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Technology Acceptance Model: Which factors drive the acceptance of AI among employees?

Abstract In recent years, artificial intelligence (AI) has rapidly moved from an ideal concept to a technology that can be deployed. Due to its capabilities of mimicking human intelligence, many firms in various industries have started integrating AI. However, AI cannot improve an organization's performance if it is not used. Unfortunately, employees' resistance to innovative technologies is a widespread problem. To minimize the adverse effects and costs of employees' resistance, it is valuable to predict and better understand which factors drive the acceptance of AI among employees. This thesis addresses the ability to predict employees' acceptance of AI. For this purpose, the traditional Technology Acceptance Model (TAM), which exists of behavioral intention to use (BI), perceived usefulness (PU), and perceived ease of use (PEOU), is extended with trust and social influence related factors such as compliance, image, technological trust, and behavioral uncertainty. In addition, the moderating effect of prior experience with AI was investigated. A survey was designed with 199 participants (N=199) to measure the magnitude and directionality of the effects of the driving factors of acceptance. Within the survey, participants were presented with a tax- or audit-related case. The results demonstrate that the extended TAM model is a valid model to predict employees' acceptance of AI. PU exhibited the strongest significant influence on BI. In contrast, no significant direct effect of PEOU on BI was found. The findings further demonstrated that acceptance behavior differs for experienced compared to inexperienced employees. Another significant result is that employees' sentiment regarding their prior experience significantly affects the magnitude of the driving factors. These findings advance theory and contribute to future research focused on improving understanding of employees' acceptance of AI.

Keywords: Artificial intelligence, Technology Acceptance Model, Social influence, Trust, Experience

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Contents

List of Figures

List of Tables

1

Introduction

"Whoever controls the strongest artificial intelligence controls the world."
- Westerheide (2019)

Artificial intelligence (AI) refers to the science and engineering domain that focuses on developing theories and applications of systems used to exhibit the characteristics associated with human intelligence, including natural language-processing, problem-solving and planning, learning, and adapting (Tecuci, 2012; Xu & Wang, 2019). The goal of this domain is to develop intelligent agents that, in their essence, are knowledge-based systems that perceive their environment and therefrom determine their actions. By developing intelligent agents, researchers tend to optimize the interaction between humans and machines in such a way that working with a machine feels as easy as working with a human. AI has its origins in and intersects with many research fields—not only computing disciplines, but also economics, linguistics, statistics, psychology, neuroscience, philosophy, and many others. In recent years, many concepts from these disciplines have been adopted into AI, and it has also contributed back to those disciplines (Tecuci, 2012). Today, AI is capable of extracting, interpreting, and learning from vast amounts of data, including audio and visual material (Schwab, 2017). As the algorithms are constantly improving, some of today's AI tools already exceed human performance. For example, image recognition tools are able to detect skin cancer with greater accuracy than doctors, and AI algorithms outperform human lawyers in analyzing and predicting legal cases (Markoff, 2011; Xu & Wang, 2019).

As a result, AI has rapidly moved from an ideal concept to a technology that can be deployed. Many firms in various industries have now started integrating the use of AI (Lichtenthaler, 2019). Following the Fortune Business Insights study of 2019, the global AI market in 2018 was worth USD 20.67 billion and is predicted to reach USD 202.57 billion by 2026, implying a compound annual growth rate (CAGR) of 33.1% over that period (Fortune, 2020). Virginia Marie Rometty, CEO of IBM from 2012 to 2020, stated that by 2021 most strategic business decisions will be influenced by the cognitive capabilities of technology (Davenport, 2016). According to Rometty, the combination of human intelligence and the cognitive capabilities of AI will soon be the key driver of success in organizations' strategic decision-making processes (Reeves, Levin, & Ueda, 2016).

While integrating intelligent algorithms and advanced data analytics seems logical from a strategic perspective, the growing application of AI causes additional challenges due to the required transformation within the firm

(Lichtenthaler, 2019). The continuous technological developments regarding AI will have significant effects on a firm's decision-making process, its interaction with external stakeholders, and the current job profiles of its employees (Haenlein & Kaplan, 2019). Previous research has focused on the impact of the introduction of AI into the workplace (Li, Bonn, & Ye, 2019; Schneider & Leyer, 2019; Xu & Wang, 2019). Generally, research has identified possible factors that could inadvertently affect the employee's psychological and emotional well-being. Many fear that the rapid developments will cause a growing number of employees to be replaced by AI robots, especially jobs in the service sector (Huang & Rust, 2018). In addition, several researchers suggest that for a successful collaboration between AI and employees, trust in the technology is needed (Gaines-Ross, 2016; Marler, Fisher, & Ke, 2009). For AI to reach its potential it is therefore crucial for an employer to understand the drivers of the individual employee's acceptance of AI. However, apart from an awareness of its potential negative impact, little time has been given to understanding the individual employee's drivers of acceptance of AI. Therefore, the aim of this thesis is to answer the research question: *"Which factors drive the acceptance of AI among employees?"*.

The structure of this research is as follows: Chapter 2 discusses prior literature on the topic, and concludes with hypotheses derived from the literature review; Chapter 3 discusses the methodology, the variables, and the model used in the experiment; Chapter 4 discusses the results of the statistical analyses and tests the hypotheses; and Chapters 5 presents the results, limitations of the research, and recommendations for future research, and offer conclusions.

2

Literature Review

This chapter presents an overview of the existing literature on the subject. First, findings from previous literature on the impact of emerging technologies on employees are provided. The relevance of technology acceptance by employees is then clarified. Subsequently, the technology acceptance model and two extensions are explained, and the effect of prior experience with a technology is discussed. Finally, the chapter concludes with hypotheses that have arisen in the literature.

2.1 Previous literature on the impact of emerging technologies on employees

A considerable amount of literature has been published on the effect of the adoption of new technologies and the change in work environments (Black & Lynch, 2001; Ichniowski, 1992; Krafcik, 1988; Womack, Jones, & Roos, 2007). Generally, employers implement new technologies to increase the business' efficiency (Herbert & Tuminaro, 2007). However, previous studies have demonstrated that the adoption of new technologies may cause an increase in errors resulting in lower productivity (Lohr, 2007). In addition, the adoption of computer and telecommunications technologies has radically transformed the workday, resulting in boundaryless workplaces. While this boundarylessness has increased the flexibility of employees, it has also eroded the separation between work and home (Stone, 2001). New technologies have also made it possible to monitor employee performance, which has helped to diminish free-riding problems. A noted counter-effect of the increased transparency is an increase in the employee's perceived pressure by the employer (Herbert & Tuminaro, 2007). Moreover, employers are likely to underestimate the consequences of changes in the employee's working environment, which may affect the employee's psychological health. According to Hoopes (2005), new technologies may provoke stress, alienation, and even dehumanization, reinforcing the decrease in productivity and job satisfaction (Hoopes, 2005). Such negative effects may cause psychological contract violation. According to Levinson, Price, Munden, Mandl, and Solley (1962), a psychological contract is a relationship between the employee and the employer, originating from a social exchange where the employee and employer make the exchanges based on their respective needs, which often depend on the expectation of return. As stated by Rousseau (1990), psychological contracts have two sets of terms: employee-focused obligations, and employer-focused obligations. Following Lester, Turnley, Bloodgood, and Bolino (2002), obligations are actions or promises made by an individual toward the relational exchange between the employee or employer. Examples of such obligations are expectations of salary, promotion opportunities, and job security. When an employer fails to meet the employee's expectations, it may result in feelings of unfair treatment, betrayal, and anger. Consequently, these negative attitudes may increase an employee's turnover intentions or cause internal resistance to technological innovations (Pate & Malone, 2000; Robinson & Wolfe Morrison, 2000; Rousseau, 1990).

2.1.1 Internal resistance to technological innovations

In this research, employee resistance is described from the employee's perspective, which maximizes their rational utility. This implies that employees resist new technologies in order to avoid a reallocation of their payoffs, even if their resistance decreases their firm's payoff (P. Milgrom & Roberts, 1988; P. R. Milgrom, 1988). According to Hauschildt (1999), internal resistance to new technologies reveals a conflict of interest between the employer and the employee. While the new technologies may enforce the competitiveness of a firm in the long run, employees may also withstand those innovations due to anxiety of being less well off as a result of the implementation of the new technologies (P. R. Milgrom, 1988). In particular, employees tend to be resistant to co-operating in planned innovations when the payoff of their cooperation is uncertain. By being resistant, employees hope to preserve the old situation (Zwick, 2002). Following Sichel (2001), the rejection of new technologies by employees is one of the major drivers of the productivity paradox. This is the perceived discrepancy between the investment in new technology and its performance, as a result of low usage. It is therefore crucial for an employer to understand why employees resist the adoption of new technologies, in order to improve the employees' acceptance of the change (Davis, Bagozzi, & Warshaw, 1989).

Since AI is unlikely to entirely replace human labor in most cases, effective interaction between human and machine is of great importance for the employee's acceptance (Ghazizadeh, Lee, & Boyle, 2012). The application of AI is likely to change the employees' job structure, i. e. a vast part of their prior tasks will be automated. Subsequently, these automated activities need to be monitored and coordinated by the employees Sarter, Woods, Billings, et al. (1997). While substitution of human labor relieves employees of highly demanding tasks in most cases, it can also have adverse implications, such as decreasing job satisfaction, deskilling, and mode confusion (Hollnagel & Woods, 2005; Parasuraman & Riley, 1997). In addition, Ghazizadeh et al. (2012) stated that systems applying AI that restrict the employees' behavior, or those that require behavioral change, are more likely to experience employees' resistance than nonrestrictive systems.

For AI to reach its potential, it needs to be adequately adopted by a firm's employees and requires an accurate integration into the employees' job structure (Hollnagel & Woods, 2005). Prior research has noted the potential adverse effects of AI on employees (Ghazizadeh et al., 2012; Sarter et al., 1997). Consequently, several researchers have tried to understand the drivers of AI adoption on a firm-level (Alsheibani, Cheung, & Messom, 2018). However, far too little research has been done to identify the drivers of employees' acceptance. To overcome internal resistance and reach the promised benefits, a better understanding of the drivers of

AI acceptance among employees is needed. Numerous models, including the Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB), have attempted to explain the individual employee's technology acceptance (Ajzen, 1991; Sheppard, Hartwick, & Warshaw, 1988). Likewise, Davis et al. (1989) constructed the technology acceptance model (TAM), which is a framework originally designed to predict the use of new technologies in the workplace. The model has been applied to a diverse set of technologies and is possibly the most widely used model in measuring technology acceptance among employees (Ahmed, 2016; Venkatesh, Thong, & Xu, 2012). Nevertheless, TAM has not yet been applied on AI technology. This research therefore attempts to identify the individual employee's drivers of acceptance of AI with the use of the TAM model.

