PU2	2.273
PU3	2.715
PU4	2.142
T1	2.230
T2	4.995
T3	5.034
T4	4.877
T5	2.143
Experience	1.000

Table 17 shows the R^2 and the adjusted R^2 values for the constructs EoU,IoU and PU

Table 17 The R^2 and adjusted R^2 values.

	R^2	R^2 adjusted
EoU	0.388	0.356
IoU	0.690	0.643
PU	0.554	0.539

Table 18 show the results for the F^2 test.

Table 18 The F^2 values for the AITUAM.

The F-square values	Ai-Anx	Age	EoU	Gender	IoU	PU	Trust	Exp	Age x AI-Anx
AI-Anxiety			0.007		0.342				
Age					0.011				
Ease of Use					0.217	0.001			
Gender					0.079				
Intention to Use									
Perceived Usefulness					0.462				
Trust			0.370		0.072	0.892			
Experience			0.118		0.159				
Age x AI-Anx					0.071				

Table 19 shows the Model Fit for the AITUAM. The findings show a great difference between the Chi-square value for the saturated model and the estimated model. This indicates a poor model fit.

Table 19 Goodness of Fit values.

	Saturated Model	Estimated Model
SRMR	0.094	0.112
d_ULS	2.061	2.897
d_G	0.997	1.398
Chi-square	298.723	572.499
NFI	0.667	0.362

Table 20 shows the significance of the indirect effects in the AITUAM. Only Trust has a significant indirect effect on Intention to Use at the 1% level (0.000). Experience has a significant indirect effect on Intention to Use at the 5% level (0.050)

Table 20 the indirect effect results in the AITUAM.

Indirect effects	Original sample	Sample mean	STDEV	T statistics	P values
AI-Anx -> IoU	0.026	0.023	0.053	0.479	0.632
Ai-Anx -> PU	-0.002	-0.003	0.018	0.128	0.898
EoU -> IoU	-0.017	-0.015	0.058	0.292	0.770
Trust -> IoU	0.625	0.629	0.139	4.507	0.000
Trust -> PU	-0.016	-0.014	0.056	0.287	0.774
Exp -> IoU	0.183	0.172	0.081	2.268	0.023
Exp -> PU	-0.016	-0.019	0.058	0.277	0.782

Table 21 shows the significance of the total effects in the AITUAM.

Table 21 the total effect results for the AITUAM.

Total effects	Original sample	Sample mean	STDEV	T statistics	P values
AI-Anx -> EoU	0.077	0.073	0.158	0.488	0.625
AI-Anx -> IoU	-0.373	-0.375	0.110	3.387	0.001
Ai-Anx -> PU	-0.002	-0.003	0.018	0.128	0.898
Age -> IoU	-0.063	-0.060	0.093	0.684	0.494
EoU -> IoU	0.332	0.323	0.114	2.917	0.004
EoU -> PU	-0.029	-0.026	0.098	0.298	0.766
Gender -> IoU	-0.350	-0.362	0.168	2.081	0.037
PU-> IoU	0.581	0.586	0.144	4.034	0.000
Trust -> EoU	0.554	0.561	0.108	5.150	0.000
Trust -> IoU	0.354	0.349	0.116	3.044	0.002
Trust -> PU	0.744	0.746	0.056	13.296	0.000
Exp -> EoU	0.552	0.554	0.199	2.772	0.006
Exp -> IoU	-0.314	-0.320	0.182	1.722	0.085
Exp -> PU	-0.016	-0.019	0.058	0.277	0.782
Age x AI-Anx	0.156	0.140	0.074	2.113	0.035

Statistically significant on at least the 5% level are Ai-Anxiety on IoU, Ease of Use on IoU, Gender on IoU, Perceived Usefulness on IoU, Trust on Ease of Use, Trust on Intention to Use, Trust on Perceived Usefulness, Experience on Ease of Use, Experience on Intention to Use, Experience on

Ease of Use, as well as Age a moderator on the relationship between AI-Anxiety and Ease of Use. Trust has a positive total effect on IoU.

