THE ROLE OF ATTITUDE TOWARDS USE IN THE ACCEPTANCE OF HIGHLY COMPLEX TECHNOLOGY

Towards a Revised Implementation of Attitude in the Technology Acceptance Model

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August 2023

Master's Thesis

to confer the academic degree of

Master of Science

In the Master's Program

Psychology

focus in Technology and Economy

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List of Abbreviations

Abbreviation	Full Expression
HR	Human Resources
AI	Artificial Intelligence
HRM	Human Resource Management
TM	Talent Management
SMS	Skill Management Software
TTF	Task Technology Fit
TOE	Technology Organization Environment
UTAUT	Unified Theory of Acceptance and Use of Technology
TAM	Technology Acceptance Model
HCI	Human-Computer-Interaction
TRA	Theory of Reasoned Action
TPB	Theory of Planned Behavior
PU	Perceived Usefulness
PEU	Perceived Ease of Use
ATT	Attitude Towards Using
TR	Technology Readiness
ATTU-TAM	Attitude Towards Use Technology Acceptance Model
ATTU	Attitude Towards Use
T	Trust Towards Use
AP	Appreciation Towards Use
F	Fairness Towards Use
IAT	Implicit Association Test
IATT	Implicit Attitude Scale
SEM	Structural Equation Model

Abstract

This thesis challenges the Technology Acceptance Model (TAM) for its insufficient focus on attitude. It introduces the acceptance of highly complex technology, particularly Artificial Intelligence-based Skill Management Software in Human Resources. It argues that both the attitude toward the system and the attitude towards the use of the system influence the acceptance of highly complex technology, encompassing active and passive use. The Attitude Towards Use Technology Acceptance Model (ATTU-TAM) is developed based on the final Technology Acceptance Model (Venkatesh & Davis, 1996), incorporating the variable of Attitude Towards Use (ATTU).

To test the ATTU-TAM, an empirical study involving $N = 286$ employees from the DACH (Germany, Austria, Switzerland) region was conducted. It examines the implementation of AI-based Skill Management Software in Human Resources. The research is based on mainly Structural Equation Models and Monte Carlo simulations. The findings reveal that Attitude Towards Use is essential in accepting AI-based Skill Management Software. The ATTU-TAM demonstrates superior power in explaining data and Behavioral Intention compared to various TAM model adjustments. Moreover, it adds a significant amount of additional variance explained for active but particularly passive users. Trust (TT) and Appreciation (AP) towards the use of the system impact the ATTU. Additionally, there are differences in ATTU and its influencing variables between active and passive users.

This research offers an in-depth analysis of the complex dynamics of implementing AI-based Skill Management Software in Human Resources. Furthermore, it validates the development of the ATTU-TAM as a valuable framework for explaining the acceptance of highly complex technologies. Additionally, it emphasizes the importance of ATTU, and shedding light on the nuances of active and passive use.

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The Acceptance of Highly Complex Technology

In the Fourth Industrial Revolution, sophisticated technology is expanding in various fields, such as the economy and daily life (Schwab, 2015). Highly complex technology, for example, Artificial Intelligence (AI), often connotes dystopia or utopia perceptions in media and society (Cools et al., 2022). Some of these technological breakthroughs are implemented with rapid adaptation and high user adoption, such as the current natural language processing program ChatGPT (2023), which had a million users within a few days (Hu, 2023). Others have to cope with solid implementation difficulties, for example, autonomous vehicles (Fraedrich & Lenz, 2016). Due to various challenges for companies in the Fourth Industrial Revolution, such as the implementation of Artificial Intelligence, agility, and the emerging Skill Gap (Oosthuizen, 2022), Human Resources (HR) play a vital role in future business transformations (Rana & Sharma, 2019). This thesis argues that implementing AI-based software in HR significantly contributes to addressing these challenges. Especially the use of AI-based Skill Management Software to close the prevailing Skill Gap, which describes a gap between required and available skills in a company.

While the adoption into business models is straightforward, there are several indices that humans might play a hindering role (Agarwal, 2022; Pillai & Sivathanu, 2020). Although the utility of AI-based software in Human Resources is well-researched (cf. Kaur & Kaur, 2022; Tewari & Pant, 2020), and there are a lot of suitable tools available (cf. Albert, 2019; Michel, 2022), the implementation seems to be lagging behind (Jansen et al., 2020; Seufert et al., 2020).

When new technology is developed or implemented, it is useful to research the Human Factor and their particular needs (Nielsen, 1994). Psychology was one of the first fields to address the broad area of Technology Acceptance, investigating the underlying concepts in accepting a technology to use (Marangunić & Granić, 2015). As a result, various fundamental frameworks of nowadays research, such as the Technology Acceptance Model (TAM; Davis, 1985), have been significantly shaped by psychological concepts.

Through conducting a comprehensive literature review and engaging in a profound theoretical discussion, this thesis presents a challenging perspective on the development and utilization of the TAM. It emphasizes the model's inadequate attention to attitude, stating that in highly complex technology, besides attitude toward the system, attitude towards the use of the system plays a major role in accepting technology. Likewise, those systems are subject to both active and passive use. Active use describes the direct interaction with the technology, while passive use describes the effects of the use of the technology. Subsequently, this thesis introduces the Attitude Towards Use Technology Acceptance Model (ATTU-TAM), adding Attitude Towards Use as a variable. The model is based on the final TAM (Venkatesh & Davis, 1996), establishing an extension in the core model of Technology Acceptance research where the attitude toward the system and towards the use are operationalized separately. Furthermore, active as well passive use can be modulated.

This thesis aims to investigate the acceptance of AI-based Skill Management Software by applying this use-case example to the model, exploring the theoretical discourse, and validating the ATTU-TAM by answering the following research questions. Does ATTU-TAM provide a complex, in-depth view of the Technology Acceptance of implementing AI-based Skill Management Software in Human Resources? Does ATTU-TAM better explain the Technology Acceptance of highly complex systems than the final Technology Acceptance Model and further TAM adjustments? To investigate the proposed questions, this thesis conducted a quantitative online study involving employees within the DACH region

(Germany, Austria, Switzerland), underpinning findings by sophisticated statistical analysis, primarily utilizing a Structural Equation Model and Monte Carlo simulations.

Human Resources in the Fourth Industrial Revolution

„In recent years, information technology has had a profound effect on human resources processes and practices.“ (Stone et al., 2015, p. 216). Studying the challenges and opportunities of the future and present Human Resources (HR), Stone et al. (2015) pointed out that digitalization is a key driver and barrier to modern HR.

While eight years ago, HR tackled the implementation of basic information technology, nowadays, Human Resources is an evolving part of the Fourth Industrial Revolution. It is driven by innovations such as Big Data, Artificial Intelligence (AI), and automatization (Hecklau et al., 2016). Simultaneously, HR is fuelled by changes in the employee generation and new expectations in a modern working environment implementing feedback, open culture, and data-driven decisions (Sivathanu & Pillai, 2018). Moreover, it is in charge of becoming an important strategic business partner in managing and developing human capital. HR faces challenges such as talent acquisition, re-skilling, and cultural agility. (Rana & Sharma, 2019)

The first chapter of this thesis closely examines two of the prevailing challenges in the Fourth Industrial Revolution, the emerging Skill Gap and the Adoption of AI. It draws a picture of HR as a driver to close the Skill Gap by implementing AI-based Skill Management Software, simultaneously as a barrier to adopting highly complex technology.

Facing the Skill Gap

Structurally, embracing new technology demands new skills which are not immediately available. This emerges in two major challenges, skill shortages (insufficient workforce skills) and skill mismatches (qualification-employment disparity). (Brunello & Wruuck, 2021)

In the upcoming years, one of the most challenging tasks for companies will be overcoming this Skill Gap to prevent productivity, innovation, and growth costs in business and society (Bennett & McGuinness, 2009). In 2018 Deloitte Insights described that over 2.5 Million positions remain unfilled and put 2.5 trillion US Dollars at risk over the decade (Giffi et al., 2018). In 2020 on average, 73% of EU firms reported limited availability of skills as a blockade of investments (EIB, 2020).

Big Data & Artificial Intelligence in Human Resources

Nowadays, HR has an immense amount of data. A data-driven approach, by collecting and analyzing this data, leads to better, faster, and more comprehensible decisions (Hacioglu, 2020; Rana & Sharma, 2019). Referring to the term of Big Data, which definition is rather vague, as well still open for discussion. It generally defines data in volume, velocity, and variety, out of different sources, multiple kinds, and increasing rapidly over time (Dahlbom et al., 2020). Additionally, Big Data is often used to name a collection of different technologies, analyzing and managing large amounts of data that humans cannot process (Ullah & Ullah, 2018). One way to use Big Data is by applying AI to simplify, analyze, and gain essential insights through collecting and structuring data (Leary, 2013).

The recent and prevailing trend is AI reshaping HR with innovations such as data mining, machine learning, or deep learning (Tewari & Pant, 2020). Artificial Intelligence is based on machine learning, which means algorithms that parse data, learn from data, and then apply what they learned (Agrawal et al., 2018). AI encompasses the ability to comprehend, reason, learn, and interact with data and can analyze structured and unstructured data, identify pertinent information, contextualize it, and generate hypotheses from it (Crawford, 2021). The actual value of AI for HR is shown in different opportunities across various HR fields (e.g., recruiting, development, talent planning, performance management). AI can automate repetitive and time-consuming processes across all task areas (e.g., analyzing data, contacting applicants) to make space for human-human interactions. (Kaur & Kaur, 2022; Tewari & Pant, 2020)

A study by Baakeel (2020) shows a moderate to strong correlation between the use of AI and the effectiveness of HR functions in Saudi Arabia. Additionally, a study by Cassar et al. (2018) involving over 300 experts from three EU countries discovers that utilizing data-driven HR operations can decrease judgment biases, provide insight into future trends, and enhance understanding of the strategic importance of HR.

The implementation of AI in HR is increasing transparency, cost-effectiveness, and data-driven decision-making, resulting in reduced biases and improved retention of top performers by revealing major helping points (attracting and developing new skills, improving employee experience, providing analytical decision support, making more efficient use of HR budgets; Guenole & Feinzig, 2018; Kaur & Kaur, 2022).

Reinventing Talent Management

The development of HR has gone through different phases, starting with Personnel Management (organizing workers), moving on to Human Resource Management (HRM; becoming a strategic business partner), and finally evolving into Talent Management (TM;

Liu et al., 2021). HRM connects different practices according to the Human Factor of the organization. This includes various strategies for managing human skills and competencies, acquiring talent, and organizing employees. (Armstrong, 2006)

In the Fourth Industrial Revolution, HRM supports digital transformation, accompanies a change process through employee development and training, and reinforces business strategy achievement (Gunathunge & Lakmal, 2021; Nicolas-Agustin et al., 2022). The goal of this Strategic Human Resource Management is to improve organizations by promoting a corporate culture that encourages the development of individual employee abilities, potentials, and the efficient utilization of human capital resources (Kaufman, 2015; Rana & Sharma, 2019; Wright & McMahan, 1992).

One key aspect of developing the company's employees is Talent Management. TM emerged in the late 90s with The War for Talent (cf. Michaels et al., 2001). The main goal is to ensure that the right strategic decisions in personal activities lead to a competitive advantage by using the right employee, with the right competencies, in the right location, at a minimum cost (Claus, 2019). TM consists of three steps in the employee life cycle; talent acquisition attracts and hires candidates, talent retention engages them, and talent development trains and prepares skilled personnel for future organizational needs (Tarique & Schuler, 2010).

Recent Talent Management is primarily based on gaining and retaining employees (Michaels et al., 2001). A future strategy for TM is using people analytics for resource and performance evaluation (Boudreau & Ramstad, 2007). Various internal and external data are organized, analyzed, and presented in a way that gives them meaning (Bassi et al., 2012). In order to meet the needs of employees and to find strategic decisions assisting HR managers in harnessing TM (Kaur & Fink, 2017; Marler & Fisher, 2013).

The use of AI in TM is significant. It provides a superior perspective by integrating and analyzing Big Data (e.g., employees' skills and experiences) to promote intelligent and accurate selection (resource to task fit), intelligent Education (developing future resources), and intelligent talent reserve (constructing the future needed talent pool; Collings & Mellahi, 2009; Franca et al. 2023; Liu et al., 2021).

Using Artificial Intelligence for Skill Management

The common approach in TM is the job- and role-based description lacking flexibility, details, and a uniform language for a holistic aggregation across organizations and functions. In contrast, skill management is highly detailed, personalized, and dynamic. Thereby works well in a rapidly changing environment in need of personal development. (Meier & Seufert, 2022)

Due to Mishra et al. (2020), a skill is the ability to perform a task well. Regarding the management of skills, taxonomies are key. Taxonomies are a structured, often hierarchical representation of relevant global or domain-specific skills required for different organizational roles. They serve as a reference framework for creating skill profiles, aligning resources and employees, and making development recommendations, by connecting required needs to available resources. Taxonomies either conduct a top-down approach, starting with the organizational needs; a bottom-up approach, serving the individual needs of employees; or a middle-out approach, a combination of both reviewed by employees and supervisors. Employee development is mainly achieved through reskilling, a process of acquiring new skills; or up-skilling, incorporating existing skills through further education and training. However, the implementation is labor-intensive as taxonomies must be updated and interpreted. (Meier & Seufert, 2022; Sawant et al., 2022; Vetter & Semenova, 2020)

AI-based Skill Management Software (SMS) can analyze Big Data and present logical interpretations using skill mapping. For example, It can connect available employees with specific development to a particular job. Furthermore, it helps to update taxonomies, maintain a searchable talent pool, enable internal mobility, career planning, and provide data-driven development decisions as well as self-service capabilities for employees. The software operates either as an assisted intelligence, which supports managers by collecting and processing information; an augmented intelligence, which analyses data and provides recommendations to human decision-makers; or an autonomous intelligence, which independently makes decisions based on different and evolving situations. (Ward et al., 2021; Yorks et al., 2022)

Practical Implementations

The integration of AI into HR has gained significant attention. Related start-ups have achieved high capital contributions (Faqihi & Miah, 2023). A survey in 2018 identified 300 HR technology start-ups focused on further developing AI tools (Bailie & Butler, 2018, as cited in Charlwood & Guenole, 2022, p. 730). The actual software offer includes all areas of modern HR management (e.g., AI-personnel planning, -supported learning, -performance management, -recruitment, -personnel development; Albert, 2019; Michel, 2022). KI-HR-LAB (https://ki-hr-lab.de), a German website about using AI for HR in practice, investigates more than twenty solutions regarding Talent Management (TM) and several solutions regarding Strategic Management Systems (SMS). For example, Gloat (US company) and HR-Forecast (German company) offer suitable AI-based SMS for the operations outlined. (Gloat, 2023; HRForecast, 2023)

Technologization & Digitalization in Human Resources

The opportunities of technology in HR are commonly known in research and business. According to PWC (2022), today's top challenges are data analytics, learning development, and employee upskilling. While other departments have widely adopted AI, HR often remains behind (Groß, 2021).