2.2 Technology Acceptance Model

According to TAM, the actual usage of a new technology is determined by the individual employee's behavioral intention (BI) to use the new technology and therefore determines the technology acceptance (Davis et al., 1989). Hence, in this research BI can be considered as an employee's behavioral intention to use AI technology during their daily job. Originally, the employee's BI to use new technologies was determined by two salient components: perceived usefulness (PU) and perceived ease of use (PEOU). Following Davis et al. (1989), PU refers to the extent to which employees believe that using the new technology will improve their job performance. Moreover, Davis et al. (1989); Fishbein and Azjen (1975) argue that PU is considered to be the main component of TAM. Davis et al. (1989) have also proven the reliability and validity of the component. Consequently, PU has been used to predict several technology acceptances, including telecommuting, word processing, and e-learning (Alrafi, 2007; Alsabawy, Cater-Steel, & Soar, 2016). In the present research, PU is defined as the employee perceiving the use of AI technology as beneficial. Thus, an increase in the PU of a technology from the employee's point of view is likely to positively affect their BI to use the technology (Davis et al., 1989). This perceived usefulness is also affected by the complexity of the use of the new technology—that is, the easier a new technology is to use, the more the PU will increase, (i.e., PEOU). In addition, an employee is less likely to be resistant of using a new technology when they expect it to be free of effort (Davis et al., 1989). Nonetheless, meta-analytic studies provide weak effects of PEOU on BI to use. Moreover, existing research by Gefen, Karahanna, and Straub (2003a) indicates strong results for the indirect effect of ease of use through PU. The researchers argue that the ease of use captures the employees' motivation, which is determined by their assessment of the intrinsic aspects of using the new technology, such as its interface clarity and navigational ease. However, with regard to AI, limited interaction with the technology is required. For the purposes of this research, PEOU can be defined as the employee's perception of how easily they can interact and work with AI-driven technologies. Hence, the PEOU of a technology is likely to positively affect the employee's BI to use it (Davis et al., 1989).

2.2.1 Social influence

In order to improve the predicting power of TAM, Venkatesh and Davis (2000) extended the model with subjective norm. This component captures social influence processes and refers to the degree to which an employee perceives that important others think that he should or should not use the new technology. Based on the TRA model, Venkatesh and Davis (2000) included this component as a direct determinant of BI. If employees are very susceptible to the beliefs of colleagues or friends, they are likely to perform a behavior consistent with that of the people who are important to them, even though this behavior may not always be favorable to them. Several studies have shown that the effect of subjective norm increases in mandatory settings (French, Raven, & Cartwright, 1959; Hartwick & Barki, 1994; Kelman, 1958; Warshaw, 1980). Venkatesh and Davis (2000) name this underlying causal mechanism compliance. Generally, this direct effect of compliance on BI to use comes into play when an employee perceives that a colleague wants them to exhibit specific behavior, and this colleague is in a position to reward the behavior or punish the non-behavior. As a result, the employee's BI to use is likely to increase, to avoid negative consequences. In addition to the positive effect on behavioral intention to use, an employee's PU may increase, since they may perceive the AI technology to be more useful, due to the fact that it helps them avoid negative consequences (Davis et al., 1989). In the case of AI, this can be seen as a manager who obligates his employees to use AI during their job. If an employee refuses to use it, the manager is able to impose punishments.

Another underlying causal mechanism pointed out by Venkatesh and Davis (2000) is image, which is described as the degree to which the use of an innovation is perceived to strengthen an employee's status in their social environment. Following Venkatesh and Davis (2000), the employee's elevated status provides an overall basis for higher productivity. Hence, employees might perceive using AI technology as a possible improvement of their job performance, which enhances their PU. In the present research, this could be the case if an employee believes that using AI technology will enhance their favorable status within their reference group.

2.2.2 Trust

Certain aspects of recent technological developments may lead to higher levels of uncertainty, such as the potential global accessibility of information, grown intangibility, and the spatial separation between employees who engage in online communication and transactions (McKnight & Chervany, 2002; Pavlou, 2003; Suh & Han, 2003). Poorly calibrated trust may cause serious problems for the employee's acceptance of new technology. In these situations, employees might overtrust AI, making them vulnerable to ignoring contradictory information (Lee, 2004). On the contrary, employees might refuse to engage with AI even if it could enhance their job performance, due to a lack of trust in the technology (Lee, 2004). Consequently, several researchers have considered the effects of trust on the individual employee's acceptance of new technologies (Featherman & Pavlou, 2003; Gefen, 2000; Gefen, Karahanna, & Straub, 2003b). Hence, in this research the core TAM is extended by adding employees' trust.

Following Pavlou (2003), trust is required when uncertainty is present. Uncertainty is either technology-driven (technological uncertainty), and therefore derived from the underlying technological environment, or relational (behavioral uncertainty), based on the relationship with the employer. Moreover, Mitchell (1999) stated that uncertainty may increase an employee's perceived risk, which is defined as the employee's perception of the possibility of experiencing adverse consequences or losses in uncertain situations. Generally, technology-driven uncertainty exists because of the unpredictability of a technology, which is often beyond the control of the employee or the employer. Nevertheless, AI-developing companies are unlikely to openly share the technology they have used, due to the fear of competitors copying them (Feldman, 2019). Although AI might be designed to be objective and to act without prejudice, it does not imply that systems that use AI cannot be biased—indeed, due to the self-learning nature of AI, any mistakes in the input data persist and could possibly cause biases (Haenlein & Kaplan, 2019). The responsibility for such mistakes in algorithms is a related issue. It is often unclear who should take ultimate responsibility for such errors, causing an increase in the employee's perceived risk (Haenlein & Kaplan, 2019). Mayer, Davis, and Schoorman (1995) stated that employers should attempt to make new technology's actions more comprehensible, in order to strengthen trust in it. For example, a widely used technique underlying AI is Deep Learning, and this technique is often perceived as very complicated and complex. As a result, employees are only able to assess the output, and not the process used to obtain the output (Haenlein & Kaplan, 2019). Deep Learning is therefore often seen as a black box, which increases its unpredictability, which in turn negatively influences employees' trust. Several researchers suggest that transparency diminishes the uncertainty and therefore has a positive effect on the employee's BI to use the technology and on the PU of it (Featherman & Pavlou, 2003; Gefen et al., 2003b). A higher level of comprehensibility will thus imply a lower level of technological uncertainty. This will result in a higher level of employee trust in the technology, resulting in higher engagement.

Behavioral uncertainty also derives from the possibility of employers taking advantage of the employee. Since AI is currently capable of mimicking (or even exceeding) human intelligence, it is likely that in the near future a vast section of human labor will be substituted by systems using AI (Brougham & Haar, 2018; Huang, Rust, & Maksimovic, 2019). Brougham and Haar (2018) state that the implementation of AI-driven tools may signal an intention to replace employees. When employees are more aware of the impact of AI on their job security, they are less likely to adopt the new technology. This is due to the fact that employees may interpret the intention to replace human labor as the employer undervaluing them. The introduction of AI by an employer is therefore likely to have a negative effect on the employee's BI to accept AI.

2.2.3 Prior experience and adoption intentions

Several research papers have noted a salient effect of employees' prior experience with technology on their adoption behavior (Choi, Kim, & Kim, 2010; Gefen et al., 2003a, 2003b; Schwarz, Junglas, Krotov, & Chin, 2004). Karahanna, Straub, and Chervany (1999) state that generally the attitude toward new technology adoption among inexperienced employees is driven by their indirect experience with a technology, which dictates whether or not they are susceptible to change. In contrast, the attitudes of experienced employees are based on their prior experience with a technology, and they are therefore far more enduring. As a result, the experienced employees' acceptance of a new technology is likely to be better predicted than that of inexperienced employees (Choi et al., 2010). Taylor and Todd (1995) also found relative differences in the impact of determinants of technology acceptance between experienced and inexperienced users. They noted a salient difference between both groups regarding the impact of PU and technological trust. Perceived usefulness was found to have a greater impact on behavioral intentions to use for inexperienced compared to experienced users, while experienced users placed more weight on the effect of technological trust.

Furthermore, several researchers have reported that prior experience with a technology enforces the relationship between the intention to use and PEOU of a technology (Choi et al., 2010; Gefen et al., 2003a, 2003b; Yu, Ha, Choi, & Rho, 2005). According to Fazio and Zanna (1978), prior experience causes knowledge to be more accessible in an employee's memory. This type of knowledge is called procedural knowledge—the employee's knowledge used in the accomplishment of their tasks. An employee's procedural knowledge increases in relation to their prior experience (Pearson, Wiechula, Court, & Lockwood, 2007). An increase in procedural knowledge is thus likely to enable the employee to accomplish tasks with greater ease. In addition, greater procedural knowledge is likely to enlarge an employee's technological trust (Choi et al., 2010).

Rempel, Holmes, and Zanna (1985) stated that technological trust is a social emotion that is affected by the interaction between humans and technology. Trust has three different dimensions that evolve over time: predictability, dependability, and faith. These dimensions are highly influenced by the employee's degree of experience of interaction with the technology. According to Ghazizadeh et al. (2012), employees' technological trust is affected by their personal experience with AI technology. When employees have experienced the positive effects of the technology, their technological trust is likely to increase, which positively affects their intention to use the technology in the future. Brougham and Haar (2018) stated that the adverse effect of behavioral uncertainty on BI to use is strengthened by employees' awareness regarding the capabilities of AI. Therefore, they expect employees with prior experience to be more aware of the possibility of being replaced by AI-driven tools. Hence, it is expected that the negative effect of behavioral uncertainty is greater for employees with prior experience of AI compared to employees without prior experience.

2.3 Hypotheses

Based on the literature review, several hypotheses have been constructed. The research model that explains the expected effects can be found in figure 2.1. The hypotheses are phrased in terms of the expected outcome instead of the statistical null hypotheses. These hypotheses will contribute to answering the main research question: *"Which factors drive the individual employee's acceptance of AI?"*

2.3.1 Behavioral intention to use

In accordance with prior TAM research, the individual employee's behavioral intention to use was used as a proxy of acceptance of AI. This resulted in the following hypotheses:
H1a: The employee's perceived usefulness will have a positive direct effect on their intention to use AI.
H1b: The employee's perceived ease of use will have a positive direct effect on their intention to use AI.
H1c: Compliance will have a positive direct effect on the employee's intention to use AI.
H1d: The employee's technological trust in AI will have a positive direct effect on their intention to use AI.
H1e: The employee's behavioral uncertainty will have a negative direct effect on their intention to use AI.