Further considerations:

The impact of AI2:

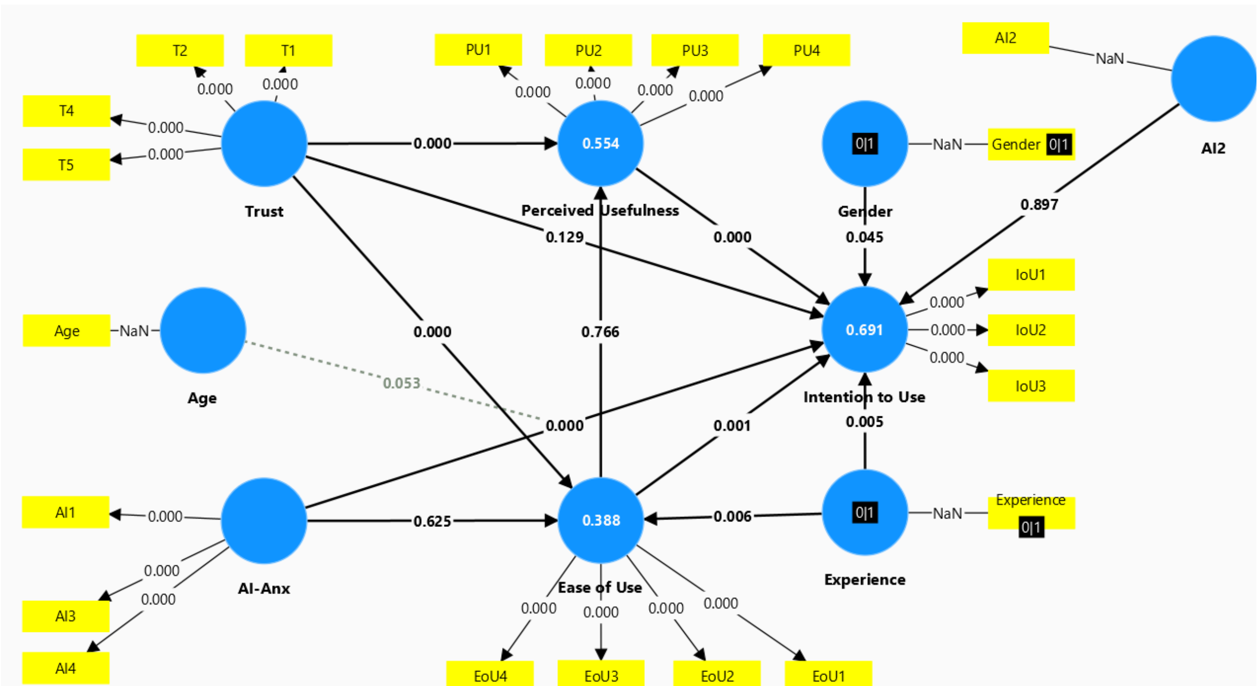

Figure 28 testing if AI2 has a direct impact on IoU.

To determine if AI2 which determines the fear that the implementation of Ai tools in the application process leads to job loss, is statistically significant, the model visualized in Figure 28 was used. AI2 was included in this model as a single item construct. The results of the bootstrapping method show that for the HR managers in the survey this was not a significant predictor on Intention to Use.

Functional aspects of the AI:

Using Functional Aspects about AI as an umbrella term instead of using perceived Ease of Use, perceived Usefulness and Trust.