International research indicates that HR professionals believe technology is essential, but few intend to use it. Misconceptions about the tools, a traditional compliance-based HR culture, and a lack of technological and strategic business skills hinder the adoption through technical and human barriers. HR professionals focus primarily on digitalization within their day-to-day operations rather than on future projects exploring AI's potential benefits. (Dahlbom et al., 2020; Nankervis et al., 2021; Spirgi et al., 2022)

Research from German-speaking countries reveals a complex picture. HR professionals, in general, are optimistic about future developments and digitalization. They see it as an opportunity in HR. Additionally, they believe they can draw advantages from it and are not afraid of being replaced by a machine. Tools have arrived in HR departments, but the degree of implementation differs greatly. Compared to other departments, HR lacks behind without having a digitalization concept or strategy for developing competencies or implementing tools. Especially HR data analytics or implementing AI software is rather low. Professionals have basically dealt with the topic but have no sufficient knowledge about concrete processes and methods; soft skills mainly reflect the skill profile. (Jansen et al., 2020; Seufert et al., 2020)

Facing Challenges in Transforming Human Resources

HR is currently facing internal, structural, and organizational transformation, affected by the Fourth Industrial Revolution through changes within the department and its role in the company (cf. chap. Human Resources in the Fourth Industrial Revolution). A key solution is implementing AI to make HR´s work more efficient (cf. chap. Big Data & Artificial Intelligence in Human Resources). In the context of the prevailing Skill Gap, managing human skills is becoming an increasingly important role (cf. chap. Facing the Skill Gap). Focusing on the development of employees, AI tools for Talent Management can drive a significant benefit by using data-based decisions and predictions. They can help to close the Skill Gap by developing talents that meet the business's current needs with AI-based Skill Management Software. (cf. chap. Using Artificial Intelligence for Skill Management)

AI-based software has various implementations across all task areas, ranging from simple support systems for repetitive work to management systems for decision-making. In skill management, different offerings can support companies in the best possible way, such as Gloat or HR forecast. (cf. chap. Practical Implementations)

Digitalization has arrived in HR with a positive attitude and an awareness of advancements. However, implementation lags behind. Especially in AI and data analytics, due to a shortage of technical skills, management priority, and human barriers. (cf. chap. Technologization & Digitalization in Human Resources)

While the advancement, availability, and awareness of AI tools are present, the question arises: why is the technology not implied, why are the necessary skills not developed?

Technology Implementation

Adopting innovation in a company is influenced by external factors (market competition and regulations) and internal factors; divided into technological and organizational resources (Ghobakhloo et al., 2012). Research in the field of technology implementation focuses on two main areas: first, examining the relationship between technology performance and the tasks it is being used for, and second, understanding the factors that influence people's attitudes and beliefs towards technology (Lai, 2017). It is helpful to investigate the technology adoption literature and identify the most common theoretical frameworks (Gangwar et al., 2014). There exist approaches such as the Task Technology Fit (TTF; Goodhue & Thompson, 1995), the Technology Organization Environment (TOE; Tornatzky et al., 1990), the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003), and the Technology Acceptance Model (TAM; Davis, 1985).

The TOE framework analyses how a company's environment impacts technological innovation adoption, utilization, and spread (Tornatzky et al., 1990); focusing on technology infrastructure, employees’ skills, management support, regulatory support, and market competition (Gurusinghe et al., 2021). The TTF model investigates the compatibility between the technology employed and the tasks being executed (Thompson et al., 1991).

Research under the use of TOE and TTF frameworks reveals a positive impact of AI adaption on HR, even indicating that while technological products have all the necessary cornerstones, the stickiness of HR professionals engaging with new technology might prevent their widespread use (Agarwal, 2022; Pillai & Sivathanu, 2020). This is in line with the proposed findings, stating that the use-case, the technological and company resources are available to implement AI-based tools for HR. Further, it amplifies the assumption that the Human Factor might play a hindering role.

Technology Acceptance

Human-Computer-Interaction (HCI) studies technology focusing on the Human Factor, how people interact and use technology. It assumes that success or failure can be impacted by usability, user experience, or user-centered design, to frame a technology that is easy to use. (Nielsen, 1994)

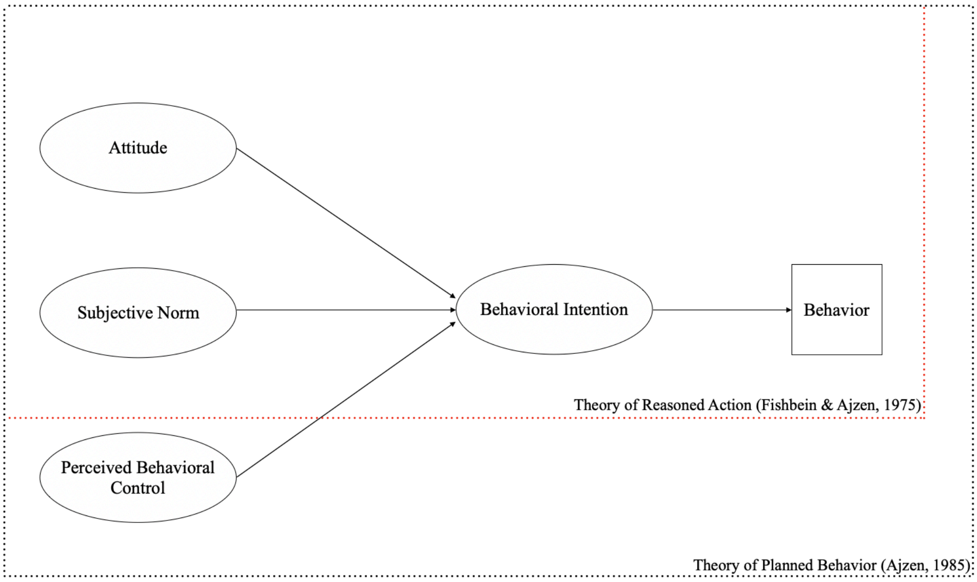
Central to understanding HCI is Technology Acceptance, which refers to an individual's willingness to adopt and utilize a specific technology, examining the relationships between attitudes, beliefs, and the use of technology (Hornbæk & Hertzum, 2017; Papagiannidis, 2022). The Technology Acceptance Framework is the most used model for various types of technology and explains the behavior of humans regarding Technology Acceptance (Lee et al., 2003).

Technology Acceptance Model

Psychology was one of the first fields studying the acceptance and rejection of technology as it entered daily life, referring to two base models (Marangunić & Granić, 2015). The Theory of Reasoned Action (TRA) explains human behavior through three cognitive components: attitudes, social norms, and intentions (Ajzen & Fishbein, 1980). The Theory of Planned Behavior (TPB) adds the variable of perceived behavioral control, which describes resources, opportunities, and skills, for achieving goals. Concluding, behavioral intention influences individual behavior and is explained by perceived behavioral control, subjective norm, and attitude toward behavior. (Ajzen, 1985)

Figure 1

Theory of Reasoned Action, Theory of Planned Behavior

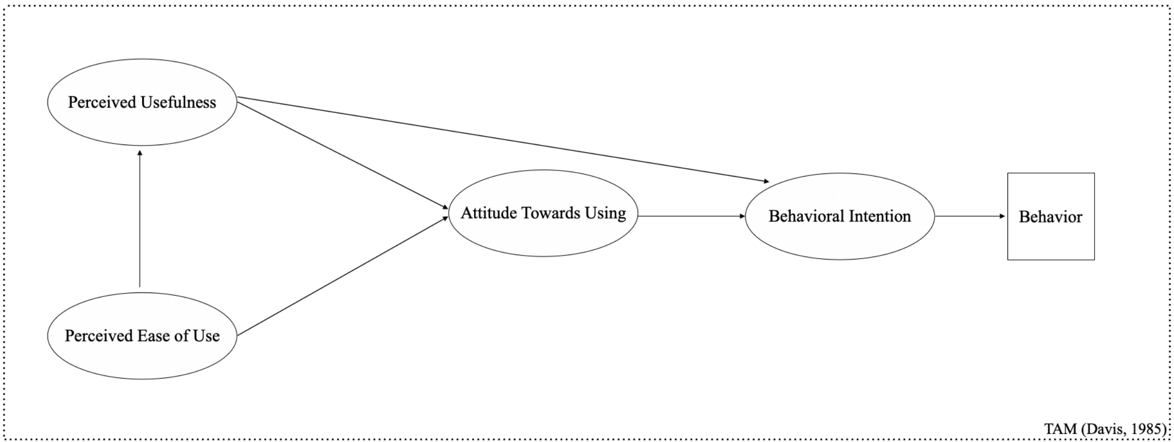


Note. Own presentation.

Fred Davis (1985) described the technology acceptance concept, which suggests that the use of technology can be predicted by an individual's motivation to use it. This motivation is influenced by external stimuli to present the capabilities and functions of a system. Based on TRA, Davis proposes the basic Technology Acceptance Model, which explains an individual's motivation to use technology, influenced by the perception of how easy the technology is to use, the perceived benefits of using it, and the overall Attitude Towards Using it (Davis, 1985). Attitude Towards Using is described as the overall users' feelings to whether use or not use a system (Davis, 1993). This is influenced by two crucial beliefs. Perceived Usefulness (PU) describes the belief that the system will improve work performance. Perceived Ease of Use (PEU) describes the belief in how easy a system is to use. (Sharp, 2006)

Figure 2

Basic Technology Acceptance Model



Note. Own presentation.

In further research, Davis and Davis et al. (both 1989) discovered that Attitude Towards Using (ATT) does not entirely mediate the relationship between PU, PEU, and behavior. Subsequently, the variable Behavioral Intention (BI) is introduced, suggesting that an individual might develop a strong BI to use a system without forming an attitude toward using it (Davis et al., 1989). After intensive research and testing, a final version of the TAM is introduced, excluding ATT (Venkatesh & Davis, 1996).

TAM-Limitations

TAM is theoretically robust and has strong predictive power for assessing people's intention to use technology (Goodhue, 2007); however, there are two main discussions regarding the TAM. The constant evolution and adaption to individual environments of TAM lead to instability and confusion in the theoretical conceptualization (Benbasat & Barki, 2007). With its holistic approach, the TAM distracts from the essential questions of technology, focusing on factors that lead people to use technology, blurring the effect of the impact of the technology (Malatji et al., 2020). Additionally, some concrete questions remain about the effect sizes and importance of PU and PEU, forced and voluntary use, the intention-behavior gap, the role of ATT, as well as the close relationship between Behavioral Intention and attitude (Kim & Hunter, 1993; Sharp, 2006; Sheeran, 2002).

Excluding Attitude

According to Fishbein and Ajzen (1975), attitude can influence behavior positively and negatively, increasing or decreasing the likelihood of displaying a particular behavior. „Attitude refers to an individual's degree of evaluative affect toward the target behavior“ (Fishbein & Ajzen, 1975, p. 216). This concept is vital in the field of Technology Acceptance as it can impact the success or failure of technology. Attitude comprises two main components: affective attitude, which represents emotions towards a behavior; and cognitive attitude, which means cognitive perceptions regarding the practical advantages and potential drawbacks of a particular course of action. How these attitudes impact a person's actions and behavior refers to the behavioral component. Further, attitude can be divided into explicit and implicit attitudes; while explicit attitudes are introspectively accessible, implicit attitudes are unidentified perceptions. (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1977; Greenwald & Banaji, 1995)

According to Venkatesh and Davis (1996), eliminating the ATT from TAM explains the effects of PEU on actual behavior. Any unexplained influence between system characteristics (PU, PEU) and the ATT is eliminated. In addition, the way is cleared to include additional variables that might change belief pressures toward the system (Venkatesh &

Davis, 1996). According to Thompson et al. (1991), the ATT is removed from the model because it is not closely related to technology use.

In contrast, previous research suggests that attitude plays a supportive role in the basic TAM (c.f. Angela Lee Siew et al., 2017; Djamasbi et al., 2009; Lau & Woods, 2008; Teo, 2008; Yang et al., 2021). However, this varies according to the technology used (c.f. López-Bonilla & López-Bonilla, 2011; Teo, 2009; Ursavas, 2013) and the conception of attitude, recommending to include affective as well as cognitive attitude (c.f. Kim et al., 2009; Yang & Yoo, 2004). Likewise, the connection between implicit as well as explicit attitude is unclear. However, evidence suggests implicit and explicit measurement methods assess distinct psychological constructs, despite their alignment (Hofmann et al., 2005). Moreover, there seems to be a relation between attitude, behavior intention, and behavior; while attitude and behavior intention are closely linked, a gap exists between behavior intention and actual use (Kim & Hunter, 1993; Sheeran, 2002).

Clarifying Effect Sizes

Regarding the TAM, various meta-analyses were conducted to clarify the use and effects of the model. Due to the exclusion of ATT in the final TAM, most of the research does not include this variable in their studies (Ma & Liu, 2004). „The table also addresses "attitude" for those studies that have measured this construct." (King & He, 2006, p. 743). „Out of the 22 studies, only seven included both AT and BI." (Legris et al., 2003, p. 196). „ […] it became the norm to exclude the attitude construct from the TAM." (Yousafzai et al., 2007a, p. 265). To illustrate the respective effect sizes, the results of two comprehensive meta-analyses are presented in Table 1 (Yousafzai et al., 2007b).

Table 1

Effect Sizes Basic Technology Acceptance Model

Relationship	Study 1	Study 2
PU ➙ BI	.55*	.17*
PEU ➙ BI	.34*	.14*
PU ➙ ATT	.53*	.39*
PEU ➙ ATT	.45*	.33*
ATT ➙ BI	.56*	.43*
PEU ➙ PU	.44*	.40*

Note. *p > .05. Values study 1 from Feng et al. (2021, p. 93). Values study 2 from Yousafzai et al. (2007b, p. 287). Own presentation. Perceived Usefulness (PU), Perceived Ease of Use (PEU), Behavior Intention (BI), Attitude (ATT).