2.3.2 Moderating effect of prior experience

In past TAM research, it has been noted that prior experience with a technology affects the impact of the determinants of technology acceptance. Hence, to test whether the relative influence of the determinants of AI acceptance is the same for experienced and inexperienced employees, the following hypotheses were tested:
H2a: Prior experience with AI will weaken the direct effect of the employee's perceived usefulness on their intention to use AI.
H2b: Prior experience with AI will strengthen the direct effect of the employee's perceived ease of use on their behavioral intention to use AI.
H2c: Prior experience with AI will strengthen the direct effect of the employee's technological trust on their behavioral intention to use AI.
H2d: Prior experience with AI will strengthen the direct effect of the employee's behavioral uncertainty on their behavioral intention to use AI.

2.3.3 Moderating effect of sentiment related to prior experience

It was noted that limited research has focused on the moderating effect of the employee's sentiment related to his prior experience of the different determinants of acceptance. Nonetheless, it can be assumed that the effects of the determinants differ per sentiment (e.g., the acceptance of AI is different for employees who have had a negative prior experience compared to employees with a positive prior experience). In order to obtain a more detailed understanding of the effect of prior experience, it was tested whether the employee's sentiment affects the effect of the different constructs. This resulted in the following hypotheses:
H3a: The employees' sentiment related to their prior experience with AI affects the direct effect of perceived usefulness on behavioral intention to use AI.
H3b: The employees' sentiment related to their prior experience with AI affects the direct effect of perceived ease of use on behavioral intention to use AI.
H3c: The employees' sentiment related to their prior experience with AI affects the

direct effect of compliance on behavioral intention to use AI.
H3d: The employees' sentiment related to their prior experience with AI affects the direct effect of technological trust on behavioral intention to use AI.
H3e: The employees' sentiment related to their prior experience with AI affects the direct effect of behavioral uncertainty on behavioral intention to use AI.

2.3.4 Perceived usefulness

Since PU is considered to be the main predictor of technology acceptance, identifying the determinants of the concept can contribute to a better understanding of technology acceptance, and therefore increase the success of its acceptance.
H4a: The employee's perceived ease of use will have a positive direct effect on their perceived usefulness of AI.
H4b: Compliance will have a positive direct effect on the employee's perceived usefulness of AI.
H4c: Image will have a positive direct effect on the employee's perceived usefulness of AI.
H4d: The employee's technological trust in AI will have a positive direct effect on his perceived usefulness of AI.

figure 2.1 gives an overview of the expected effects on the employee's BI to use and PU of AI. The arrows indicate the direction of the direct effects, and the circles indicate the moderating effect of experience.

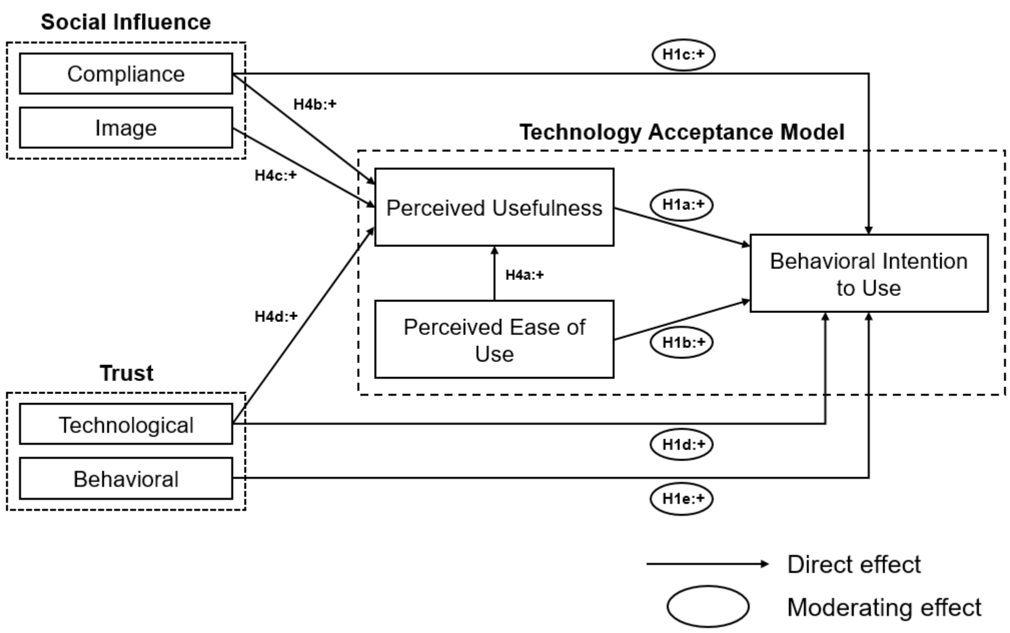

Figure 2.1: Hypothesized effects based on previous literature.

3

Methods

This chapter discusses the methodology of the research. First, the experimental design is described, and an overview of the sampling procedure is then provided. The variables of interest are then introduced, and the chapter concludes with an explanation of the statistical tests used to test the hypotheses.

3.1 Experimental design

The aim of this research is to explain employees' acceptance in terms of behavioral intentions to use AI-driven technology. AI technology is a wide-ranging set of technologies, which can be applied in many industries. Therefore, to narrow the concept of AI technology for the purposes of this thesis, we focus on AI technologies in the tax and audit industry. In both industries, the decision-making bases rely on vast amounts of data and information. Following its rapid development, AI has become a useful tool for data collection, classification, and processing (Shan, 2019). Consequently, the use of AI has augmented in both the tax and audit industries in recent years (KPMG, 2018; Milner & Berg, 2017), making them a good fit for this research. The thesis was mainly conducted at KPMG in Amstelveen during a five-month internship in a team that was developing AI-driven tools for the tax and audit industry. This setting provided access to in-depth knowledge about the use and applicability of AI in both industries.

To test all the hypotheses, an experiment was set up, divided into three stages. To ensure the content validity, the questions used in the experiment were adopted from prior TAM studies, with just small changes in the wording to fit the AI-specific context (Brougham & Haar, 2018; Davis et al., 1989; Ghazizadeh et al., 2012; Haenlein & Kaplan, 2019; Huang et al., 2019; Pavlou, 2003; Venkatesh & Davis, 2000). Accordingly, the experiment is solely available in English to overcome errors in the translations of the original TAM measures.

Stage 1. Introduction
At the start of the survey, gratitude was expressed for the participants' willingness to take part in the experiment. More information was given concerning the expected duration of the survey and the anonymity of participation. On the second page of the survey, the participant was asked whether they were active in the tax or audit industry.

Stage 2. Description of the scenarios

Based on participants' answers to the final question of stage 1, they were assigned to a tax or audit-related scenario. If participants answered that they were active in the tax industry, they were automatically assigned to the tax scenario; the participants who answered that they were active in the audit industry were automatically assigned to the audit scenario; participants answering that they were active in both industries or in neither of the industries were equally and randomly assigned to one of the scenarios.

In both scenarios, the participants were asked to imagine being a VAT expert or an auditor. In both scenarios, the management team of the VAT expert or auditor was considering implementing an AI-driven tool that would automate a significant part of the manual checks the employee needed to perform. As a result, the correctness of the checks would increase by 10%, which is likely to affect the participants' PU of the AI-driven tool. No explanation regarding the underlying technology was provided, which decreased the comprehensibility of the AI-driven tool. This non-transparency was introduced to affect participants' technological trust. The VAT job structure of the expert or/auditor is also affected, as the AI-driven tool would remove the need for employees to spend 60% of their time applying manual checks. As a result, the VAT expert/auditor concentrates solely on correcting errors noted by the tool. Such a change in job structure was chosen to affect participants' behavioral uncertainty. In addition, as a result of the increased efficiency, the probability of the VAT expert/auditor losing their job would increase by 40%. This increased job insecurity was chosen to affect the participants' behavioral uncertainty. Finally, the scenarios stated that the management team wanted to implement the new AI-driven tool, which was used to affect the participants' degree of compliance. The scenarios used in the survey can be found in Appendix A.

Stage 3. Measuring the TAM constructs and demographics

To measure the influences of the different constructs of the model, the participants were given 23 statements. The order of the statements was randomized to prevent potential order biases. In accordance with Churchill Jr (1979), multi-item scales were used for all constructs to capture comprehensive conceptual meanings. Once again, the participants were asked to rate all statements in the adopted roles of VAT expert and auditor. Consistent with prior TAM studies, they had to rate the statements on a seven-point ordinal Likert scale, where 1 = strongly disagree, 2 = moderately disagree, 3 = slightly disagree, 4 = neutral, 5 = slightly agree, 6 = moderately agree, and 7 = strongly agree (Davis et al., 1989). Afterwards, the participants were asked to rate their prior experience with AI technology in their job. The experience was rated on a 0-10 scale from 0 = very negative to 10 = very positive. Participants with no prior experience were asked to rate their experience with a 5.

Finally, the third stage was concluded with demographic-related questions regarding participants' gender, age, and education level. Afterwards, the participants were informed that the experiment had come to an end and were thanked for their participation.

3.2 Sampling procedure

The research was quantitative in nature, and to generate data an online survey was conducted using Qualtrics XM (Qualtrics, Provo, UT; 2018) during February 2020. Internet-based surveys provide researchers with a time-saving and cost-effective way of reaching large numbers of participants with specific characteristics (Wright, 2005), and most of the recent TAM research has used online surveys to gather data (Alharbi & Drew, 2014). The survey was distributed among personal networks and via social media, and in order to obtain a greater number of participants with prior experience with AI within the audit and tax industry, the survey was also posted on the online participant recruitment platform Prolific.co [1].

3.3 Variables

An overview of the variables that were used in the analysis are presented below.

3.3.1 TAM variables

Behavioral Intention (BI): this variable is the dependent variable in all the regressions, except the fourth, and represents the individual employee's behavioral intention to use AI technology during his job. The statements used to measure the participants' attitudes are adopted from Davis et al. (1989). In total, four different statements were used to capture the participants' behavioral intention. These statements can be found in table 3.1. The value of the variable is the participant's average score over the four statements.

Perceived Usefulness (PU): this variable is an explanatory variable in all the regressions, except the fourth, and represents the individual employee's perceived usefulness of AI technology while performing their job. The statements used to measure the participants' attitudes are adopted from Davis (1989) and Davis et al. (1989). In total, four different statements were used to measure the participants' perceived usefulness. These statements can be found in table 3.1. The value of the variable is the participant's average score over the four statements.

Perceived Ease Of Use (PEOU): this variable is an explanatory variable in all the regressions and represents the individual employee's perceived ease of use of AI technology during their job. The statements used to measure the participants' attitudes are adopted from Davis (1989) and Davis et al. (1989). In total, three different statements were used to capture the participants' perceived ease of use. These statements can be found in table 3.1. The value of the variable is the participant's average score over the three statements.