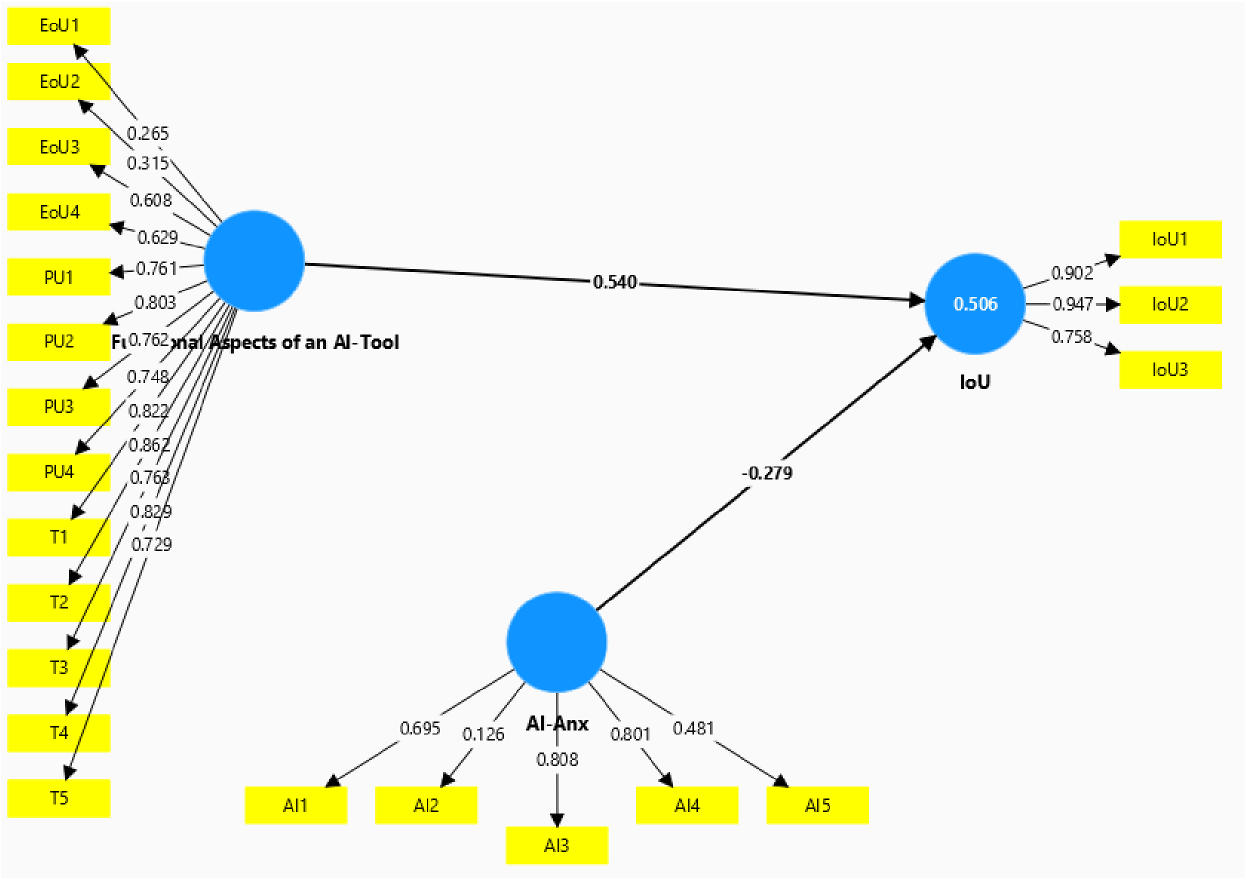

Figure 29 shows the PLS-SEM result for functional aspects of AI.

For the construct functional aspects of an AI tool, all Indicators besides EoU 1 and EoU3 which determine the ease of learning to use AI, are higher than 0.5. Thus, this aspect should be removed from evaluating the functional aspects of an AI tool. Table 22 shows the construct reliability of the constructs: For the umbrella term functional aspects of AI internal reliability is given, indicating that all items of the construct consistently measure the construct (Table 22).

Table 22 the construct reliability for functionality of AI as a construct.

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE
AI-Anx	0.620	0.680	0.740	0.405
Functional Aspects of AI	0.910	0.941	0.924	0.501
Intention to Use	0.842	0.883	0.905	0.762