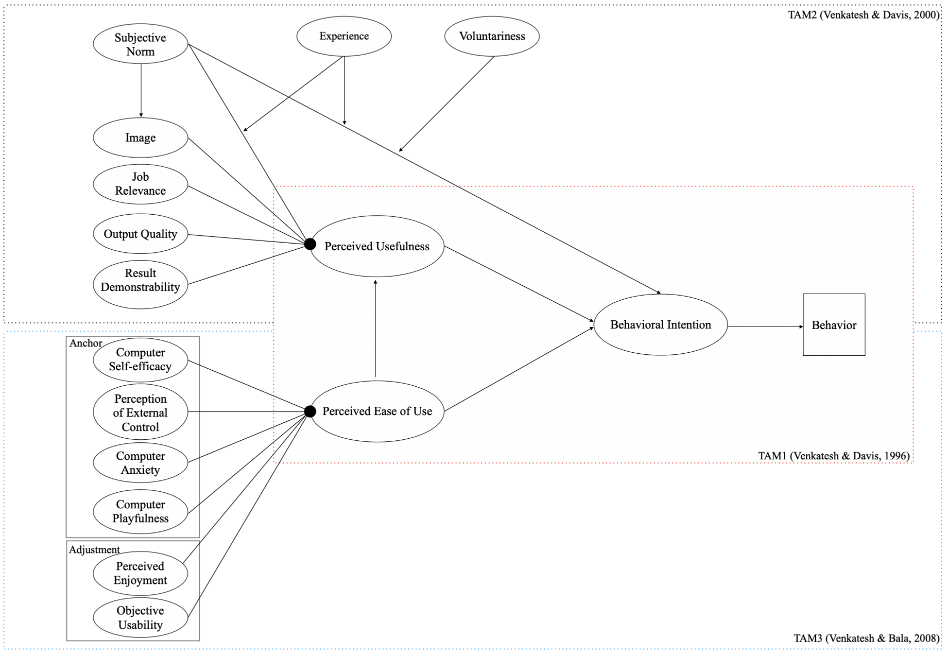
TAM-Development

Over time TAM has undergone various adaptations and modifications. To clarify, Venkatesh and Davis proposed an extended version of the model TAM2. This model includes additional variables such as subjective norm (the influence of others on an individual's decision to use technology), image (the user's desire to be perceived positively by others), relevance to work (the extent to which technology applies to the user's work), quality of outcome (the extent to which the technology effectively fulfills the required tasks), and demonstrability of outcome (the extent to which the technology produces tangible results), supplemented by two moderators, experience, and voluntariness (Venkatesh & Davis, 2000).

Venkatesh (2000) examined the factors influencing PEU through anchors and adjustments. Anchors refer to general beliefs about computers and their use, while adjustments are based on experiences directly using the system. This research leads to the development of TAM3, which includes different anchor points and adjustments, such as computer anxiety or perceived enjoyment. (Venkatesh, 2000; Venkatesh & Bala, 2008)

Figure 3

Technology Acceptance Model Development

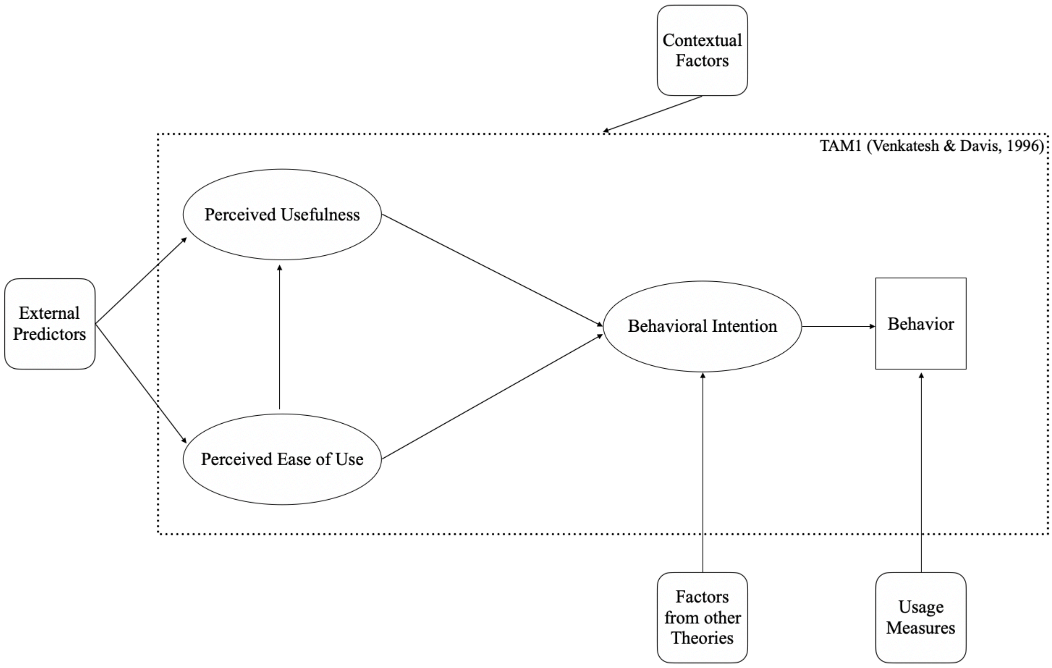


Note. In TAM3, Output Quality affects Job Relevance. In TAM3, Experience acts as a moderator for many effects; these have been omitted for simplicity. Own presentation.

The modification of the TAM includes four categories of additional variables: external predictors, factors from other theories, contextual variables, and the measurement of actual technology use (Marangunić & Granić, 2015). Additional variables are commonly included as external variables (Abdullah & Ward, 2016; Yousafzai et al., 2007a).

Figure 4

Four Categories of Extensions



Note. In the style of Marangunić and Granić (2015). Own presentation.

The Impact of Highly Complex Technology

Highly complex technology, such as AI, reveals various attitudes toward their system. A systematic literature review of 2021 studies (Cubric, 2020) among different businesses shows barriers such as safety and trust in adopting AI. Regarding trust, findings on the employee's acceptance of AI suggest that technological trust significantly affects employees' intention to use it (Cubric, 2020). Research of an integrated AI acceptance-avoidance model examines the positive and negative factors of using AI for decision-making. It confirms that attitude significantly affects the intention to use technology. (Cao et al., 2021)

Gursoy et al. (2019) assert that Technology Acceptance theories (such as TAM) are not suitable for studying the adoption of AI because they are primarily focusing on the use of functional technologies and do not fully capture the complex decision-making process involved in explaining customers' attitudes toward the use of AI. Theoretically, Ulrich

Lichtenthaler (2019) emphasizes the significance of attitudes, especially when AI has a direct influence on humans; they might have a perception toward the system, as well as towards the use of the system. Toward the system, e.g., the impact of the disadvantages of AI, such as lousy decision-making (Mikalef et al., 2022; Rana et al., 2022). Towards the use, e.g., the undervalue of employees, pertaining to decreased job security, leads to a fear of potential job losses (Brougham & Haar, 2018; Ransbotham et al., 2018).

A Model Comparison

Sohn and Kwon (2020) compared different Technology Acceptance theories in assessing the use of AI by employing the UTAUT, TPB, and TAM. The Unified Theory of Acceptance and Use of Technology emerges as a combination of several existing theories, such as the TAM and the TRA, to provide a more comprehensive explanation and clarify TAM's developments (Venkatesh et al., 2003). Recent studies argue that the individual's attitude as an additional variable is crucial in understanding their behavior intention toward technology adoption in UTAUT (cf. Chao, 2019; Dwivedi et al., 2019; Kim & Shin, 2015). The updated UTAUT Version suggests that people's attitude toward technology is crucial in determining their acceptance of it (Dwivedi et al., 2019). Attitude is typically positioned between endogenous variables, such as performance and effort expectancy, and the intention to use the technology, such as BI (Wanner et al., 2022). Comparing those models, the results show that the UTAUT explains the most variance in BI at 72% (R^2 = .72), followed by the TPB at 67% (R^2 = 0.67) and the TAM at 63% (R^2 = .63). (Sohn & Kwon, 2020)

The Acceptance of AI in HR

The Technology Acceptance Model is generally useful for studying applications in HR. For powerful results, it is emphasized to define, describe and examine the specific use case and the essential task area. (Iyer et al., 2020)

Examining the acceptance of AI in HR, Dahm and Dregger (2019) conducted a TAM-based study in Germany. The participants are generally open to using AI-based technologies in HR and less afraid of being replaced by such a technology. The most remarkable acceptance is found when systems act as augmented intelligence. Trust, perceived risks, and appreciation through the use of AI, as well as computer playfulness and perceived enjoyment, are particularly important. (Dahm & Dregger, 2019)

A conceptual study highlights employees' attitudes toward AI, shaped by personal characteristics and rational, emotional, and cognitive factors (Giudice et al., 2021). A literature review reveals that trust in the context of AI is multifaceted; a system not only needs to be trustworthy in itself (e.g., decision-making) but also to be handled in a trustworthy manner (by HR managers; Bärmann, 2022).

Laurim and colleagues (2021) investigated the reasons for the acceptance or rejection of AI in the recruitment process by conducting 15 interviews with recruiters, managers, and applicants in a German medical company. TAM basic factors such as PU and PEU are found to be necessary. Additionally, external factors, namely sense of control, trust, and the Technology Readiness framework (TR). TR describes general attitudes toward the system based on dimensions of optimism, innovativeness, discomfort, and insecurity (Parasuraman & Colby, 2015).

Additionally, investigating workers' perspectives on using AI in HR reveals six different burdens. The emotional (afraid of the system), mental (cognitive effort to understand

AI), bias (concerns about biased algorithms), manipulation (manipulating AI systems), privacy (use of the data), and social (concerns about changes in the society) burden (Park et al., 2021). Besides these barriers, some drivers support the acceptance, such as innovation, unbiased decision-making, comprehensibility, or diversity beliefs (Ochmann & Laumer, 2020)

HR- and computer-experts identified the dimension of perceived fairness affecting the adoption of AI. A higher perceived fairness of a system leads to a greater likelihood of the system. The more individuals perceive that AI leads to unbiased, comprehensible decisions and less discrimination, the higher the perceived fairness of AI recruiting. Further, studying applicants reveals that there is a difference between active and passive users. Applicants only experience a passive influence through the use of the technology, consequent beliefs such as privacy concerns strengths. (Ochmann & Laumer, 2019, 2020)

Towards a Revised Implementation of Attitude in the TAM

The basic Technology Acceptance Model (Davis, 1985) posits Attitude Towards Using as a central variable based on the assumptions of TRA. In the final TAM, ATT is excluded and not further considered in developments such as TAM2 and TAM3. (cf. chap. Technology Acceptance Model)

In contradiction, subsequent research strengthens the role of ATT in the basic TAM, varying across technology applications, concepts, and measurements of attitude (cf. chap. Excluding Attitude). In using the TAM for research, ATT is rarely included, even if the overall effect sizes advocate for the variable (cf. chap. Clarifying Effect Sizes). A model comparison of different frameworks, including ATT versus the TAM (excluding ATT), reveals that those including the variable performed best, generally posited influencing BI (cf. chap. A Model Comparison).

Especially in the context of highly complex technology, attitudes are fundamental. Reflecting the system characteristics (e.g., computer playfulness) and the system's use (e.g. fairness; cf. chap. The Impact of Highly Complex Technology). A closer look at the literature on accepting AI-based systems in the context of HR reveals that several variables connected to attitude are particularly important. Trust, appreciation, fairness, perceived risks, and several barriers and drivers of Technology Acceptance. Some of these are multifaceted (e.g., trust), while some are seen in relation to the system (e.g., bias burden). Furthermore, AI-based HR tools are subject to both active (HR) and passive use (non-HR). (cf. chap. The Acceptance of AI in HR)

Based on these findings, this thesis assumes. When people evaluate their Technology Acceptance towards a highly complex technology, in addition to questions about the system itself, its usefulness, and its ease of use, several variables in relation to the concept of attitudes, reflecting emotions, and cognitions play a significant role. These are multifaceted regarding the system itself but also towards the use of the system. It is noted that attitudes towards technology can influence behavior intention even without affecting the user-friendliness or usefulness of a system. Even if a system is perceived as useful and user-friendly, yet at the same time, concerns about its usage influence the intention to use it. It is not just the perception of the system that is crucial, but also the manner in which it is used. Additionally, highly complex technology underlies active as well as passive use. While active use describes the interaction with the system, passive use describes impacts towards the use of the systems; these modalities entail different perceptions in terms of attitude. However, this is not to be understood as a one-dimensional role model but as a continuum. Thus, an active user may also be exposed to passive use simultaneously.

The TAM risks being extended with various external variables in relation to the system design (external variables influencing PU, PEU; cf. chap. TAM-Development). Additionally, further developments (TAM3) imply operationalizing attitudes regarding system design by introducing variables such as computer anxiety or perceived enjoyment. As a result, even attitudes towards the use are operationalized in terms of system design (c.f. Abdullah & Ward, 2016; Baroni et al., 2022; Dahm & Dregger, 2019; Rosli et al., 2022; Yousafzai et al., 2007a). However, this does not sufficiently consider the complex relationship between attitude toward the system and towards the use of the system, as well as active and passive use of highly complex systems. Furthermore, it ignores evidence that models in which Attitude directly influences Behavioral Intention perform best.