3.3.2 Social influence variables

Variables related to social influence capture the degree to which an individual employee perceives that important others think they should or should not use AI tech-

[1] Prolific.co is an online participant recruitment platform, which enables you to recruit participants with specific criteria. In this research, the following filters were applied: active in tax industry, active in audit industry, and prior experience with AI. https://www.prolific.co/

nology during their job. In this research, social influence is divided into two different processes:

Compliance (COM): this variable is an explanatory variable in all the regressions. Compliance captures the employee's behavior when a colleague wants them to exhibit specific behavior, and this colleague is in a position to reward the behavior or punish the non-behavior. Two different statements were used to measure the participants' susceptibility to compliance. These statements can be found in table 3.1. The value of the variable is the participant's average score over the two statements.

Image (IMA): this variable is an explanatory variable in all the regressions. Image represents the degree to which an employee believes that using AI technology will elevate their status in their social environment. In total, two different statements were used to capture participants' susceptibility to image. These statements can be found in table 3.1. The value of the variable is the participant's average score over the two statements.

All the items related to these processes were adopted from (Venkatesh & Davis, 2000). The statements used in the survey can be found in table 3.1.

3.3.3 Trust variables

Variables related to trust represent the individual employee's social emotion that affects the interaction between the use of AI technology and the employee during their work (Rempel et al., 1985). In this research, trust is divided into two different processes:

Technological trust (TECH): this is an explanatory variable in all the regressions. Technological trust represents the individual employee's feelings regarding their interaction with AI technology driven by their confidence in the underlying technology. In total, two different statements were used to capture participants' susceptibility to technological trust. These statements can be found in table 3.1. The value of the variable is the participant's average score over the two statements.

Behavioral uncertainty (BEHA): this is an explanatory variable in all the regressions. Behavioral uncertainty represents the individual employee's perceived relationship with their employer influenced by AI technology. In total, two different statements were used to capture the participants' susceptibility to behavioral uncertainty. These statements can be found in table 3.1. The value of the variable is the participant's average score over the two statements.

The items related to technological trust were adopted from Rempel et al. (1985) and Haenlein and Kaplan (2019), and the items related to behavioral uncertainty were adopted from Brougham and Haar (2018) and Huang et al. (2019). The statements used in the survey can be found in table 3.1.

3.3.4 Experience variables

In order to test the hypotheses related to the participants' prior experience with AI, the survey was concluded with a question regarding their prior experience with AI in their job. In this question, participants were asked to rate their prior experience with AI on a 0-10 scale. This resulted in the following experience-related variables:

Inexperienced (INEXP):this is an explanatory variable in all the regressions. *INEXP* is a dummy variable that indicates whether the participant has had prior experience with AI within their job. Participants who did not have prior experience, or were not sure if they had prior experience, were asked to rate their prior experience with a 5. Moreover, participants who rated their prior experience with a 5 were grouped into the inexperience category.

$$INEXP = \begin{cases} 0, & \text{if participant has prior experience with AI} \\ 1, & \text{if participant has no prior experience with AI} \end{cases} \tag{3.1}$$

Experience (Experience): this is an explanatory variable in all the regressions. Experience is a categorical variable with three different categories. Participants with a score between 0 and 3 were pooled in the Negative experience group; participants with a score between 4 and 6 were pooled in the Neutral experience group; and participants with a score between 7 and 10 were pooled in the Positive experience group.

$$Experience = \begin{cases} 0, & \text{if participant has had a negative prior experience with AI} \\ 1, & \text{if participant has had a neutral prior experience with AI} \\ 2, & \text{if participant has had a positive prior experience with AI} \end{cases} \tag{3.2}$$

3.3.5 Control variables

In accordance with previous TAM research, the following control variables are used in the analyses (Alharbi & Drew, 2014; Ooi & Tan, 2016):

Gender (Female): this variable is a dummy variable representing the participant's gender.

$$Female = \begin{cases} 0, & \text{if participant is a male} \\ 1, & \text{if participant is a female} \end{cases} \tag{3.3}$$

Age (Age): this variable is a categorical variable representing the participant's age.

$$Age = \begin{cases} 0, & \text{if Less than 25 years old} \\ 1, & \text{if 25-30} \\ 2, & \text{if 30-40} \\ 3, & \text{if 40-50} \\ 4, & \text{if Above 50 years old} \end{cases} \tag{3.4}$$

Education (Educ):this variable is a categorical variable representing the participant's highest level of educational attainment. This variable has three different categories: Low, Medium, and High. Participants whose highest educational attainment was less than a high school diploma or a high school degree were pooled in the Low category. Participants whose highest educational attainment was a bachelor's degree were pooled in the Medium category. Participants whose highest educational attainment was a master's degree or a doctorate were pooled in the High category.

$$Educ = \begin{cases} 0, & \text{if Low education} \\ 1, & \text{if Medium education} \\ 2, & \text{if High education} \end{cases} \tag{3.5}$$

Table 3.1: Overview of all variables used.

TAM variables	**Items**
Behavioral intention to use	Assuming I have access to the use of AI, I intend to use it Given that I have access to the use of AI, I predict that I would use it I intend to increase my use of AI technology in the future I believe my interest toward AI technology will increase in the future
Perceived usefulness	I think that using AI technology would enhance the effectiveness of my job I think that the use of AI technology would be useful in my job I think that using AI technology in my job would increase my productivity I think that using AI technology would improve my performance in my job
Perceived ease of use	Interacting with AI technology would not require a lot of mental effort I think that working with AI technology is as easy as working with humans Learning how to use AI technology would be easy for me
Social influence variables	**Items**
Compliance	Since the management team would like to implement the AI technology, I should use the tool Since my manager would like to implement the AI technology, I should use the tool
Image	Using AI technology would give me more prestige I think that using the AI technology will strengthen my social status
Trust variables	**Items**
Technological Trust	Because of too many uncertainties, I cannot trust in the adequate functioning of AI technology I think that AI technology is understandable and provides logic output I believe that AI technology is objective and without biases I think that AI technology is unlikely to make mistakes
Behavioral Uncertainty	I think that my job can be replaced by AI technology in the near future I am worried about my future in my organization due to AI technology replacing employees
Experience variable	**Items**
Experience	Please rate your prior experience with AI in your job
Control Variables	**Items**
Gender	Male Female Other
Age	Less than 25 25-30 31-40 41-50 Above 50
Education	Low Medium High
Note. Participants had to rate all a 0-10 scale.	items on a 1-7 Likert-scale, except Experience which was rated on

3.4 Analyses

The statistical software STATA was used for the statistical analysis. Since the dependent variables are based on multiple items, they were treated as continuous variables. As a result, all hypotheses were tested with an ordinary least squares (OLS) regression. The significance of the coefficients was based on a two-tailed test, unless reported otherwise, since an effect in the untested direction is not negligible. Therefore, p-values up to α=0.10 are reported. The required assumptions that need to hold are explained and tested in Appendix B, and the models used to test the hypotheses are specified in section 4.3.

4

Results

This chapter discusses the results of the analysis. First, an overview of the sample and the participants is provided, and the reliability of the constructs is then checked. Subsequently, the hypotheses is tested and the regression results are described. The chapter concludes with a robustness check of the results.

4.1 Descriptive statistics

In total, 238 participants participated in the survey, but 39 were omitted because they did not finish the survey. Hence, 199 participants were usable for analysis. An overview of the demographic characteristics of the sample can be found in table 4.1. The majority of the sample consisted of males (56.3%), of whom 105 were below the age of 31 (52,8%). Most of the participants were highly educated (53.3%) and had prior experience of AI in their job (61.3%). A large part of the sample rated their prior experience with AI as 'Neutral' (54.8%). An overview of the demographic statistics can be found in table 4.1.

Multi-item scales were used to fully capture the conceptual meanings of the constructs (Nunnally, 1994; Schwab, 2017). Participants had to rate all items on a seven-point Likert scale from 1 = strongly disagree to 7 = strongly agree, except experience-related items, which were rated on an 11-point scale from 0 = Negative to 10 = Positive, and 5= No prior experience/Neutral. The descriptive statistics of the attitudes per construct can be found in table 4.2. On average, all seven-point Likert scale variables, except *IMA*, have a mean above the midpoint 4.00. Moreover, the highest standard deviation is 1.558, which indicates a narrow spread around the mean. However, more variation in the attitudes is observed once the variable scores are filtered by the participants' prior experience and sentiment related to this prior experience. An overview of the descriptive statistics of the variables can be found in table 4.2.

To test for differences between employees with prior experience compared to employees without prior experience, a Mann-Whitney U test was conducted. Under the null hypothesis, there is no difference between the groups. But, the result showed a p-value of 0.0304 and therefore it can be concluded that the *BI* mean for employees with prior experience compared to employees without prior experience is statistically different at a 5% level of significance. The Kruskal-Wallis test was also conducted, which ascertains whether employees with different sentiments related to their prior experience come from the same population. Under the null hypothesis, the median of each group is equal. Nonetheless, the result of the test showed a p-value of 0.0001 and therefore it can be said that a significant difference exists between employees driven by their sentiment at a significance level of 1%.

Table 4.1: Descriptive demographic statistics of the participants.

Freq. (%)	
Gender	
Male	112 (56.3)
Female	87 (43.7)
Age	
Less than 25	24 (12.1)
25-30	81 (40.7)
31-40	55 (27.6)
41-50	16 (8)
Above 50	23 (11.6)
Education	
Low	35 (17.6)
Medium	58 (29.1)
High	106 (53.3)
Experience	
Negative	21 (10.6)
Neutral	109 (54.8)
Positive	69 (34.7)
Inexperience	
Prior experience	122 (61.3)
No prior experience	77 (38.7)

Note. N(total) = 199

Table 4.2: Descriptive statistics of the variables.

Variables	N	mean	sd
BI	199	5.632	1.051
Prior experience	122	5.754	0.988
No prior experience	77	5.438	1.123
Negative	21	5.048	1.582
Neutral	198	5.454	1.004
Positive	69	6.091	0.715
PU	199	5.714	1.008
Prior experience	122	5.785	0.934
No prior experience	77	5.601	1.112
Negative	21	5.214	1.256
Neutral	198	5.569	1.052
Positive	69	6.094	0.716
PEOU	199	4.782	0.982
Prior experience	122	4.833	0.999
No prior experience	77	4.701	0.956
Negative	21	4.778	0.770
Neutral	198	4.602	0.964
Positive	69	5.068	1.012
COM	199	5.369	1.157
Prior experience	122	5.307	1.149
No prior experience	77	5.468	1.171
Negative	21	4.976	1.178
Neutral	198	5.427	1.128
Positive	69	5.399	1.190
IMA	199	3.947	1.306
Prior experience	122	4.045	1.321
No prior experience	77	3.792	1.276
Negative	21	3.881	1.474
Neutral	198	3.826	1.227
Positive	69	4.159	1.365
TECH	199	4.686	1.127
Prior experience	122	4.699	1.111
No prior experience	77	4.666	1.160
Negative	21	4.071	1.253
Neutral	198	4.638	1.113
Positive	69	4.949	1.039
BEHA	199	4.678	1.558
Prior experience	122	4.389	1.604
No prior experience	77	5.136	1.371
Negative	21	4.667	1.653
Neutral	198	4.876	1.478
Positive	69	4.370	1.622

4.2 Reliability of constructs

To assess the reliability in terms of internal consistency of the multiple items per construct, a Cronbach's alpha reliability test was performed. The commonly used threshold for such a test is 0.7. As can be seen in table 4.3, all items, except *PEOU*, exhibited strong psychometric properties, as all Cronbach's alpha coefficients exceeded the 0.7 threshold. In addition, the Average Variance Extracted (AVE) was calculated. The latent factors accounted for a substantial amount of the variance in the measurement items, since all variables except *PEOU* exceeded the threshold of 0.5 (Hair, Black, Babin, Anderson, & Tatham, 1998). The AVE values are in line with conclusions based on the values of the Cronbach's alphas. Finally, we checked to see whether the removal of a *PEOU*-related item would improve its Cronbach's alpha and AVE, but the deletion of one of the items did not solve the low alpha or AVE. Hence, section 4.3, robustness tests that solely included the item *PEOU3* in the regressions were performed.

Table 4.3: The internal consistency of the variables measured by Crohnbach's alpha and average variance extracted (AVE).

Variables	**Alpha**	**AVE**
BI	0.90	0.78
PU	0.87	0.61
PEOU	0.67*	0.41*
COM	0.86	0.75
IMA	0.72	0.57
TECH	0.80	0.50
BEHA	0.72	0.57

* Does not pass the threshold.

4.3 Testing the hypotheses

To compare the relative impact of the effects of the different constructs on *BI* and *PU*, the standardized values of the OLS estimates were used in all the regressions. In this way, the unit of measurement were standard deviations regardless of the original measurement.

4.3.1 Hypothesis 1

The first hypothesis was split into five sub-hypotheses. In all of these, *BI* was the dependent variable. To test the hypotheses, the following linear regression model was estimated:

$$BI = \beta_0 + \beta_{PU}PU_i + \beta_{PEOU}PEOU_i + \beta_{COM}COM_i + \beta_{TECH}TECH_i + \beta_{BEHA}BEHA_i + \beta_z Z_i + \varepsilon$$

where Z indicates the control variables and ε the error term.
All the sub-hypotheses were phrased in terms of the expected outcome instead of the statistical null hypotheses:

$H1a : \beta_{PU} \ \ > 0$
$H1b : \beta_{PEOU} > 0$
$H1c : \beta_{COM} \ \ > 0$
$H1d : \beta_{TECH} > 0$
$H1e : \beta_{BEHA} < 0$

The first column of table 4.4 summarizes the results of the first hypothesis related to the relationship between an employee's *BI* to use AI and their *PU*, *PEOU*, susceptibility to compliance, perceived technological trust, and perceived behavioral uncertainty. Consistent with much prior research, the coefficient of *PU* is positive as expected and significant at 1% level of significance. Hence, it can be stated that an increase of one standard deviation in *PU* increases *BI* by 0.685 standard deviations, ceteris paribus. This effect is significant at 1% level of significance. Also, the coefficient of *PEOU* is positive as expected, but is insignificant at 10% level of significance. Because hypothesis 1b is a directional hypothesis, it is justified to test the hypothesis one-sided. The result of the one-sided t-test still shows no significant effect of *PEOU* on *BI* at a significance level of 10%. The p-value of *PEOU* is 0.6591. Moreover, the coefficient of *COM* is positive as expected and significant at a 10% level of significance. Thus, it can be stated that an increase of one standard deviation in *COM* increases *BI* by 0.123, ceteris paribus. This effect is significant at a 10% level of significance. Furthermore, the coefficient of *TECH* is positive as expected and significant at a 10% level of significance. Hence, it can be stated that an increase of one standard deviation in *TECH* increases *BI* by 0.111, ceteris paribus. This effect is significant at a 10% level of significance. Finally, the coefficient of *BEHA* is negative as expected and is significant at a 1% level of significance. It can therefore be concluded that an increase of one standard deviation in *BEHA* decreases *BI* by 0.151, ceteris paribus. This effect is significant at a 1% level of significance.

As an indicator of the fit of the linear model, the F-statistic of the overall significance is included in table 4.4. The F-test assesses the joint significance of the coefficients—that is, it compares a model without any explanatory variables (intercept-only model) to the specified model used in the regression. Under the null hypothesis, the fit of both models are equal. If the null hypothesis can be rejected, it can be concluded that the model that has been used in the regression provides a better fit than the intercept-only model. Thus, in the final row of table 4.4, the F-value is 29.76 which is significant at 1% level of significance.

4.3.2 Hypothesis 2

To further investigate the apparent difference in the acceptance of AI for experienced compared to inexperienced employees. It was tested whether the effects of the constructs were different for experienced compared to inexperienced employees. In this regression, *BI* was the dependent variable and *INEXP* was included as a moderator. Hence, the following linear regression model was estimated:

$$BI \mid INEXP_i = \beta_0 + \beta_{PU} PU_i + \beta_{PEOU} PEOU_i + \beta_{COM} COM_i + \beta_{TECH} TECH_i + \beta_{BEHA} BEHA_i + \beta_z Z_i + \varepsilon$$

where Z indicates the control variables and ε the error term.

All the sub-hypotheses related to inexperienced compared to experienced employees are phrased in terms of the expected outcome instead of the statistical null hypotheses:

H2a : $\beta_{PU}\_exp < \beta_{PU}\_inexp$
H2b: $\beta_{PEOU}\_exp > \beta_{PEOU}\_inexp$
H2c: $\beta_{TECH}\_exp > \beta_{TECH}\_inexp$
H2d: $\beta_{BEHA}\_exp < \beta_{BEHA}\_inexp$

The second column of table 4.4 shows the results of the model for inexperienced employees per construct. It is noted that for employees without prior experience, the coefficient of PU has a positive sign and is significant at a 1% level of significance. Hence, it can be stated that for employees without prior experience, an increase of one standard deviation in PU increases BI by 0.775 standard deviations, ceteris paribus. This effect is significant at 1% level of significance. In the third column of table 4.6 displays the results of the model for employees with prior experience with AI. The results illustrate a positive coefficient of PU at a 1% level of significance. Therefore, it can be said that, for employees with prior experience of AI, an increase of one standard deviation in PU increases BI by 0.628 standard deviations, ceteris paribus. This effect is significant at 1% level of significance. It is apparent from these results that the PU for inexperienced employees is bigger than the PU for experienced employees. To see whether these results were statistically different, a t-test was conducted. The result reported no statistical significant difference between PU_inexp and PU_exp at a 10% level of significance. However, there were reasons to conduct a one-sided test, based on the fact that Taylor and Todd (1995) noted a salient difference between both groups, with PU having a greater impact on BI for inexperienced compared to experienced users. When conducting a one-sided t-test to test whether $PU\_exp < PU\_inexp$, the p-value was equal to 0.1051, close to significance at a 10% level of significance. A greater sample size might cause the result to become significant. This is something that would benefit from further examination in future research.

It is notable that no other variable had a significant effect for employees with no prior experience. For employees with prior experience, the coefficient of $BEHA$ has a negative sign and is significant at a 5% level of significance. Hence, it can be stated that for employees with prior experience, an increase of one standard deviation in $BEHA$ decreases BI by 0.166 standard deviations, ceteris paribus. This effect is significant at 5% level of significance. Again, to test for a statistically significant difference of the effect of $BEHA$ for experienced and inexperienced employees, a t-test was conducted, and the result showed a difference that was statistically significant at 1%, with a p-value of 0.0009. When a one-sided t-test was performed to test whether $BEHA\_exp > BEHA\_inexp$, the p-value was equal to 0.0004. This confirms the expectation based on the findings of Brougham and Haar (2018), who stated that the impact of $BEHA$ on BI would be greater for experienced employees than inexperienced employees. Furthermore, no significant difference was noted in the impact of the variables for experienced compared to inexperienced employees.

The final row in table 4.4 reports F-values of 17.05 and 18.80, both of which are significant at a 1% level of significance. Thus, it can be concluded that the models used in the regressions better fit the data than the intercept-only model.

4.3.3 Hypothesis 3

To further investigate the apparent difference in the acceptance of AI for employees with different sentiments related to their prior experience, the third hypothesis focused on the moderating effect of the employee's sentiment related to their prior experience with AI. This resulted in the following linear regression model being estimated:

$$BI \mid Experience_i = \beta_0 + \beta_{PU}PU_i + \beta_{PEOU}PEOU_i + \beta_{COM}COM_i + \beta_{TECH}TECH_i + \beta_{BEHA}BEHA_i + \beta_z Z_i + \varepsilon$$

where Z indicates the control variables and ε the error term.

In the fourth column of table 4.4, a negative prior experience (*Experience=0*) with AI is represented. In the fifth column, the moderating effect of a neutral prior experience (*Experience=1*) with AI is represented. In the sixth column, the moderating effect of positive (*Experience=2*) prior experience with AI is presented.

As can be seen in the fourth column of table 4.4, for employees who perceived their prior experience as neutral, the coefficient of *PU* has a positive sign and is significant at a 1% level of significance. Hence, it can be stated that for employees with a neutral prior experience of AI, an increase of one standard deviation in *PU* increases *BI* by 0.668 standard deviations, ceteris paribus. For employees who have had a positive prior experience of AI, the coefficient of *PU* has a positive sign and is significant at a 1% level of significance. Consequently, it can be stated that for employees with a positive prior experience of AI, an increase of one standard deviation in *PU* increases *BI* by 0.645 standard deviations, ceteris paribus. Both effects are significant at 1% level of significance. To test whether the effect of *PU* on BI is statistically different for employees with a neutral prior experience compared to those who have had a positive prior experience, a Wald test was performed. However, the result shows that no significant difference is present at a 10% level of significance with a Chi2-value of 0.03 and a p-value of 0.8522. Nonetheless, for employees who rated their prior experience of AI as negative, no significant effect of *PU* was observed at a 10% level of significance. Thus, it can be concluded that there is a difference in effect of *PU* for employees with a neutral or positive prior experience compared to employees with a negative prior experience.