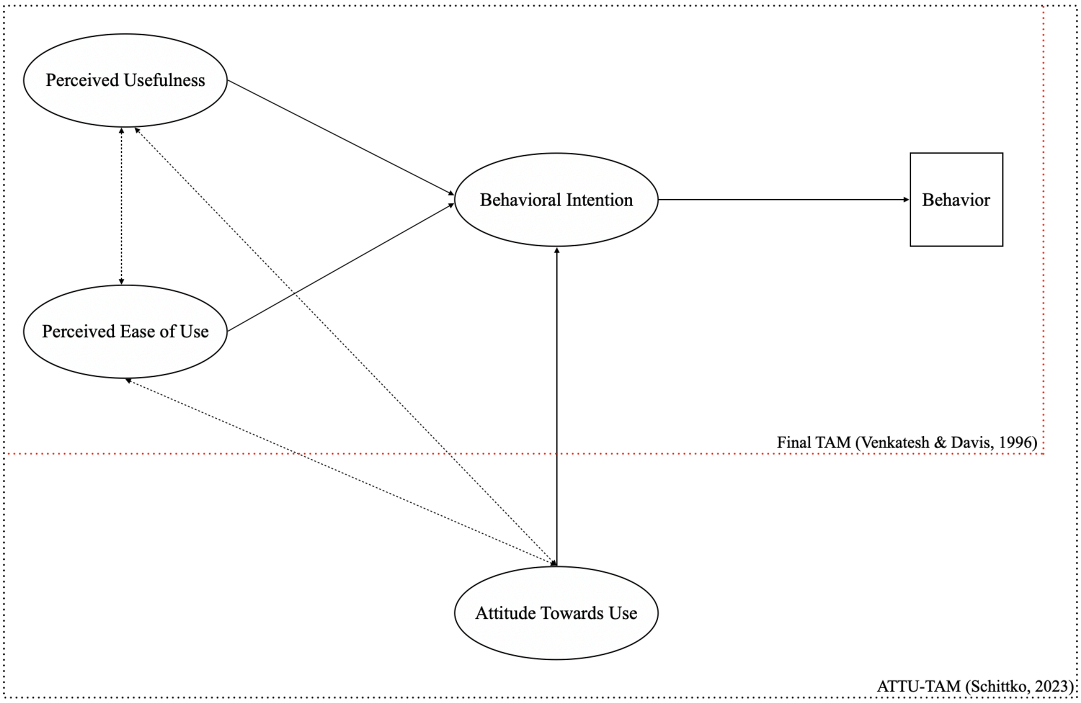
Presenting a Model

Based on these considerations, an extension of the final TAM (Venkatesh & Davis, 1996) called the Attitude Towards Use Technology Acceptance Model (ATTU-TAM) is proposed. In accordance with and based on the general effects of the basic TAM (cf. Table 1). It replaces Attitude with Attitude Towards Use (ATTU), which refers to an individual's degree of evaluative affects toward the use of a system. Furthermore, it considers the developments of the TAM2 and TAM3, which includes the operationalization of several variables related to the concept of attitude toward the system design as external variables. Moreover, it excludes the mediating role between PU/PEU over ATTU on BI and the direct effect of PEU on PU to simplify the model in its first stage (but allowing for covariances).

The ATTU-TAM establishes a significant extension in the core model of Technology Acceptance research and development, effectively distinguishing between attitudes towards the system and attitudes towards the use of a system. This novel differentiation allows for the measurement of both aspects, providing a noteworthy concept, and clarifies the definition of attitude in the TAM, particularly when dealing with highly complex systems. Furthermore, the model facilitates the modulation of both active and passive technology usage, thereby enabling differentiation and examination between these forms of utilization. Consequently, the ATTU-TAM overcomes the general limitations of the TAM, clears misconceptions regarding attitudes toward the TAM's use and development, and strengthens the understanding of the impact of highly complex technologies. This acknowledges the research findings that highlight the central role of attitudes in technology acceptance. Furthermore, ATTU can be investigated in more detail under the influence of external variables. Moreover, evidence is taken into consideration to support the notion that attitude's explanatory power is most significant when influencing BI. In sum, the ATTU-TAM addresses crucial facets of the TAM discussion by clarifying the misconception of attitude and focusing on the impact of the use of technology.

Figure 5

Attitude Towards Use Technology Acceptance Model



Note. Dashed lines represent investigated covariances. Own presentation.

Applying AI-based Skill Management Software

To date, research on the acceptance of AI in HR is limited. Studies demonstrate the general applicability of the TAM for examining Technology Acceptance. It is emphasized that a specific application must be applied for meaningful results. (Iyer et al., 2020)

Generally, users are open to using AI in HR; usefulness and ease of use are perceived to be good and essential, as well as adding external variables regarding the system itself (e.g., computer playfulness; Dahm & Dregger, 2019). In the context of the implementation of AI-based Skill Management Software in HR, the following is noted.

AI-based Skill Management Software is highly complex and subject to both active and passive use (Ochmann & Laumer, 2020). This is even more visible as AI-based SMS is recommended by research interacting as augmented systems (Dahm & Dregger, 2019), and therefore the implementation is heavily influenced by its use. HR managers are affected by its active use, e.g., by making data-driven decisions. Employees are affected by its passive use, e.g., by making career planning suggestions. This makes it worthwhile to take a closer look at the attitude toward the use of the technology to understand the complex relationship between technology, implementation, and acceptance of AI-based SMS, applying ATTU-TAM.

Regarding attitudes toward the system, barriers and drivers in the context of attitudes influence Technology Acceptance (Laurim et al., 2021). This is consistent with the view of the Technology Readiness concept. According to Parasuraman (2000), TR is a trait-like variable that captures people's general attitude toward new technologies influenced by their level of optimism, innovativeness, discomfort, and insecurity, and can be a precursor of attitude (Blut & Wang, 2020; Venkatesh et al., 2012).

In terms of attitudes towards the use of the system, besides the general ATTU, three other variables are identified as particularly influential, trust, appreciation, and fairness (cf. chap. The Acceptance of AI in HR). They are mainly formed by the application, as trust must be placed in the use, appreciation is caused by it, and fairness through the use is expected and desired. This leads to Trust Towards Use (T), Appreciation Towards Use (AP), and Fairness Towards Use (F) as influencers of ATTU.

With regard to Attitude Towards Use and its influencing factors, two particularities reveal. Since the system is characterized by active and passive use, which have different effects on the users, the perception through the two modalities may differ. It should be noted that attitude can be measured as explicit and implicit (Greenwald & Banaji, 1995). Implicit attitude is to be understood as an inaccessible perception that varies from explicit attitudes and should act similarly to ATTU (Hofmann et al., 2005).

Research Questions

This research combines a profound theoretical discussion as well as intensive literature research to develop the ATTU-TAM and apply the implementation of AI-based SMS to the model. The following research questions aim to provide an in-depth view of the acceptance of AI-based SMS. Furthermore, to give a deep understanding of the influence of ATTU under active as well as passive use. Additionally, to validate the ATTU-TAM by examining a use case example. Moreover, the research questions are formulated to explore the influence of external variables on ATTU as well as the influence of active and passive use.

RQ1: Does ATTU-TAM provide a complex, in-depth view of the Technology Acceptance of implementing AI-based Skill Management Software in Human Resources?

RQ1.1: What role do Attitude Towards Use and those extended influencing factors play in the Technology Acceptance of AI-based Skill Management Software?

RQ1.2: Can differences among active and passive users be identified, especially in the Attitude Towards Use and those influencing factors?

RQ2: Does ATTU-TAM better explain the Technology Acceptance of highly complex systems than the final Technology Acceptance Model?

RQ2.1: Does ATTU-TAM better explain the Technology Acceptance of highly complex systems than modeling ATTU as an external variable in the final TAM?

RQ2.2: Can the final Technology Acceptance model adaption to the ATTU- TAM be validated by applying this use case example?

Hypothesis

The use-case of implementing an AI-based SMS in HR is applied to the model and considered in the context of both active (HR) and passive users (non-HR). As providing conceptual research to investigate the intention to use a product, this thesis does not include actual use as a variable.

Core Hypothesis. The following hypotheses aim to substantiate the fundamental statements of this thesis by confirming the advancement of the ATTU-TAM. This will be achieved by testing the superiority of the presented model in comparison to the final TAM and further developments. Furthermore, through investigating the significance of the ATTU variable and the distinction between active and passive usage within the ATTU-TAM.

H1: The ATTU-TAM can better explain the collected data than the final TAM.

H1a: The ATTU-TAM can better explain the collected data than modeling ATTU as an external variable in the final TAM.

H2: The ATTU-TAM can better explain BI than the final TAM.

H2a: The ATTU-TAM can better explain BI for active users than the final TAM.

H2b: The ATTU-TAM can better explain BI for passive users than the final TAM.

H3: ATTU directly influences BI, whereas a more positive ATTU increases BI.

H3a: ATTU directly influences BI for active users, whereas a more positive ATTU increases BI.

H3b: ATTU directly influences BI for passive users, whereas a more positive ATTU increases BI.

Exploratory hypotheses. For exploratory investigation, some further hypotheses are tested. They are tested to investigate the influence of ATTU's external variables, to further examine the influence of active as well as passive use, and to integrate TAM- and attitude-research findings.

In the context of implementing AI-based SMS, different variables might play a particularly significant role in influencing ATTU, namely Fairness, Trust, and Appreciation. Further, TR, representing the basic attitudes toward the system, might be a precursor of ATTU. Additionally, the perception of ATTU and its influencing variables differ between active and passive users as representing various system experiences.

H4: F directly influences ATTU, whereas a higher perceived F increases ATTU.

H5: AP directly influences ATTU, whereas a higher AP increases ATTU.

H6: T directly influences ATTU, whereas a higher T increases ATTU.

H7: TR directly influences ATTU, whereas a higher TR increases ATTU.

H8: ATTU differs between active and passive users.

H9: F differs between active and passive users.

H10: T differs between active and passive users.

H11: AP differs between active and passive users.

H12: TR differs between active and passive users.

Since implicit and explicit attitudes should be understood in different concepts, they are distinguished between concepts and active and passive use. While the ATTU's mediating role between PEU/PU and BI, as well as the direct impact of PEU on PU in the basic TAM, were omitted for the sake of simplifying the ATTU-TAM model, covariances are still taken into account.

H13: Implicit ATT and ATTU differ.

H13a: Implicit ATT differs between active and passive users.

H14: ATTU covariates with PU.

H15: ATTU covariates with PEU.

H16: PEU covariates with PU.

Methodology

Participants & Procedure

This study is based on an anonymous, fully structured online questionnaire via SoSci survey (https://www.soscisurvey.de). Adult employees in the DACH region were asked to answer the form in relation to the implementation of AI-based Skill Management Software in HR. For this purpose, a fictitious application example was introduced. Participants were tested on the proposed model, including all latent variables of the ATTU-TAM as well as the use-case-specific external latent variables (Trust, Appreciation, Fairness) influencing ATTU. The questionnaire could be completed on both computer and mobile devices. A pre-registration in accordance with the Open Science Framework is available at the following address (https://osf.io/m7u4z/?view_only=ce74cab9606c4747b85a57fd920d7add).

The participants were recruited through different methods. Via social media, especially in groups on the topic of AI, HR, and workforce on LinkedIn and Facebook. Through dissemination via various advertisements as social media marketing on LinkedIn. Here, 107 referrals to the questionnaire were achieved. Furthermore, materials with different posters were sent to multiple related HR media. Likewise, over 500 companies from Germany, Austria, and Switzerland were informed by cold-calling emails. In addition, a panel was conducted via Consumerfieldwork (https://www.consumerfieldwork.de) for $N = 300$ questionnaire participants employed in the DACH region. Overall resulted in $N = 647$

interviews being started and *n* = 386 questionnaires completed, accounting for 60% completion. Due to data cleaning *n* = 285 participants were included in the total sample.

Out of the sample, *n* = 156 participants (54.7%) did not work in HR, while *n* = 129 participants (45.3%) did work in HR. The average age of all participants was 42.22 years (*SD* = 9.35), ranging from 22 to 62 years. Among participants working in HR, the average age was 41.72 years (*SD* = 9.34), while those not working in HR had an average age of 42.64 years (*SD* = 9.36). Regarding gender distribution, the sample consisted of *n* = 158 male participants (55.4%) and *n* = 127 female participants (44.6%). Among those working in HR, *n* = 66 were male, and *n* = 63 were female. In terms of educational background, *n* = 159 participants (55.8%) had a degree, *n* = 110 (38.6%) had completed training or apprenticeships, and *n* = 16 (5.6%) had completed primary education. Among participants working in HR, *n* = 86 had a degree, *n* = 41 had completed training or apprenticeships, and *n* = 2 had completed primary education. The majority of participants, *n* = 222 (77.9%), worked in Germany, followed by *n* = 50 (17.5%) in Austria, and *n* = 8 (2.8%) in Switzerland, *n* = 5 did not contribute any details. Among participants working in HR, *n* = 106 were from Germany, *n* = 20 were from Austria, and *n* = 2 were from Switzerland. All participants' average weekly working hours were 39.61 hours (*SD* = 5.66), ranging from 10 to 60 hours. Specifically, participants working in HR had an average of 40.09 hours (*SD* = 5.29), while those not working in HR had an average of 39.21 hours (*SD* = 5.93). In terms of company size, *n* = 158 participants (55.4%) worked in large companies (more than 250 employees), *n* = 76 (26.7%) worked in medium-sized companies (50-249 employees), *n* = 33 (11.6%) worked in small companies (10-49 employees), *n* = 13 (4.6%) worked in very small companies (less than ten employees), and *n* = 5 (1.8%) did not provide any details. Among participants working in HR, *n* = 58 worked in large companies, *n* = 44 in medium-sized companies, *n* = 18 in small companies, and *n* = 8 in very small companies. Regarding employment duration in the current company, *n* = 127 participants (44.6%) had worked for more than ten years, *n* = 81 (28.4%) had worked from five to ten years, *n* = 76 (26.7%) had worked for less than five years in their company, and *n* = 1 (0.4%) did not provide any details. Among participants working in HR, *n* = 55 had worked for more than five years, *n* = 48 had worked for five to ten years, and *n* = 25 had worked for less than five years in their company. The average self-reported Expert-Status of participants in relation to AI was 2.75 (*SD* = 1.04). Approximately 25% of the participants had scores below 2.00, while another 25% had scores above 3.50. Specifically, participants working in HR had a higher average Expert-Status of 3.11 (*SD* = 1.09), while those not working in HR had an average of 2.45 (*SD* = .91). Regarding the usage of comparable systems in their companies, *n* = 213 participants (74.7%) reported that their companies did not use any comparable system, *n* = 44 (15.4%) reported using a comparable system, and *n* = 28 (9.8%) did not provide details. Among participants working in HR, *n* = 31 reported that their companies use a comparable system.

Measurement

The questionnaire was divided into four parts. The introduction presented the study and provided information on key points such as response instructions, data protection, the subject of the study, and the contact person.

Further, demographics and general data were collected, allowing for more precise respondent specifications. The demographics, age, gender, and education status. The current employment status and the employment status in the last six months were used as exclusion criteria. Participants had to meet these criteria to be included in the study. The weekly working hours, the working location, the company size of the employer, and the employment duration in the current company. As well as the affiliation with the HR department, which allowed a subdivision into two groups, HR and non-HR workers.

The third part of the questionnaire introduced a definition of Talent Management, Artificial Intelligence, Machine Learning, and Deep Learning. Furthermore, a fictitious application example of an AI-based Skill Management Software implementation in HR was introduced. The example was based on previous scientific results representing an augmented system (cf. chap. The Acceptance of AI in HR). It was described as a good validated operating system, protecting data and delivering all functions of an AI-based SMS outlined (data-based decisions, career planning, development recommendations, employee self-service). The example explained a generally well-accepted and holistic use-case similar to available software on the market. Afterward, three control questions were asked regarding the example described. These questions were used as exclusion criteria for quality control whenever two of the three questions could not be answered correctly.