No significant impact of any of the variables was noted for employees who perceived their prior experience as neutral or positive at a 10% level of significance. On the contrary, for employees who have had a negative prior experience, a positive coefficient of *COM* was observed at a 1% level of significance. It can therefore be said that for employees with a negative prior experience of AI, an increase of one standard deviation in *COM* increases *BI* by 0.487 standard deviations, ceteris paribus. Also, a positive coefficient of *TECH* was observed at a 1% level of significance. Thus, it can be stated that for this group, an increase of one standard deviation in *TECH* increases *BI* by 0.866 standard deviations, ceteris paribus. Finally, a negative coefficient of *BEHA* was observed at a 1% level of significance. It can therefore be said that for employees with a negative prior experience of AI, an increase of one standard deviation in *BEHA* decreases *BI* by 0.550 standard deviations, ceteris paribus. These effects are all significant at 1% level of significance. No other significant effect of any of the variables was noted for employees with a negative prior experience at a significance level of 10%.

Further, it is noted that the F-values in all models are significant. The reported F-values in the final row of table 4.4 are 15.17, 31.43, and 12.10, which are all significant at a 1% level of significance. Hence, it can be concluded that all models used in the regressions provide a better fit of the data than an intercept-only model.

Table 4.4: Regression results of hypothesis 1, 2, and 3.

VARIABLES	(1) **BI**	(2) **INEXP=1**	(3) **INEXP=0**	(4) **Negative**	(5) **Neutral**	(6) **Positive**
PU	0.685***	0.775***	0.628***	0.240	0.668***	0.645***
	(0.0622)	(0.0902)	(0.0748)	(0.169)	(0.0863)	(0.0991)
PEOU	0.0185	0.0572	-0.00358	-0.0332	0.0387	-0.0526
	(0.045)	(0.067)	(0.0615)	(0.202)	(0.0642)	(0.0522)
COM	0.123*	0.0731	0.141	0.487***	0.103	0.0869
	(0.0669)	(0.082)	(0.0877)	(0.145)	(0.0737)	(0.0736)
TECH	0.111*	0.0273	0.137	0.866***	0.0481	-0.0173
	(0.0663)	(0.0813)	(0.0912)	(0.202)	(0.0705)	(0.0623)
BEHA	-0.151***	-0.0645	-0.166**	-0.550***	-0.0459	-0.0831
	(0.0535)	(0.075)	(0.0689)	(0.151)	(0.0636)	(0.0629)
Constant	-0.0823	-0.311	0.0317	-1.702	-0.272	0.0125
	(0.138)	(0.216)	(0.165)	(1.002)	(0.172)	(0.199)
Control variables	YES	YES	YES	YES	YES	YES
Observations	199	77	122	21	109	69
R-squared	0.662	0.752	0.597	0.908	0.671	0.519
F-statistic	29.76	17.05	18.80	31.43	15.17	12.10

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.3.4 Hypothesis 4

As can be seen in the first column of table 4.4, the first regression confirm that an employee's *PU* of AI is the construct with the biggest impact on the employee's *BI* to use AI. Investigating this construct in more detail will therefore provide further insight. Hence, the second hypothesis has *PU* as a dependent variable and was split into four sub-hypotheses. To test the hypotheses, the following linear regression model was estimated:

$$PU = \beta_0 + \beta_{PEOU} PEOU_i + \beta_{COM} COM_i + \beta_{IMA} IMA_i + \beta_{TECH} TECH_i + \beta_z Z_i + \varepsilon$$

where Z indicates the control variables and ε the error term.
All the sub-hypotheses are phrased in terms of the expected outcome instead of the statistical null hypotheses:

$H4a : \beta_{PEOU} > 0$
H4b: $\beta_{COM} > 0$
H4c: $\beta_{IMA} > 0$
H4d: $\beta_{TECH} > 0$

table 4.5 summarizes the results of the fourth hypothesis related to the relationship between an employee's *PU* of the use AI and their *PEOU*, susceptibility to compliance, susceptibility to image, and perceived technological trust. The coefficient of *PEOU* is positive as expected and significant at 1% level of significance. It can therefore be stated that an increase of one standard deviation in *PEOU* increases *PU* by 0.156 standard deviations, ceteris paribus. This effect is significant at 1% level of significance. Furthermore, the coefficient of *COM* is positive as expected and significant at 1% level of significance. Hence, it can be stated that an increase of one standard deviation in *COM* increases *PU* by 0.301, ceteris paribus. This effect is significant at a 1% level of significance. Moreover, the coefficient of *IMA* is positive as expected; however, it is insignificant at 10% level of significance. The coefficient of *TECH* is also positive as expected and significant at 1% level of significance. Thus, it can be concluded that an increase of one standard deviation in *TECH* increases *PU* by 0.330, ceteris paribus. This effect is significant at a 1% level of significance.

The F-statistic in table 4.5 reports an F-value of 9.19, which is significant at a 1% level of significance. Thus, it can be concluded that the model used in the regression better fits the data than the intercept-only model.

Table 4.5: Regression results of hypothesis 4.

	(1)
VARIABLES	**BI**
PEOU	0.156***
	(0.0584)
COM	0.301***
	(0.0766)
IMA	0.0364
	(0.0564)
TECH	0.330***
	(0.0699)
Constant	0.109
	(0.223)
Control variables	YES
Observations	199
R-squared	0.423
F-statistic	9.19

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.3.5 Summary of results

To summarize, table 4.6 and table 4.7 provide an overview of the hypotheses and their results.

Table 4.6: Results of the tested effects of hypotheses 1, 2, and 4.

H1	**Sign**	**Significance**
$\beta_{PU} > 0$	Yes	Yes
$\beta_{PEOU} > 0$	Yes	No
$\beta_{COM} > 0$	Yes	Yes
$\beta_{TECH} > 0$	Yes	Yes
$\beta_{BEHA} < 0$	Yes	Yes
H2		
$\beta_{PU}\_exp < \beta_{PU}\_inexp$	Yes	No
$\beta_{PEOU}\_exp > \beta_{PEOU}\_inexp$	Yes	No*
$\beta_{TECH}\_exp > \beta_{TECH}\_inexp$	Yes	No
$\beta_{BEHA}\_exp < \beta_{BEHA}\_inexp$	Yes	Yes
H4		
$\beta_{PEOU} > 0$	Yes	Yes
$\beta_{COM} > 0$	Yes	Yes
$\beta_{IMA} > 0$	Yes	No
$\beta_{TECH} > 0$	Yes	Yes

Note. *Close to significance (p=0.1051).

Table 4.7: Results of the tested effects of hypothesis 3.

H3	**Direction**	**Significance**
Difference between the sentiments of PU <>0	Neg <Neu, Pos	Yes
Difference between the sentiments of PEOU <>0	Neu >Neg, Pos	No
Difference between the sentiments of COM <>0	Neg >Neu, Pos	Yes
Difference between the sentiments of TECH <>0	Neg >Neu, Pos	Yes
Difference between the sentiments of BEHA <>0	Neg <Neu, Pos	Yes

4.4 Robustness check

4.4.1 PEOU3

In section 4.2, it was noted that *PEOU* did not pass the reliability tests. Hence, to check for robustness of the results given in section 4.3, the same regressions were conducted with statement *PEOU3* only, instead of the average score of the three *PEOU*-related questions. *PEOU3* is the most widely used *PEOU*-related question in prior research. In addition, a small amount of change in wording was needed to match this question with the topic of this research. As a result, *PEOU3* was selected to check the robustness of the results described in section 4.3. All regression results can be found in Appendix C. In order to test for differences between the outcomes of regressions, including all *PEOU*-related questions, compared to regressions with solely *PEOU3*, several Wald-tests were conducted. In the regressions used to test the first, second, and third hypotheses, the outcomes of the regressions were not statistically different at a 10% level of significance. In the fourth regression, the Wald test showed a Chi2 value of 1.13, which has a p-value of 0.0291. This implies a statistically significant difference between both effects at a significance level of 5%. To obtain a more detailed insight into the difference of the effect, both the effects were standardized to compare the difference in impact on *BI*. The effect of *COM_all* was 0.3013, and the effect of *COM_PEOU3* was 0.2765, ceteris paribus. Both effects are statistically significant at a significance level of 1%. Hence, the difference between both effects is 0.0248 *BI* standard deviations, ceteris paribus. Nonetheless, this difference does not change the outcome of hypothesis 4b.

5

Discussion and Conclusion

In this chapter, the main findings of the analyses are discussed in light of the theoretical model and formulated hypotheses. The managerial implications are then highlighted, the limitations of the study and recommendations for future research are set out, and conclusions are drawn.

5.1 Theoretical implications

The primary objective of this study was to examine which factors drive individual employees' acceptance of AI-driven tools in terms of behavioral intentions. During the study, a core model based on the original TAM (Davis et al., 1989) was used. This model established relationships between PU, PEOU, and BI to use. The TAM model was extended with two social influence-related factors: compliance and image. Two trust-related factors were also added to the research model: technological and behavioral uncertainty. As a secondary objective, the moderating effect of prior experience of AI technology on employees' drivers of behavioral intentions was investigated. Finally, a better understanding of employees' individual PU of AI-driven tools—the biggest driver of BI to use—was studied.

Employees' individual behavioral intention to use AI-driven tools as a function of perceived usefulness, perceived ease of use, compliance, technological trust, and behavioral uncertainty

Consistent with most prior TAM and TRA research (Alrafi, 2007; Davis et al., 1989; Fishbein & Azjen, 1975), PU had a significant positive effect on employees' individual BI to use. Perceived usefulness was even found to have the biggest impact on BI to use, which supports existing research (e.g., Alsabawy et al. (2016); Davis et al. (1989); Pavlou (2003); Venkatesh and Davis (2000)).

In contrast, no significant effect of PEOU on employees' individual BI to use was found. This result concurs with Gefen (2000), who stated that the effect of PEOU depends on the nature of the task the technology is applied to. Hence, a possible explanation for the limited importance of PEOU on employees' acceptance of AI-driven tools may be that these tools replace job tasks rather than requiring a higher competence and cognitive capacity from employees. Since AI is automated, it relieves employees of highly demanding tasks in most cases, which is likely to increase PEOU; but it might cause a simultaneous decrease in employees' intrinsic motivation to use the tools due to decreasing job satisfaction and mode confusion (Hollnagel & Woods, 2005; Parasuraman & Riley, 1997). Furthermore, in accordance with the findings of Venkatesh et al. (2012), a significant positive effect of compliance was noted on employees' individual BI to use. Additionally, two trust-related constructs were investigated: technological and behavioral uncertainty. The findings of this research indicate a significant positive effect of technological trust on employees' individual BI to use AI-driven tools. This finding corresponds with the idea that a general understanding of the underlying technology of AI-driven tools positively affects employees' BI to use (Featherman & Pavlou, 2003; Gefen, 2000; Gefen et al., 2003b). Conversely, a significant negative effect of behavioral uncertainty was found on employees' individual BI to use AI-driven tools. This is consistent with the theory stated by Brougham and Haar (2018), which says that employees are likely to perceive the introduction of AI-driven tools as a substitution for human labor. Consequently, they might feel undervalued by their employer and decrease their perceived job security.