Furthermore, the application of similar software in the associated company and the general expert status in relation to AI (Expert-Status) were queried. Followed by questions related to the proposed latent variables. A short description introduced every block of questions. Items were adapted from previous research, modified to the use case, and further translated from English to German. Thereupon retranslated to prove a general fit, which happened by two natural language processing AIs´ Deepl (DeepL, 2023) and ChatGPT (ChatGPT, 2023). Moreover, some items were formulated out of theoretical assumptions. The entire item pool can be found in Appendix A.

Items mainly used Five-Point-Likert scales with the ratings (1) strongly disagree, (2) somewhat disagree, (3) undecided, (4) somewhat agree, and (5) strongly agree. The general expert status in relation to AI was measured by four own items using a Five-Point-Likert-

Scale and described the overall self-reported Expert status, the use, information, and knowledge of AI. The latent variables PEU and PU were measured by four items, each with a Five-Point-Likert scale adapted from Venkatesh and Davis (2000). Regarding reliability analysis, the latent variable PEU exhibited good consistency (α = .80) with an *AVE* of .50, indicating a moderate convergent validity. The latent variable PU demonstrated excellent consistency (α = .91) with an *AVE* of .72, indicating a moderate convergent validity. The latent variable TR was measured by 16 items with a Five-Point-Likert scale adapted from the Technology Readiness Index (Parasuraman & Colby, 2015). Regarding reliability analysis, the latent variable TR suggested a good consistency (α = .85) with an *AVE* of .60, indicating a moderate convergent validity. The latent variable T was measured by twelve items with a Five-Point-Likert scale adapted from the Trust Scale in Automated Systems (Jian et al., 2000). Regarding reliability analysis, the latent variable T suggested an excellent consistency (α = .91) with an *AVE* of .71, indicating a moderate convergent validity. The latent variable AP was measured by three items with a Five-Point-Likert scale, according to Jacobshagen et al. (2008). Regarding reliability analysis, the latent variable AP suggested an excellent consistency (α = .94) with an *AVE* of .83, indicating a strong convergent validity. The latent variable F was measured by three items with a Five-Point-Likert scale based on the Equity Theory (Adams & Freedman, 1976), the Perceived Fairness (Greenberg, 1986), and following the concept of Procedural Fairness in using Artificial Intelligence (Hughes et al., 2019). Regarding reliability analysis, the latent variable F suggested an excellent consistency (α = .92) with an *AVE* of .80, indicating a strong convergent validity. The latent variable ATTU was measured as an explicit attitude by eight items with a semantic differential adapted from Davis (1989) and Van der Laan et al. (1997), conducting four pairs each, related to the cognitive and emotional components. Due to their similarity, the items were randomly assigned to prevent careless answers. Regarding reliability analysis, the latent variable ATTU exhibited excellent consistency ($\alpha = .95$) with an *AVE* of .84, indicating a strong convergent validity. The latent variable BI was measured by an extended eight-item scale out of various research with a Five-Point-Likert scale adapted from Venkatesh et al. (2012), Davis et al. (1989), and Chao (2019) to achieve the best possible separation from Behaviour Intention. Regarding reliability analysis, the latent variable BI demonstrated excellent internal consistency ($\alpha = .97$) with an *AVE* of .87, indicating a strong convergent validity. The implicit attitude was also tested with the Implicit Association Test (IAT; Greenwald et al., 1998). The categories, negative and positive triggers, were created based on the best practice recommendations of Greenwald et al. (2022).

The chi-squared difference test between pairs of all latent variables was significant, suggesting that they differ from unity, indicating discriminant validity of the measures for all constellations, except of the variable pair ATTU and T. The measurement invariance test between groups achieved partial measurement invariance allowing for comparisons between means or other relevant variable parameters between groups. (cf. Appendix D)

In the last section of the questionnaire was thanked for the participation and offered the opportunity to make comments on the study. Followed by data of the contact person. The questionnaire was pre-tested by a number of $N = 20$ applicants to hinder problems in understanding, wording, and technical issues. The entire questionnaire can be found in Appendix B.

An a priori power analysis was conducted using the A-priori Sample Size Calculator for Structural Equation Models (Soper, 2023). This analysis determined the required sample size for validating the structural model and the effects, aiming for a desired power level of ≥ .80. The effect size was considered to be small ($d = .10$) with a significance criterion of $\alpha =$

.05 and a desired power of .80. The minimum sample size to detect this power in the model structure of all three primary Models is $N = 116$, with the largest model of eight latent variables and 30 manifest variables. The minimum sample size to detect this power in the effects of all three primary Models was $N = 1889$, with the largest model of eight latent variables and 30 manifest variables.

Analysis

All analyses were conducted using R developed by the R Core Team (2023). In addition to the base installations, the following packages were employed: dplyr (Wickham et al., 2023), lavaan (Rosseel, 2012), semTools (Jorgensen et al., 2022), Amelia (Honaker et al., 2011), psych (William, 2023), lavaanPlot (Lishinski, 2021), sjmisc (Lüdecke, 2018), epiDisplay (Chongsuvivatwong, 2022), MVN (Korkmaz et al., 2014), nonnest2 (Merkle & You, 2020), semTable (Johnson & Kite, 2020), simsem (Pornprasertmanit et al., 2021), ggplot2 (Wickham, 2016).

Monte Carlo Simulations

Several post hoc Monte Carlo simulations were performed for each primary model and respective group comparisons. These simulations validated the necessary sample size for achieving a desired power of $\beta \geq .80$ for the individual structural models and effects. A dataset consisting of $N = 285$ samples, divided into two groups, was simulated for the group comparisons.

Data Cleaning

In the first place, the dataset underwent a data-cleaning process to enhance the overall quality of the data set. Samples that not met the exclusion criteria were removed. Expressly, participants who did not provide their consent to the data privacy policy and were currently unemployed or had been unemployed in the past six months were excluded. Subsequently, samples that did not meet the necessary data quality standards (careless answers) were excluded. Always if; two out of three comprehension questions were answered incorrectly (Kung et al., 2018); the response time was significantly shorter than the average and expected response time based on the questionnaire's pretest (Meade & Craig, 2012); more than 90% of the five-point scaled items were answered with the highest value (5), lowest value (1), or middle value (3). This is done to mitigate the tendency for extreme responses and central tendency bias (Douven, 2018), as well as to reduce straight-lining samples (Kim et al., 2019).

In total, $N = 386$ participants completed the anonymous online questionnaire. However, after applying exclusion criteria, the final sample consisted of $N = 285$ participants. Initially, $n = 2$ participants were excluded due to not meeting the requirements of current employment. Additionally, $n = 11$ participants were excluded as they did not meet the criterion of being employed in the last six months. Furthermore, $n = 52$ participants were excluded for failing to correctly answer two out of three comprehensive questions. The median response time for the questionnaire, excluding the IAT, was $Mdn = 443$ seconds. Trained individuals completed the questionnaire in the pre-test for at least two minutes; $n = 23$ participants were excluded due to an unusually short response time, less than two and a half minutes. Moreover, $n = 9$ participants were excluded as they responded with either the highest, lowest, or mid-value to more than 90% of the questions. Participants with z-scores less than $z < -3$ or greater than $z > 3$ were excluded from the analysis leading to a final sample size of $N = 285$ participants. Upon inspecting the data, it was observed that the IATT exhibited a substantial number of missing values. Specifically, the frequency distribution revealed that $n = 95$ samples, accounting for 33.3% of the total, had missing data. Furthermore, a test of multivariate normality indicated that both dependent variables, ATTU and BI, deviated from normality (BI [*skew* = $p < .001$, $k = p < .001$], ATTU [*skew* = $p < .001$, $k = p < .001$]).

Scales Preparation & Outliers

In preparation for the analyses, individual items were aggregated to create scale scores for the following constructs: Scale-Expert, BI, PU, PEU, ATTU, AP, F, T, and TR. Furthermore, the Implicit Association Test values were converted to the IATT scale (IATT) following the standard decoding guidelines (https://implicit.harvard.edu/implicit/). Additionally, the IAT scores were rescaled to a five-point scale. Furthermore, a manual inspection of the dataset was conducted to gain a comprehensive understanding of the data and identify missing values. Even scales exhibiting notable characteristics were examined in greater detail. Next, a multivariate normality test (Korkmaz et al., 2014) was performed with the dependent variables ATTU and BI to check normality assumptions. Additionally, each scale was z-standardized, and values that fell below $z < -3$ or exceeded $z > 3$ were identified as influential points to exclude outliers (following Shiffler, 1988).

Descriptive Analyses

Initial descriptive analyses were conducted in order to provide a comprehensive overview of the sample's demographics and composition. It also included the variables of age, gender, education, workplace location, weekly working hours, company size, years of employment in the organization, employment in HR/non-HR roles, and usage of a comparable system. They were examined in terms of frequencies, means, and group membership. Additionally, the individual scales corresponding to the proposed models were subjected to descriptive statistical analyses, including means and various quantiles (0%, 25%, 50%, 75%, 100%).

Structural Equation Models

In the next step, the proposed models were established using Structural Equation Models (SEM; Hoyle, 2012) following the two-step approach (Anderson & Gerbing, 1988; Herting & Costner, 2000). Due to violating the normal distribution assumption, all calculations were conducted using the robust estimator maximum likelihood ratio test (Huber, 1967). Additionally, all analyses were performed without imputing missing values, utilizing the full maximum likelihood estimation procedure (Arbuckle et al., 1996). Subsequently, robust and standardized results are reported.

In the first step, the measurement models for each construct were established by confirmatory factor analysis. Item parceling using item-to-construct-balance parcels (Little et al., 2022) was conducted for scales with more than four items (BI, ATTU, TR, T), limiting the number of parcels to a maximum of four. Subsequently, the measurement models were estimated based on the data. The variants of each factor were examined for potential Heywood Cases (Kolenikov & Bollen, 2012). The reliability of the scales was assessed using Cronbach's alpha (Cronbach, 1951) with the cut-off values > .90 = Excellent, > .80 = Good, > .70 = Acceptable, > .60 = Questionable, > .50 = Poor, and < .50 = Unacceptable (Gliem & Gliem, 2003). The convergent validity using Average Variance Extracted (*AVE*) should exceed > .50 so that it is adequate (Fornell & Larcker, 1981). The discriminant validity uses chi-squared difference tests between pairs of latent variables (Jöreskog, 1971). Fit indices of the user model, including the test statistic and chi-square test, were examined in terms of model fit. Moreover, the measurement models were assumed to be identified if three or more variables loaded on each indicator, one of these loadings was constrained to a factor of one (Urban & Mayerl, 2013). Additionally, the Comparative Fit Index (*CFI*), Root Mean Square Error of Approximation (*RMSEA*), and Standardized Root Mean Square Residual (*SRMR*) were assessed using commonly accepted cutoff criteria (CFI ≤ .98 for a close fit, CFI ≤ .95 for a reasonable fit, RMSEA ≤ .05 for a close fit, RMSEA ≤ .08 for a reasonable fit, SRMR ≤ .08; Browne & Cudeck, 1993; Hu & Bentler, 1999; Kline, 2023). Modification indices ≥ 10 were examined, and covariances were included if they possessed theoretical plausibility, while a simpler model was preferred over a more complex one. Respecifications were allowed within the same latent construct between manifest variables, one modification at a time, iteratively repeating the process until the best achievable fit was obtained. (Urban & Mayerl, 2013)

In the second step, the respective structural models were established and examined using the same procedure of investigation and respecification. The primary structural models were assumed to be identified if, according to the *t*-rule, the number of known values (t) were equal to or exceeded the number of degrees of freedom (*df*) in the model (see Equation 1, [Bollen & Davis, 2009]).

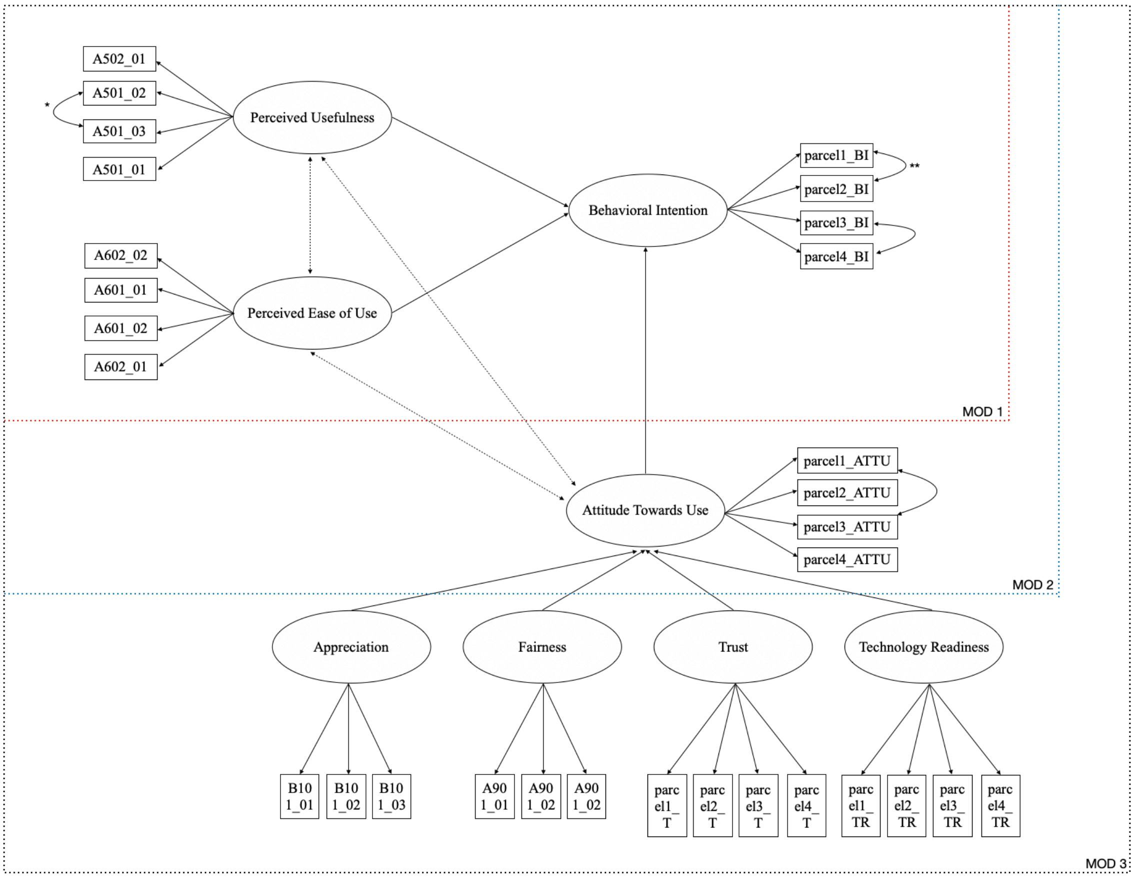
$$t \leq n(n+1)/2 \tag{1}$$

Furthermore, the Akaike Information Criterion (*AIC*) and Bayesian Information Criterion (*BIC*) were assessed to compare the fit of different models. Additionally, the coefficient of determination (R^2) of the dependent variable was examined to assess the extent of explained variance. To test the assumptions of linearity between the effects of independent and dependent variables of the primary models, the factor scores of the latent variables were estimated, a bivariate scatter plot was put out, and a non-parametric visual regression was introduced (Cleveland & Devlin, 1988). Moreover, the model's regression coefficients and relevant covariances were examined to investigate effects. Afterward, model restrictions and group comparisons were carried out. (Kwan & Chan, 2011; Urban & Mayerl, 2013)

The following models were established and adjusted using the described procedure: the final TAM (MOD1), the ATTU-TAM (MOD2), and the extended ATTU-TAM (MOD3). Two restricted models of MOD2 were created. In MOD2_R1, the regression between ATTU and BI was set to zero, representing a nested model with the covariance of ATTU with PU and PEU. Additionally, MOD2_R2 set the covariances between ATTU and PEU, as well as PU, to zero. This represents a non-nested model simultaneous to MOD1 but with the same number of included variables as MOD2. The final TAM and the ATTU TAM underwent a group comparison (MOD1G, MOD2G). The total sample was divided into active (HR) and passive (non-HR) users by self-reported affiliation with the HR department using a dummy variable. Furthermore, the measurement invariance of the latent variables between groups was tested. A measurement invariance test by fitting a sequence of models with increasing constraints on factor loadings, intercepts, and means, further comparing each model's fit to the previous and baseline models using chi-square difference tests was used (Vandenberg & Lance, 2000).

Figure 6

Final Respecification Model



Note. *Not considered in MOD3. **Only considered in MOD3. Dashed lines represent investigated covariances. Own presentation.

Model Comparisons

In addition, Monte Carlo simulations were conducted to examine the cut-off values assessing the appropriateness of fit indices for model comparisons. A dataset with non-normal distribution (k = 2, *skew* = -1) and N = 285 samples were simulated. Further cut-off indices for the *AIC* and *BIC* values were determined. (Pornprasertmanit et al., 2013; Pornprasertmanit et al., 2012; Vrieze, 2012)

A chi-squared difference test to compare nested models was conducted (Werner & Schermelleh-Engel, 2010) and a Vuong test (Vuong, 1989; Wilson, 2015) to compare non-nested models.

Further Analysis

Additionally, the measurement invariance test for multiple groups was used to examine mean invariance between groups regarding the external variables influencing ATTU (T, AP, F, TR) and ATTU itself (van Dijk et al., 2021; Vandenberg & Lance, 2000). Subsequently, a Wilcoxon rank sum test with confidence intervals was conducted to examine differences in means between the two independent groups of the latent variables (Wild & Seber, 2011). Furthermore, differences between ATTU and IATT, as well as between the groups, were examined, handling missing data by excluding those samples.

Results

A correlation matrix with all relevant variables, means and standard deviations can be found in the Appendix (cf. Appendix A, Table 4).

Sample Size & Power

A post hoc power analysis was conducted using Monte Carlo simulations for sample size detection. The factor loadings were assumed to be .80, the average standard variance of the manifest items s^2 = .20, and the latent constructs s^2 = 1. Based on previous findings (cf. Table 1), the effect sizes are considered to be small (*d* = .30) for effects between PEU and BI and medium (*d* = .60) for effects between PU and BI in MOD1. Based on previous findings (cf. Table 1), the effect sizes were considered to be small (*d* = .30) for effects between PEU and BI, PU and BI, as well as external effects on ATTU, and medium (*d* = .60) for the effect between ATTU and BI in MOD2 and MOD3. With a significance criterion of α = .05 and power .80, the minimum sample size needed to detect this power in the effects of all three primary Models was *N* = 227. These findings suggested that a sample size of at least *N* = 227 participants is required to detect the hypothesized effects in the proposed models adequately. A sample size of at least *N* = 116 was indicated to detect the structural model.

Descriptive Statistics

The participants' average PU score was 3.7 (*SD* = .77). Among the participants, 25% of the responses were below 3.25 but not under 1.50, while 25% were above 4.25. Participants working in HR had a slightly higher average PU score of 3.89 (*SD* = .77) than those not working in HR, who had an average score of 3.54 (*SD* = .73).

Regarding PEU, the average score for all participants was 3.44 (*SD* = .71). Specifically, 25% of the responses fell below 3.00 but not under 1.25, while 25% were above 4.00. Participants working in HR reported a higher average PEU score of 3.64 (*SD* = .69) compared to those not working in HR, who had an average score of 3.27 (*SD* = .67).

For BI, the average score was 3.26 (*SD* = .99). About 25% of the responses were below 2.50, while 25% were above 4.00. Participants working in HR had a higher average BI score of 3.61 (*SD* = .92) than those not working in HR, who had an average score of 2.98 (*SD* = .95).

The participants' average ATTU score was 3.44 (*SD* = .88). Among the responses, 25% were below 2.87, while 25% were above 4.00. Participants working in HR had a slightly higher average ATTU score of 3.68 (*SD* = .88) than those not working in HR, who had an average score of 3.25 (*SD* = .82).

Regarding TR, the average score was 3.21 (*SD* = .53). About 25% of the responses were below 2.88 but not under 1.75, while 25% were above 3.50. There were no substantial differences in the average TR scores between participants working in HR (*M* = 3.24, *SD* = .57) and those not working in HR (*M* = 3.18, *SD* = .50).

For T, the average score was 3.23 (*SD* = .65). Approximately 25% of the responses were below 2.83 but not under 1.25, while 25% were above 3.75. Participants working in HR had a slightly higher average T score of 3.40 (*SD* = .69) than those not working in HR, who had an average score of 3.08 (*SD* = .59).

The participants' average AP score was 3.04 (*SD* = 1.03). About 25% of the responses were below 2.33, while 25% were above 4.00. Participants working in HR had a slightly higher average AP score of 3.30 (*SD* = 1.06) than those not working in HR, who had an average score of 2.83 (*SD* = .96).

The participants' average F score was 3.44 (*SD* = .94). About 25% of the responses were below 3.00, while 25% were above 4.00. Participants working in HR had a slightly higher average F score of 3.68 (*SD* = .95) than those not working in HR, who had an average score of 3.24 (*SD* = .89).

Finally, among the participants who completed the IAT (*n* = 190), the average IATT score was 2.7 (*SD* = 1.18). Around 25% of the responses were below 1.67, while 25% were above 3.01. There were no substantial differences in the average IATT scores between participants working in HR (*M* = 2.64, *SD* = 1.20) and those not working in HR (*M* = 2.74, *SD* = 1.18).

Structural Equation Models

In front, the items of BI, ATTU, T, and TR were parceled into four packages (cf. Appendix A, Table 3). In the first step, for every model, the validity of the measurement model was assessed through confirmatory factor analysis. The results of the final model revealed that each item loaded significantly on its corresponding latent variable, with no error variances falling below zero or exceeding one, indicating the absence of Heywood Cases (cf.

Appendix C). Furthermore, a minimum of three manifest variables loaded on every latent variable, indicating overidentification of the measurement model (cf. Appendix C, Figure 1). The model fit indices for all models suggested a close fit of the measurement model to the data, as indicated by the chi-square statistic.

Table 2

Measurement Model Fit Indices

	X^2	*CFI*	*RMSEA*	*SRMR*
MOD1	(50,285) = 80.83, p = .004	.99	.05	.04
MOD2	(95,285) = 170.34, $p < .001$	.98	.06	.04
MOD3	(375,285) = 623.61, $p < .001$	.97	.05	.05

Note. Own presentation.

MOD1

In the second step, the structural model of MOD1 was evaluated. The model fit indices suggested a close fit of the structural model to the data, indicated by the chi-square statistic (X^2[50,285]= 80.83, p = .004), *CFI* = .99, A*IC* = 6328.33, *BIC* = 6474.43, *RMSEA* = .05, and *SRMR* = .04. Additionally, the *t*-value of 78 in comparison to the degrees of freedom of 50 indicated an overidentification of the structural model. All relationships between independent and dependent variables were classified as linear (cf. Appendix E).

The results of the regression analysis revealed that the latent constructs explained 58% of the variance in BI (R^2 = .58). Specifically, PEU had a significant medium positive effect (β = .23, p = .005), as well as PU had a significant medium positive effect (β = .60, $p < .001$) on BI. A significant medium covariance was observed between PEU and PU (β = .65, $p < .001$).

The subsequent group comparison showed the following results. The regression analysis demonstrated that the latent constructs explained 66% of the variance in BI for the HR group (R^2 = .66) and 45% of the variance for the non-HR group (R^2 = .45). In the HR group, PEU did not significantly predict BI (β = .19, *p* = .098). At the same time, PU exhibited a significant medium positive effect (β = .68, *p* < .001). Similarly, in the non-HR group, PEU did not significantly predict BI (β = .20, *p* = .072), while PU had a significant medium positive effect (β = .53, *p* < .001). Furthermore, a significant medium covariance was observed between PEU and PU for both the HR group (β = .65, *p* < .001) and the non-HR group (β = .60, *p* < .001), indicating interrelationships among the variables.

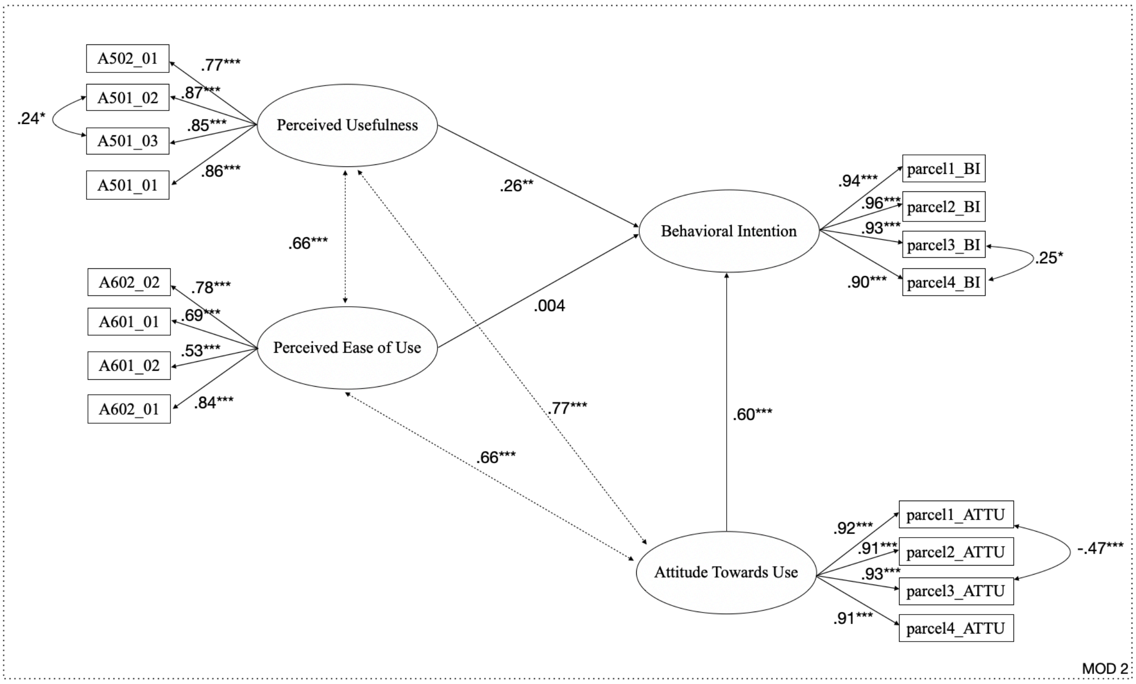
MOD2

In the second step, the structural model of MOD2 was evaluated. The model fit indices suggested a close fit of the structural model to the data, indicated by the chi-square statistic (X^2[95,285] = 170.34, *p* < .001), *CFI* = .98, *AIC* = 7892.64, *BIC* = 8100.83, *RMSEA* = .06, and *SRMR* = .04. Additionally, the *t*-value of 136 in comparison to the degrees of freedom of 95 indicated an overidentification of the structural model. All relationships between independent and dependent variables were classified as linear (cf. Appendix E).

The regression analysis indicated that the latent constructs explained 72% of the variance in BI (R^2 = .72). PEU did not significantly predict BI (β = .05, *p* = .491). At the same time, PU showed a significant small positive effect (β = .26, *p* = .001) and ATTU showed a significant medium positive effect (β = .60, *p* < .001). Both PEU (β = .66, *p* < .001) and ATTU (β = .77, *p* < .001) showed a significant medium covariance with PU. PEU showed a significant medium covariance with ATTU (β = .66, *p* < .001).

Figure 7

Attitude Towards Use Technology Acceptance Model, Structural Equation Model



Note. *p < .05, **p < .01, ***p < .001. Dashed lines represent investigated covariances. Own presentation.

To examine the model restrictions, two additional models were tested. In MOD2_R1, the regression of ATTU on BI was restricted to zero, resulting in a poor fit of the structural model to the data, as indicated by the model fit indices ($X^2[96,285] = 238.64$, $p < .001$), *CFI* = .97, *AIC* = 7963.90, *BIC* = 8168.44, *RMSEA* = .08, and *SRMR* = .06. This restriction led to a decrease in the explained variance of BI to 66% ($R^2 = .66$). PEU not significantly predicted BI ($\beta = .20$, $p = .077$), PU retained its significant medium positive effect ($\beta = .67$, $p < .001$). Furthermore, PEU showed a significant medium covariance with PU ($\beta = .66$, $p < .001$). ATTU showed a significant large covariance with PU ($\beta = .81$, $p < .001$). PEU showed a significant medium covariance with ATTU ($\beta = .68$, $p < .001$).

In MOD2_R2, the regression of ATTU on BI, the covariances between ATTU and PEU, as well as PEU, were restricted to zero. The model fit indices indicated a poor fit of the structural model to the data (X^2[98,285] = 472.22, $p < .001$), *CFI* = .91, *AIC* = 8236.88, *BIC* = 8434.11, *RMSEA* = .12, *SRMR* = .34. The latent constructs explained 59% of the variance in BI ($R^2 = .59$). PEU showed a significant small positive effect on BI (β = .21, $p = .011$), PU showed a significant medium positive effect on BI (β = .61, $p < .001$). Furthermore, PEU showed a significant medium covariance with PU (β = .65, $p < .001$).