The moderating effect of prior experience with AI technology on the determinants of employees' individual behavioral intention to use AI-driven tools as a function of perceived usefulness, perceived ease of use, compliance, technological trust, and behavioral uncertainty

Mirroring the findings of Taylor and Todd (1995), it was noted that PU has a greater impact on usage intentions for employees with no prior experience compared to employees with prior experience of AI-driven tools. It was also found that sentiment related to prior usage changes the impact of usefulness on usage intentions. For employees with neutral or positive prior experience a positive direct effect of usefulness was noted, whereas no significant effect was noted for employees with a negative prior experience.

Furthermore, contrary to the expected effect of experience on procedural knowledge (Choi et al., 2010; Gefen et al., 2003a, 2003b; Yu et al., 2005), no significant difference was found between the impact of PEOU for employees with prior experience compared to employees with no prior experience. Also, the effect of ease of use was not affected by employees' sentiment related to their prior experience with AI. Again, a possible explanation for the limited influence of experience on PEOU might be that that these AI-driven tools replace job tasks rather than requiring a higher competence and cognitive capacity from employees (Hollnagel & Woods, 2005; Parasuraman & Riley, 1997). Therefore, the positive effect of experience on procedural knowledge might be limited.

It was also observed that employees with a negative prior experience are more susceptible to compliance compared to employees with neutral or positive prior experience. This affirms the idea that employees are likely to behave in a manner consistent with that of the people who are important to them, even though their behavior may not always be favorable to them (Venkatesh & Davis, 2000). The effect of compliance might diminish for employees with a neutral or positive experience, since their sense of the usefulness of the AI-driven tools is likely to increase.

Contrary to the findings of Taylor and Todd (1995), no significant difference was found in the effect on usage intentions of technological trust between experienced compared to inexperienced employees. Taylor and Todd (1995) suggest a greater impact of technological trust for experienced compared to inexperienced employees, due to increased procedural knowledge. However, as described above, it might be that procedural knowledge plays a small part in employees' usage intentions of AI-driven tools. Nonetheless, it was noted that the effect of technological trust on usage intentions had a greater impact for employees with a negative prior experience compared to employees with a neutral or positive prior experience. Moreover, technological trust is the biggest predictor for employees with a negative prior experience of their BI to use AI-driven tools. This supports the findings of Ghazizadeh et al. (2012), suggesting that if employees rely on a technology that fails, their trust in the underlying technology decreases and negatively affects their usage intentions. At the same time, this indicates that if these employees' technological trust increases (e.g., the technology no longer fails), their positive direct effect on usage intentions is much bigger compared to employees with neutral or positive prior experience.

Finally, it was noticed that behavioral uncertainty has a negative effect on usage intentions for employees with prior experience, but has no effect on usage intentions for employees with no prior experience—that is, an effect was only observed for employees with a negative prior experience. In accordance with the findings of Brougham and Haar (2018), the effect of behavioral uncertainty increases when employees' awareness regarding the capabilities of AI technology increases. It is possible that employees with prior experience of AI were aware of the threat of their job being replaced by AI-driven tools, and their prior experience with AI was therefore negatively affected. Nonetheless, this research did not intend to comprehensively determining the factors driving employees' prior experience, and so a better understanding of the drivers of their prior experience with AI could not be provided.

Employees' individual perceived usefulness of AI-driven tools as a function of perceived ease of use, compliance, image, and technological trust

Despite the insignificant effect of ease of use on usage intentions, a positive direct effect of PEOU on usefulness was found. This indicates that its relevance should not be downplayed since employees' positive appraisal of AI-driven tools significantly influence their usage intentions. Also, this result enhances the idea that the replacement of job tasks might decrease employees' intrinsic motivation to use the AI-driven tools, but at the same time it might positively affect their PU of the AI-driven tools (Gefen, 2000). As a result, the direct positive effect of PEOU on usage intentions might be incorporated by the effect of usefulness on usage intentions.

Furthermore, compliance was found to have a positive direct effect on usefulness. This supports the idea of Venkatesh and Davis (2000) that employees are susceptible to colleagues' capabilities of rewarding their use or punishing their resistance to the use of AI-driven tools.

In contrast, no significant effect of image on PU was found. This means either the hypothesized effect does not exist in reality, or due to some other factor(s) it was not reflected in this experiment. Nonetheless, a lack of a significant direct effect does not imply that image can be ignored. According to Beldad and Hegner (2018), the widespread use of AI technology among peers might also positively affect employees' level of confidence or trust in the underlying technology.

Consistent with prior research (Featherman & Pavlou, 2003; Gefen, 2000; Gefen et al., 2003b), a positive direct effect of technological trust was noted on usefulness. Trust in the underlying technology was also found to have the greatest direct impact on usefulness. A possible explanation for the size of the effect on usefulness might be that it partly incorporates the effects of compliance and image. Employees' trust in a technology is often defined by the extent to which their peers expect them to trust the technology and from their perception of the technology's popularity (Beldad & Hegner, 2018).

5.2 Managerial implications

From a managerial point of view, the implementation of AI-driven tools requires a large investment of time and money. To minimize the potential adverse effects and costs, it is valuable to predict whether the new technology will be accepted by employees who are impacted by it. This study contributes to the development of a predictive model for the acceptance of AI among employees. In line with prior research, we conclude that PU has the biggest predictive power, while no predictive mechanism is concluded for PEOU. Nonetheless, PEOU should not be overlooked, since it appears to have a strong predictive power on PU. In addition to the traditional TAM factors, our model was extended with social influence- and trust-related factors, which have received limited attention from researchers in the context of AI technology. Both trust-related factors—technological trust and behavioral uncertainty—showed predictive mechanisms in the individual employee's acceptance of AI. However, for the social influence-related factors, predictive power only appeared for compliance.

It is beneficial to identify which factors enable and which inhibit employee's acceptance of AI-driven technology, in order to take corrective actions to increase acceptability. The findings of this study provide relevant insights into the magnitude and directionality of these factors. When communicating the implementation of an AI-driven tool, a manager should underline the capabilities of AI—the positive effect of PU is likely to encourage employees' acceptance of the new technology. It is apparent that this positive effect of PU is strengthened for employees with a neutral or positive prior experience of AI. In addition, a manager should not neglect the importance of technological trust—by explaining the underlying technology of AI, its unpredictability is diminished, as a result of which employees are likely to be more willing to accept AI-driven tools. It is concluded that this positive effect has more impact for employees with a negative prior experience with AI. In addition, a better understanding of AI technology enforces the positive effect of PU on employees' acceptance. Furthermore, our study shows the positive effect of compliance on employees' acceptance of AI. Hence, when employers communicate the implementation of AI-driven tools in a mandatory manner, employees' acceptance is likely to increase. Employees with a negative prior experience of AI are particularly susceptible to compliance. Also, by being compliant, employees' PU is likely to increase. Moreover, a manager should be cautious about communicating the implementation of AI-driven tools. The findings of this study confirm that the implementation of AI may signal an intention to replace employees. Consequently, employees may feel undervalued, causing them to resist the implementation of AI-driven tools. It is apparent that the inhibiting effect of behavioral uncertainty is strengthened for experienced compared to inexperienced employees.

5.3 Limitations and future research

The present research has several limitations that future research should address. First, there was a bias toward younger people in our study group, with 52.8% of them below the age of 31. Several studies report that older participants are more resistant to the adoption of new technologies (Brougham & Haar, 2018; Venkatesh, Morris, Davis, & Davis, 2003). In addition, 53.3% of the participants were highly educated, making them more likely to be AI literate than participants with low or medium levels of education. Hence, it cannot be claimed that the sample used in this research is representative. Future research should therefore aim to use a more representative sample..

A second limitation arises from the fact that the survey participants were asked to imagine they were either a VAT expert or an auditor. Afterwards, they faced questions regarding the possible implementation of the AI-driven tool, and although the participants had to respond as if they were in real situations, the fact that they were in a hypothetical situation may have had biasing effects (Fitzsimons & Shiv, 2001). The fictitiousness of the employees' situation also meant that there were no stakes involved for the participants—for example, job insecurity or dissatisfaction. The fact that the impact of the implementation of the AI tool could not have adverse effects on the participants in reality might have decreased the importance that they attached to the imagined employees' situation, diminishing the potential cognitive dissonance. Hence, future research should use a non-fictitious AI-driven tool that can be used by the participants in their actual jobs, and that can replace some of their daily work tasks. In this way, the biasing effects could be limited.

The third limitation is that this cross-sectional research did not take into account that participants' adoption attitudes might change over time. Currently, the adoption of AI technology is in its beginning phase, and adoption is an ongoing process (Tan, Ooi, Sim, & Phusavat, 2012). It is therefore recommended that future research uses longitudinal data to measure potential changes in adoption attitudes, such as the contingent effect of employees' experience with AI. In this way, short- and long-term adoption behavior can be analyzed, which might facilitate a more comprehensive understanding of the relationships between the different constructs.

The final limitation concerns the use of self-reported values as opposed to objectively measured attitudes. Several previous studies doubted the validity of such subjective measures of the variable, and recommended instead the use of objective measures—for example, real choice data (Szajna, 1996). An additional advantage of using real choice data is that actual behavior can be measured instead of attitudes (Venkatesh & Davis, 2000). Nevertheless, the interchangeability of self-reported versus objective measures remains a controversial point in TAM-based research (Straub, Limayem, & Karahanna-Evaristo, 1995). It is therefore recommended that future research combines different measurement methods to obtain the best possible measures.

5.4 Conclusion

The main goal of this study was to address the main research question: *"Which factors drive the acceptance of AI among employees?"* The study extended the traditional TAM model with two trust-related factors—technological trust and behavioral uncertainty—and two social influence-related factors, compliance and image. To investigate the effect of the drivers, a survey was designed and was completed by 199 participants. Within the survey, participants were presented with a tax- or audit-related case in which their attitude toward acceptance of AI was measured. The participants were asked to respond to 23 TAM-related statements. To investigate the moderating effect of prior experience, the participants were asked to rate their prior experience with AI within their job.

The results of this survey demonstrate that the extended TAM model is a valid model to predict employees' acceptance of AI. It provides valuable insights into the magnitude and directionality of the driving factors. Another significant finding of this study is that acceptance behavior differs for experienced compared to inexperienced employees. The results of this study also indicate that employees' sentiment regarding their prior experience significantly affects the magnitude of the driving factors of AI acceptance. Hence, this study can be used by businesses to successfully design implementation strategies for AI-driven tools.