The subsequent group comparison showed the following results. The regression analysis revealed that the latent constructs explained 78% of the variance in BI for the HR group ($R^2 = .78$) and 63% of the variance in BI for the non-HR group ($R^2 = .63$). For the HR group, PEU did not significantly predict BI (β = .08, $p = .342$). At the same time, PU had a significant small positive effect (β = .30, $p = .025$), as well as ATTU had a significant medium positive effect (β = .56, $p < .001$). Similarly, for the non-HR group, PEU did not significantly predict BI (β = -.04, $p = .676$). At the same time, PU had a significant small positive effect (β = .24, $p = .009$), as well as ATTU had a significant medium positive effect (β = .63, $p < .001$). Both PEU (β = .65, $p < .001$) and ATTU (β = .80, $p < .001$) showed a significant medium covariance with PU for the group HR. PEU showed a significantly medium covariance with ATTU (β = .62, $p < .001$) for the group HR. Both PEU (β = .61, $p < .001$) and ATTU (β = .72, $p < .001$) showed a significant medium covariance with PU for the non-HR group. PEU showed a significant medium covariance with ATTU (β = .65, $p < .001$) for the non-HR group.

Table 3

ATTU-TAM with Groups, Regression-, Covariance-Matrix

	BI	**PU**	**ATTU**
PEU	~ .085, -.037	.651***, .609***	.619***, .652***

PU	~ .305*, .242**	.797***, .715***
ATTU	~ .559***, .628***	

Note. *p < .05, **p < .01, ***p < .001. The tilde shows regressions. First value group active-, second value group passive-users. Own presentation.

MOD3

In the second step, the structural model was evaluated. The model fit indices suggested a close fit of the structural model to the data, indicated by the chi-square statistic (X^2[381,285] = 637.31, $p < .001$), *CFI* = .97, *AIC* = 14165.64, *BIC* = 14582.03, *RMSEA* = .05, and *SRMR* = .05. Additionally, the *t*-value of 465 in comparison to the degrees of freedom of 381 indicated an overidentification of the structural model. All relationships between independent and dependent variables were classified as linear (cf. Appendix E).

The regression analysis revealed that the latent constructs explained 73% of the variance in BI (R^2 = .73) and 86% of the variance in ATTU (R^2 = .86). PEU did not significantly predict BI (β = .07, p = .295). At the same time, PU had a significant small positive effect (β = .22, p = .003), as well as ATTU had a significant medium positive effect (β = .63, $p < .001$). Additionally, AP significantly predicted ATTU with a small positive effect (β = .13, p = .030), as well as T significantly predicted ATTU with a medium positive effect (β = .75, $p < .001$). However, F (β = .07, p = .190) and TR (β = .03, p = .527) did not have a significant effect on ATTU.

Model Comparisons

A post hoc Monte Carlo simulation was conducted to detect cut-off indices by comparing nested and non-nested models. In this simulation, the factor loadings were assumed to be .80, the average standard variance of the manifest items was s^2 = .20, and the latent constructs' standard variance was $s^2 = 1$. In the first model, the effect sizes for the relationships between PEU and BI were considered to be medium (d = .30), as well as the effect sizes for the relationship between PU and BI (d = .60), based on previous findings (cf. Table 1). In the other two primary models, the effect sizes for the relationships between PEU and BI, PU and BI, the external effects of ATTU were considered to be medium (d = .30), as well as the effect size for the relationship between ATTU and BI was considered to be medium (d = .60), based on previous findings (cf. Table 1).

To run the simulation, a non-normal dataset was simulated with a skewness of two and a kurtosis of minus one, comprising N = 285 samples. The simulation was executed with 1000 iterations on the MOD2 and its restricted versions. The cut-off indices for the model comparisons between MOD2 and MOD2_R1 were found to be AIC = 37.81 and BIC = 34.16, while for the model comparisons between MOD2 and MOD2_R2, the cut-off indices were AIC = 65.44 and BIC = 54.48.

To assess the difference between the two nested models, MOD2 and MOD2_R1, a chi-squared difference test was conducted. The results revealed a significant difference in the comparison between these models ($X^2[1,285] = 11.25$, $p < .001$). The significant chi-squared difference test indicates that the model with the more freely estimated parameters, in other words, with fewer degrees of freedom, fits the data significantly better. This suggested that including the additional parameters in MOD2 is worthwhile instead of using model MOD2_R1.

A Vuong test was conducted under the assumptions of normality to assess the difference between two non-nested models, MOD2 and MOD2_R2. The results supported the acceptance of H1, indicating that MOD2 and MOD2_R2 are distinguishable ($w^2 = .73$, $p <$

.001). Additionally, H1A was accepted (z = 12.14, p < .001), suggesting that MOD2 fits better than MOD2_R2.

Latent Mean Comparisons

A measurement invariance test was conducted to assess the equivalence of the configural model (equal factor structure) and the loadings model (equal factor structure and loadings) between the group's HR and non-HR. The results indicated that there was no significant difference in factor loadings between the two groups (X^2[22, 285] = 19.23, p = .630). Furthermore, the loadings model (equal factor structure and loadings) was compared to the intercepts model (equal factor structure, loadings, and intercepts) to examine the equivalence of intercepts between the group's HR and non-HR. The findings revealed a slight difference in intercepts between the groups (X^2[22, 285] = 34.66, p = .042). Additionally, the intercepts model (equal factor structure, loadings, and intercepts) was compared to the means model (equal factor structure, loadings, intercepts, and means) to assess the invariance of means between the group's HR and non-HR. The results demonstrated that there was a significant difference in means between the groups (X^2[8, 285] = 45.90, p < .001). This suggested that the groups differed most regarding their mean scores on the measured constructs.

A Wilcoxon rank sum test was conducted to examine the differences in AP between the groups. The results indicated a significant difference (W = 12780, p < .001), with a median difference between two samples out of both groups of .67. Similarly, a significant difference in F between the groups was found (W = 12947, p < .001), with a median difference between two samples out of both groups of .33. Furthermore, a significant difference in T between the groups was observed (W = 12897, p < .001), with a median difference between two samples out of both groups of .33. However, no significant difference in TR between the groups was detected (*W* = 10260, $p = .774$).

A Wilcoxon rank sum test was conducted to assess the differences in ATTU between the groups. The results indicated a significant difference (*W* = 13126, $p < .001$), with a median difference between two samples out of both groups of .50. Furthermore, a significant difference in IATT between the groups was observed (*W* = 4130.5, $p = .464$), with a median difference between two samples out of both groups of -.00. Additionally, a significant difference between ATTU and IATT was found (*W* = 54146, $p < .001$), with a median difference between two samples out of both groups of 3.31.

Hypothesis Testing

H1: The ATTU-TAM can better explain the collected data than the final TAM. The model fit indices for MOD2 suggested a close fit of the structural model to the data by the chi-square statistic ($X^2[95,285] = 170.34$, $p < .001$), *CFI* = .98, *AIC* = 7892.64, *BIC* = 8100.83, *RMSEA* = .06, and *SRMR* = .04. In contrast, the MOD2_R2 model fit indices indicated a poor fit to the data ($X^2[98,285] = 472.22$, $p < .001$), *CFI* = .91, *AIC* = 8236.88, *BIC* = 8434.11, *RMSEA* = .12, *SRMR* = .34. The lower values suggested that MOD2_R2 did not adequately explain the collected data. The *AIC* difference of 344.24 and *BIC* difference of 333.28 showed smaller values for MOD2, suggesting a better fit to the collected data and even exceeding the predicted cut-off indices (*AIC* = 65.44, *BIC* = 54.48). Additionally, the Vuong test supported the distinguishability between the two models ($w^2 = .73$, $p < .001$), favoring MOD2 over MOD2_R2 ($z = 12.14$, $p < .001$). In summary, the data provided strong evidence to support H1.

H1a: The ATTU-TAM can better explain the collected data than modeling ATTU as an external variable in the final TAM. The model fit indices for MOD2 indicated a close fit to the data by the chi-square statistic ($X^2[95,285] = 170.34$, $p < .001$), *CFI* = .98, *AIC* = 7892.64, *BIC* = 8100.83, *RMSEA* = .06, and *SRMR* = .04. In contrast, the model fit indices for MOD2_R1 suggested a poor fit to the data ($X^2[96,285] = 238.64$, $p < .001$), *CFI* = .97, *AIC* = 7963.90, *BIC* = 8168.44, *RMSEA* = .08, and *SRMR* = .06. The lower values suggested that MOD2_R1 did not adequately explain the collected data. The *AIC* difference of 71.26 and *BIC* difference of 67.61 showed smaller values for MOD2, suggesting a better fit to the collected data and even exceeding the predicted cut-off indices (*AIC* = 37.81, *BIC* = 34.16). Additionally, the chi-squared difference test supported the superiority of MOD2 ($X^2[1, 285] = 11.25$, $p < .001$). In summary, the data provided strong evidence to support H1a.

H2: The ATTU-TAM can better explain BI than the final TAM. The results for MOD2 indicated that the latent constructs explained 72% of the variance in BI ($R^2 = .72$). The results for MOD1 revealed that the latent constructs explained 58% of the variance in Behavioral Intention ($R^2 = .58$). Subsequently, MOD2 explained 14% additional variance in BI than MOD1. Thus the data provided evidence to support H2.

H2a: The ATTU-TAM can better explain BI for active users than the final TAM. The results for MOD2G demonstrated that the latent constructs explained 78% of the variance in Behavioral Intention for the HR group ($R^2 = .78$). The results for MOD1G demonstrated that the latent constructs explained 66% of the variance in Behavioral Intention for the HR group ($R^2 = .66$). Subsequently MOD2 explained 12% additional variance in BI for the HR group than MOD1. Thus the data provided evidence to support H2a.

H2b: The ATTU-TAM can better explain BI for passive users than the final TAM. The results for MOD2G demonstrated that the latent constructs explained 63% of the variance in Behavioral Intention for the non-HR group (R^2 = .63). The results for MOD1G demonstrated that the latent constructs explained 45% of the variance in Behavioral Intention for the non-HR group (R^2 = .45). Subsequently MOD2 explained 18% additional variance in BI for the HR group than MOD1. Thus the data provided evidence to support H2b.

H3: ATTU directly influences BI, whereas a more positive ATTU increases BI. In MOD2, ATTU showed a significant medium positive effect on BI (β = .60, $p < .001$). The results suggested that a more positive Attitude Towards Use is associated with a medium increase in Behavioral Intention, supporting H3.

H3a: ATTU directly influences BI for active users, whereas a more positive ATTU increases BI. In MOD2G, ATTU showed a significant medium positive effect (β = .56, $p < .001$). The results suggested that a more positive Attitude Towards Use is associated with a medium increase in Behavioral Intention in the group HR, supporting H3a.

H3b: ATTU directly influences BI for passive users, whereas a more positive ATTU increases BI. In MOD2G, ATTU showed a significant medium positive effect (β = .63, $p < .001$). The results suggested that a more positive Attitude Towards Use is associated with a medium increase in Behavioral Intention in the non-HR group, supporting H3b.

H4: F directly influences ATTU, whereas a higher perceived F increases ATTU. In MOD2, F did not significantly predict ATTU (β = .07, $p = .190$), rejecting H4.

H5: AP directly influences ATTU, whereas a higher AP increases ATTU. In MOD2, AP significantly predicted ATTU with a small positive effect (β = .13, $p = .030$). The results suggested that a more positive Appreciation is associated with a small increase in Attitude, supporting H5.

H6: T directly influences ATTU, whereas a higher T increases ATTU. In MOD2, T significantly predicted ATTU with a medium positive effect (β = .75, $p < .001$). The results suggested that a more positive Trust is associated with a medium increase in Attitude, supporting H6.

H7: TR directly influences ATTU, whereas a higher TR increases ATTU. In MOD2, TR did not significantly predict ATTU ($\beta = .07$, $p = .527$), rejecting H7.

H8: ATTU differs between active and passive users. The mean of the latent variable ATTU differed substantially between the groups (HR [$M = 3.68$, $SD = .88$], non-HR [$M = 3.25$, $SD = .82$]). A measurement invariance test conducting equivalence between the groups showed the most significant difference in means ($X^2[8, 285] = 45.90$, $p < .001$). A Wilcoxon rank sum test was conducted to examine the differences in ATTU between groups. The results indicated a significant difference ($W = 54146$, $p < .001$), with a medium difference of 3.31. These data suggested that passive and active users exhibit distinct levels of Attitude Towards Use, supporting H8.

H9: F differs between active and passive users. The mean of the latent variable F differed substantially between the groups (HR [$M = 3.68$, $SD = .95$], non-HR [$M = 3.24$, $SD = .89$]). A measurement invariance test conducting equivalence between the groups showed the most significant difference in means ($X^2[8, 285] = 45.90$, $p < .001$). A Wilcoxon rank sum test was conducted to examine the differences in F between groups. The results indicated a significant difference ($W = 12947$, $p < .001$), with a medium difference of .33. These data suggested that passive and active users exhibit distinct levels of Fairness, supporting H9.

H10: T differs between active and passive users. The mean of the latent variable T differed substantially between the groups (HR [$M = 3.40$, $SD = .69$], non-HR [$M = 3.08$, $SD = .59$]). A measurement invariance test conducting equivalence between the groups showed the most significant difference in means ($X^2[8, 285] = 45.90$, $p < .001$). A Wilcoxon rank sum test was conducted to examine the differences in T between groups. The results indicated a significant difference (*W* = 12897, $p < .001$), with a medium difference of .33. These data suggested that passive and active users exhibit distinct levels of Trust, supporting H10.

H11: AP differs between active and passive users. The mean of the latent variable AP differed substantially between the groups (HR [*M* = 3.30, *SD* = 1.06], non-HR [*M* = 2.83, *SD* = .96]). A measurement invariance test conducting equivalence between the groups showed the most significant difference in means (X^2[8, 285] = 45.90, $p < .001$). A Wilcoxon rank sum test was conducted to examine the differences in AP between groups. The results indicated a significant difference (*W* = 12780, $p < .001$), with a medium difference of .67. These data suggested that passive and active users exhibit distinct levels of Appreciation Towards Use, supporting H11.

H12: TR differs between active and passive users. The mean of the latent variable TR did not substantially differ between the groups (HR [*M* = 3.24, *SD* = .57], non-HR [*M* = 3.18, *SD* = .50]). A Wilcoxon rank sum test was conducted to examine the differences in TR between groups. The results indicated no significant difference (*W* = 10260, $p = .774$), rejecting H12.