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Appendix A

Survey scenarios

In the survey, the participants were asked to imagine to be a VAT expert or an auditor. In figure A.1, the VAT expert scenario can be found and in figure A.2 the auditor scenario can be seen.

A.1 VAT scenario

Imagine that you are a VAT expert for one of the biggest banks of Europe. You perform manual checks to determine the correctness of tax codes applied to transactions. You spend most time on combining different data points to come to a conclusion on what tax should be levied over specific transactions.

Recently, your management team has noted an opportunity and is thinking about implementing an AI-driven product to (partially) replace the manual categorization of transactions under particular tax codes. The tool processes invoices from the client and checks the tax code. When no potential error is detected the VAT code is automatically determined as correct. If possible errors are detected, the system forwards the invoice for manual review and suggests a correction.

The business value is recognized by the reduction in manual checks and by being more compliant to tax legislation, while reducing the amount of overpaid taxes. However, due to the implementation of the AI-driven product there will be a decrease in the need for human labour.

Effect on your job	Current situation	New situation
Correctness of applied tax codes	85%	95%
% of total time spent on manual VAT checks	60%	0%
% of total time spent on correction errors	0%	20%

Hence, as a result your team has to shrink in size from 10 to 6 FTE.

Figure A.1: VAT scenario used in the survey.

A.2 Auditor scenario

Imagine that you are an auditor for one of the biggest banks of Europe. On a random sample you perform manual controls to determine the riskiness of the transactions in the general ledger. You spend most time on combining different data points to come to a conclusion in which bucket the transaction should be put: high risk, medium risk, or low risk.

Recently, your management team has noted an opportunity and is thinking about implementing an AI-driven product to (partially) replace the manual categorization of the transactions. The tool processes transactions into the general ledger of the client and reviews the degree of riskiness automatically. If a possibly risky transaction is detected, the system forwards the specific transaction for manual review.

The business value is recognized by the reduction in manual controls and by being more in control of risky transactions, while increasing the amount of records checked. However, due to the implementation of the AI-driven product there will be a decrease in the need for human labour.

Effect on your job	Current situation	New situation
Correctness of risky transactions identified	85%	95%
% of total time spent on manual transaction checks	60%	0%
% of total time spent on reviewing risky transactions	0%	20%

Hence, as a result your team has to shrink in size from 10 to 6 FTE.

Figure A.2: Auditor scenario used in the survey.

Appendix B

OLS assumptions

An Ordinary Least Square (OLS) has six key assumptions which are required to hold. If these six assumptions hold, the OLS estimates are considered to be the best linear unbiased. For simplicity, the assumptions are tested for the model used to test the first hypothesis with BI as dependent variable.

B.1 Linearity in parameters

In the case of linear regression, the dependent variable (BI) is assumed to be a linear function of the independent variables (e.g. PU, $PEOU$, and COM) and the error term ε. In order to test for linearity the Cook's D was calculated. However, all observations had a value below 1, which implies that potential outliers do not influence the results. Hence, it can be stated that the parameters are expected to be linear.

B.2 Random sample

The sample used in this research can be considered as drawn randomly from the population. Also, the orders of the questions were randomized and the error terms are random. As a result, this assumption is expected to hold.

B.3 No perfect collinearity

Linear regression assumes that there is no perfect collinearity in the data set, which implies that there should not be a linear relationship present between the independent variables. In table B.1, a correlation matrix of all variables used in the model can be found. The highest correlation (0.7873) was observed between BI and PU, this is in line with the findings of various prior TAM researches (Davis et al., 1989; Egea & González, 2011; Venkatesh & Davis, 2000). Other correlations are negligible. Furthermore, the variance inflation factor (VIF) was also performed to test for multicollinearity, which is almost perfect collinearity. Multicollinearity causes variables to follow the same linear pattern which potentially causes misleading estimates since it inflates the standard errors. As can be seen in table B.2, the mean VIF equals 1.73 and none of the variables has a VIF-value above four, which is commonly used as a rule of thumb. This indicates that no perfect collinearity or multicollinearity is present.

Table B.1: Correlation across all the variables.

Variables	Female	Age	Education	INEXP	Experience	BI	PU	PEOU	COM	IMA	TECH	BEHA
Female	1											
Age	0.0202	1										
Education	-0.2131	-0.2531	1									
INEXP	0.1526	0.1341	-0.2635	1								
Experience	-0.1127	-0.0825	0.0722	-0.3053	1							
BI	-0.0964	0.016	0.2005	-0.1467	0.3353	1						
PU	-0.1066	-0.0215	0.1743	-0.0892	0.2926	0.7873	1					
PEOU	-0.0109	0.1552	0.1018	-0.0656	0.1617	0.2534	0.281	1				
COM	-0.0056	0.1185	-0.0584	0.0676	0.0712	0.4212	0.4295	0.0941	1			
IMA	-0.1159	-0.0505	0.0822	-0.0945	0.0985	0.1928	0.1045	0.0166	0.0255	1		
TECH	-0.0174	0.0563	-0.0305	-0.0144	0.2212	0.471	0.4763	0.2641	0.3386	0.0822	1	
BEHA	0.0846	0.121	-0.2319	0.2342	-0.1085	-0.0484	0.1011	0.0354	0.2351	-0.2567	0.0817	1

Table B.2: Results of the VIF-test for multicollinearity.

Variable	VIF	1/VIF
PU	1.87	0.535166
PEOU	1.18	0.846828
COM	1.36	0.733638
TECH	1.41	0.707068
BEHA	1.17	0.852672
EXP	1.24	0.805546
1.female	1.13	0.885742
age		
2	2.67	0.375193
3	2.53	0.395876
4	1.7	0.586985
5	1.82	0.548951
education		
1	1.99	0.50267
2	2.38	0.420432
Mean VIF		1.73

B.4 Zero conditional mean

To draw ceteris paribus conclusions about how the independent variables affect the dependent variable *BI*, the zero conditional mean assumption needs to hold. This implies that no correlation can be present between the independent variables and the error term. Hence, the error term needs to be exogenous. Nonetheless, there are multiple factors which could cause endogeneity, e.g. outliers, omitted variables, measurement errors or reversed causality.

To test for a possible misspecification in the model, a Ramsey RESET-test was performed. The outcome of the Ramsey RESET-test showed a F(3,186) of 0.0332, which implied that H0 was rejected and that the model contained missing powers. Hence, after transforming the *Education* and *Age* variables into a natural logarithm variable *Log_educ* and *Log_age* the Ramsey RESET-test showed a F(3,186) of 0.0505, which indicated that no misspecification was present in the model at a 5% level of significance.

Another potential factor causing endogeneity is the problem of outliers. But as mentioned in section B.1, a Cook's D test was performed and none of the observations exceeded the value of 1. This indicates that no outlier was present which could potentially harm the results.

B.5 Homoskedasticity

Linear regression analysis requires the data to be homoskedastic, e. g. the error terms should have the same variance given any value of the explanatory variables. If the variance of the error term changes, this is called heteroskedasticity. When heteroskedasticity is present, the linear regression model has heteroskedastic errors and is likely to give incorrect estimates. Hence, to test for homoskedasticity, the Breusch-Pagan was used. The test rejected the null hypothesis for homoskedasticity (Chi2=31.65, p=0.0000). To further analyze the skewness and kurtosis, the White's test was performed. In table B.3, the results can be seen. The outcomes of the test corroborate the result of the Breusch-Pagan test since the null hypothesis for homoskedasticity (Chi2 = 111.05, p=0.0003) is rejected. To correct for potential incorrect estimates, robust standard errors are used in the regression models.

Table B.3: White's test for heteroskedasticity, skewness, and kurtosis.

Source	**Chi2**	**Degrees of Freedom**	**p-value**
Heteroskedasticity	111.05	65	0.0003
Skewness	24.72	11	0.0100
Kurtosis	1.76	1	0.1845
Total	137.53	77	0

B.6 Normality

Linear regression analysis requires the errors to be normally distributed. To test for normality of the error terms, the Smirnov-Kolmogorov test was conducted. The result of the test (p=0.0000) showed that the null hypothesis was rejected, which stated that the error terms were normally distributed. Nonetheless, according to the Central Limit Theorem, the distribution of the sample means automatically approaches a normal distribution when the sample contains more than 30 observations. Hence, the sample is sufficiently large to assume normality of the errors.

Appendix C

PEOU 3

In order to test for robustness of *PEOU*, all regressions were done with item *PEOU3*. In table C.1, the regressions results for hypotheses 1, 2, and 3 can be found. Also, the regression results for hypothesis 4 can be seen in table C.2.

Table C.1: Regression results with PEOU 3 for hypotheses 1, 2, and 3.

VARIABLES	(1) **BI**	(2) **INEXP=1**	(3) **INEXP=0**	(4) **NEU**	(5) **NEG**	(6) **POS**
PU	0.666***	0.738***	0.611***	0.641***	0.323	0.656***
	(0.0557)	(0.0814)	(0.0788)	(0.0731)	(0.249)	(0.123)
PEOU3	0.0585	0.0669	0.0478	0.0745	-0.152	-0.0485
	(0.0467)	(0.0649)	(0.0691)	(0.0589)	(0.282)	(0.0824)
COM	0.109**	0.0543	0.132**	0.0818	0.420*	0.106
	(0.0484)	(0.0792)	(0.0626)	(0.0685)	(0.207)	(0.0696)
TECH	0.113**	0.0357	0.134**	0.0691	0.774**	-0.023
	(0.0489)	(0.0803)	(0.0646)	(0.0707)	(0.291)	(0.0713)
BEHA	-0.140***	-0.00453	-0.186***	-0.0295	-0.496**	-0.106
	(0.0443)	(0.0821)	(0.0577)	(0.0628)	(0.185)	(0.0684)
Constant	-0.176	-0.418*	-0.167	-0.333	-0.782	-0.0195
	(0.170)	(0.230)	(0.269)	(0.203)	(0.657)	(0.325)
Control variables	YES	YES	YES	YES	YES	YES
Observations	199	77	122	109	21	69
R-squared	0.679	0.786	0.619	0.693	0.921	0.536
F-statistic	32.77	19.55	14.77	18.05	9.53	5.39

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.2: Regression results with PEOU 3 for hypotheses 4.

	(1)
VARIABLES	**PU**
PEOU3	0.220***
	(0.0593)
COM	0.277***
	(0.0592)
IMA	0.0466
	(0.056)
TECH	0.322***
	(0.0599)
Constant	0.184
	(0.222)
Control variables	YES
Observations	199
R-squared	0.443
F-statistic	13.51

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1