H13: Implicit ATT and ATTU differ. The mean of the latent variables ATTU and IATT differed substantially between the variables (IATT [*M* = 2.7, *SD* = 1.18], ATTU [*M* = 3.44, *SD* = .88]). A Wilcoxon rank sum test assessed the differences between ATTU and IATT. The results indicated a significant difference (*W* = 54146, $p < .001$), with a median difference of 3.31, supporting H13.

H13a: Implicit ATT differs between active and passive users. The mean of the latent variable IATT did not substantially differ between the groups (HR [*M* = 2.64, *SD* = 1.20], non-HR [*M* = 2.74, *SD* = 1.18]). A Wilcoxon rank sum test assessed the differences in

IATT between groups. The results indicated a significant difference ($W = 4130.5$, $p = .464$), with a median difference of -.00 between the two groups, supporting H13a.

H14: ATTU covariates with PU. In MOD2, ATTU showed a significant medium covariance with PU ($\beta = .77$, $p < .001$), supporting H14.

H15: ATTU covariates with PEU. In MOD2, ATTU showed a significant medium covariance with PEU ($\beta = .66$, $p < .001$), supporting H15.

H16: PEU covariates with PU. In MOD2, PEU showed a significant medium covariance with PU ($\beta = .66$, $p < .001$), supporting H16.

Discussion

This thesis challenges the use and development of the Technology Acceptance Model by paying too little attention to Attitude. It introduces the acceptance of highly complex technology, particularly regarding the implementation of AI-based Skill Management Software in HR. Through comprehensive literature research and an in-depth theory discussion. This thesis argues that the Technology Acceptance of highly complex technology is affected by both attitudes towards the system and attitudes towards the use of the system. Likewise is subject of active as well as passive use. The ATTU-TAM is developed based on the final TAM and adds the variable Attitude Towards Use.

Within the framework of an empirical investigation regarding the implementation of AI-based Skill Management Software in Human Resources, this thesis furnishes an examination of the complex relationships of this particular technology. It investigates the role of Attitude Towards Use and the influencing variables Trust, Appreciation, Fairness, and Technology Readiness. Additionally, it validates the ATTU-TAM and compares it with alternative TAM models. This is Supported by a statistical analysis of the gathered data, primarily utilizing Structural Equation Models and Monte Carlo simulations.

Power & Sample

An a-priori sample size analysis and a post hoc Monte Carlo simulation detect the minimum sample size to validate the effects, as well as the SEM structures of the proposed theoretical models. In line with the adequate minimum sample size (N = 227), the resulting sample of N = 285 participants provides sufficient statistical power to effectively test the thesis´ hypothesis.

The sample represents employees from Germany (77.9%), Austria (17.5%), and Switzerland (2.8%) in a wide age range of 22 to 62 years, with an average age of 42 years. The sample is well-balanced in terms of gender. More than half of the participants hold a university degree, and more than a third hold completed training or apprenticeships, describing well-educated participants. Regarding work departments, n = 129 work in an HR department, referring to roughly equal proportions of HR and non-HR workers. The sample describes average full-time working employees out of diverse company sizes (large: 55.4%, medium-sized: 26.7%, small: 4.6%), as well as diverse employment durations in their companies (more than ten years: 44.6%, five to ten years: 28.4%, less than five years: 26.7%). The average self-reported Expert-Status of participants in relation to Artificial Intelligence is 2.75, showing a neutral to slightly lower Expert-Status. Participants working in HR have a higher average self-reported Expert-Status than participants not working in HR. Overall, 44 participants report the use of a comparable system.

The sample represents a well-balanced, diverse, and characteristic dataset for employees out of the DACH region, studying HR and non-HR average full-time workers within groups of equal size, out of various company sizes, and diverse employment durations.

People working in HR conduct themselves with a slightly higher but neutral AI Expert-Status, while people not working in HR with an average lower Expert-Status. Around 10% use AI-based Skill Management Software in their company. This underlines the findings that such Software is not implemented frequently.

Applying the TAM

In general, participants perceive AI-based Skill Management Software as useful, with slightly good usability and a neutral Behavioral Intention to use. This aligns with previous research on the acceptance of AI in HR (cf. chap. The Acceptance of AI in HR). Participants working in HR perceive AI-based Skill Management Software as useful, with good usability, and positive intention to use. Controversy, participants not working in HR perceive AI-based Skill Management Software as neutral user-friendly and would neither use nor not use them. The final TAM is generally applicable to explain the Technology Acceptance of AI-based Skill Management Software. Perceived Usefulness seems to be most important, Perceived Ease of Use rather strongly influences PU, than BI. Additionally, PU is slightly more important in the group of HR employees representing active users, than passive users. The TAM performs better in explaining the BI of mostly active use-related users than passive use-related users. The insignificance of PEU could be related to the use of a fictitious example. The usability of the system could be generally distorted, while the usefulness can be better constructed. Furthermore, the variable significance of PEU in TAM research is not uncommon (Sharp, 2006).

These findings show the applicability of the TAM to this specific use case example with expected results (cf. Table 1). Additionally, underline a difference in the perception of active and passive users toward the Technology Acceptance of AI-based Skill Management Software.

Validating the ATTU-TAM

Model comparisons show that ATTU-TAM performs best in explaining the data. A comparison between the ATTU-TAM and the final TAM shows that ATTU-TAM better fits the data than the final TAM. A model comparison additionally underlines that ATTU-TAM can better explain the data, even though Attitude Towards Use can interact with PEU and PU.

In conclusion, ATTU-TAM has a superior fit to the data compared to the final TAM. Likewise, the data shows that Attitude Towards Use can not be operationalized in front of PU or PEU, leading to a lower fit of the model. This indicates a difference between the attitude toward the system and the attitude towards the use of a system. Furthermore, this underlines the applicability to explain the Technology Acceptance of AI-based SMS superior, compared to presented TAM adjustments.

Additionally, ATTU-TAM performs best in explaining BI. The ATTU-TAM can better explain the variance of Behavioral Intention in the overall model, as well as in the group models. Furthermore, it explains the most additional variance for the group model related to passive users. But ATTU-TAM can also explain a decent additional amount of variance for the active user group. A more positive Attitude Towards Use positively influences Behavioral Intention. Attitude Towards Use has a significant positive influence on the BI for the overall model, as well as the group models. It shows a slightly higher effect of ATTU on BI related to passive users. Further, the covariance between PEU and PU stays regarding the basic TAM.

Attitude Towards Use emerges as the most influential predictor in explaining the acceptance of AI-based Skill Management Software for both HR and non-HR workers. Moreover, it enhances the understanding of Technology Acceptance remarkably, particularly among passive users.

Furthermore, the covariance between ATTU and PU and ATTU and PEU give indications for mediation between PEU/PU, over ATTU, on BI. This might explain the weaker effect of PU and PEU in the ATTU-TAM compared to the final TAM.

Regarding the implementation of AI-based Skill Management Software, this suggests that ATTU potentially mediates the effects of PU and PEU on Behavioral Intention. Thus ATTU can partly explain the effect of usefulness as well as ease of use on BI. This reinforces the role of ATTU in explaining the Technology Acceptance of AI-based Skill Management Software.

Extending the ATTU-TAM to a Specific Use-Case

Extending the ATTU-TAM with further external variables on ATTU show mixed results. Technology Readiness does not influence Attitude Towards Use. Technology Readiness is defined as the underlying perceptions towards a technology, consisting of barriers and drivers (Parasuraman & Colby, 2015). Those basic perceptions do not influence Attitude Towards Use and should be operationalized differently. This might be because Technology Readiness represents the basic perception of the system design and is thus no precursor of Attitude Towards Use. Furthermore, Fairness shows no significant effect on ATTU. This is might because Fairness does not arise from its use but from the system itself. Those results underpin that not every variable related to attitude affects ATTU, especially not when they are in relation to the design of the system. In contrast, ATTU is highly influenced by the perception of trust towards the use of a system. Additionally, AP provides a small positive effect on ATTU. The external variables influencing ATTU can highly explain the variance of ATTU.

The findings demonstrate that the ATTU-TAM can be adapted to use cases by incorporating external variables which influence ATTU, even if these variables must be considered carefully. Those need to be related to the use of the system or multifaceted. This adaptation enables the model to explain a significant amount of variance in ATTU and consequently provides a more accurate explanation of use-specific relationships. Although the relationship between Trust and ATTU should be considered cautious, as the two constructs are hard to separate (cf. Appendix D, Table 4).

Regarding the implementation of AI-based SMS in HR, ATTU is influenced by Trust and Appreciation. A higher Appreciation and Trust are associated with a higher ATTU and influence the BI. In contrast, basic perceptions towards AI-based SMS have no influence on ATTU. Furthermore, not every attitude is applicable in explaining ATTU.

This underlines the importance of the distinction between attitude toward the system and towards the use of the system as two concepts to be distinguished. Furthermore, it indicates that basic perceptions and attitudes towards the system should be considered in relation to the design of the system.

Investigating Active Versus Passive Use

A measurement invariance test between the group's HR and non-HR workers shows that there is the most significant difference among the means of the measured constructs. Wilcoxon rank sum tests reveal a significant difference between the external variables AP, F, and T, but no difference in TR. Furthermore, this suggests a significant difference between the Attitude Towards Use and the Implicit Attitude between groups. The data show the highest difference in AP, followed by ATTU, T, F, and the least IATT.

This provides evidence that the perception of Attitude Towards Use and those influencing factors differs between HR and non-HR employees regarding the implementation of AI-based Skill Management Software. It underlines the assumptions that active and passive users experience highly complex technology distinct regarding their Attitude Towards Use and those influencing variables. Technology Readiness with no dissimilarity between user groups indicates that underlying perceptions concerning the system design do not differ between groups. The slight difference between groups in IATT also refers to the introspectively unidentified perceptions toward the system. Additionally, the results show the highest dissimilarity between ATTU and IATT. This supports the assumption that both are distinct constructs and should be studied independently.

Conclusion

The ATTU-TAM can explain the complex relationships in the Technology Acceptance of AI-based Skill Management Software. Attitude Towards Use emerges as an essential variable influencing Behavioral Intention. A better Attitude Towards Use leads to better Technology Acceptance. This possesses validity for HR and non-HR workers. Although, the explained variance and the effect for non-HR workers increase. The attitude towards the use of AI-based Skill Management Software can explain a decent amount of the acceptance for both user groups. In total, it provides a more substantial influence and a greater explained variance for non-HR workers.

Comparing the ATTU-TAM to the final TAM reveals that the ATTU-TAM performs best in explaining the collected data and the variance of Behavioral Intention. Even if compared to a model conceptualizing ATTU concerning PU and PEU. This shows that the attitude towards the use of a system cannot be operationalized in relation to the system design. Moreover, ATTU-TAM explains the most additional variance in BI for the group of passive users. Still, it can present a decent amount of additional variance for the group of active users.

Attitude Towards Use is highly influenced by trust towards the use and slightly by appreciation towards the use of AI-based SMS. A higher Trust and Appreciation positively impact the Attitude Towards Use. Incorporating related or multifaceted external variables can explain a high amount of variance in ATTU. This provides a detailed examination of the underlying perceptions influencing the attitude towards the use of AI-based SMS.

The Attitude Towards the Use of AI-based Skill Management Software and its influencing variables differ between HR and non-HR users. This shows that different experiences with the system lead to a distinct perception towards the use of the system and thus the Technology Acceptance.

The evidence validates the development of the ATTU-TAM as an appropriate framework for explaining the Technology Acceptance of highly complex technologies. It emphasizes the importance of attitude towards the use of the system and the differences between active and passive use. Furthermore, it can be extended by additional variables to explain the ATTU better. These adaptations enable the model to examine a more accurate explanation of use-case-specific relationships.

Limitations

This thesis is subject to limitations; some have already been addressed throughout this work, such as the behavior-intention gap and the close relationship between attitudes and Behavioral Intention. Therefore, further elaboration on these limitations will not be provided.

Generally, it is essential to recognize that the study, using a fictitious use-case example, naturally requires a high level of imagination from the participants. This may limit the authenticity of the results. In addition, there is no clear distinction between the concepts of Trust and ATTU, so effect sizes should be viewed cautiously. Furthermore, the initial design of the thesis should have given more attention to implicit attitudes. However, due to numerous missing data in the IAT, the decision was made to exclude this variable to avoid potential biases. Consequently, hypotheses related to Implicit Attitude (H13, H13a) were complimented. Additionally, it should be noted that sub-hypotheses were expanded to better differentiate between groups (H1, H2, H3). However, this did not impact the core hypotheses and served only as a more detailed description. Due to an error in the pre-registration, the hypothesis on the covariance between PU and PEU (H16) and the difference of TR (H12) were also added.

Regarding the applied statistical tests, it is essential to note that the Vuong test is not typically conducted under non-normality. Due to the absence of known alternatives, the Vuong test was still calculated, but caution should be exercised when interpreting its results. Furthermore, it is worth mentioning that the statistical analyses conducted in this thesis, while valuable, still need a comprehensive validation of the proposed model. As there are currently no regulations on the use of Artificial Intelligence in research, it is noted that ChatGPT (ChatGPT, 2023) and Deepl (DeepL, 2023) have been used as a tool for translation and paraphrasing.

Practical Implementation

When it comes to practice, the following suggestions can be offered. In the implementation of highly complex technologies, especially AI-based Skill Management Software, it is crucial to consider: Besides attitudes towards the system, attitudes towards the use of the system play a vital role. Those strongly influence Technology Acceptance, especially when highly complex technology is subject to active and passive use. It should be understood that the system design and the use outcomes are important to achieve the best possible acceptance, thus, effective use. Additionally, extending the attitude towards the use of a system with external related variables can be worthwhile to gain a deeper understanding of the underlying influencing perceptions. When considering AI-based Skill Management Software, it is essential to carefully examine two crucial aspects: fairness and appreciation towards the use of the system.

By implementing these practical recommendations, organizations can enhance the acceptance and utilization of highly complex technologies. Especially including attitude towards the use of a system, those influencing factors, as well as considering active and passive use, ATTU-TAM can drive a valuable opportunity to understand the needs of all stakeholders while implementing highly complex technology.

Further Research

This research serves as a starting point to shed light on the acceptance of highly complex technology concerning attitudes towards the use of a system and active as well as passive use. Generally, research should include Attitude Towards Use when studying highly complex systems to gain a deeper understanding of Technology Acceptance. The following section highlights some specific research opportunities pertaining to the ATTU-TAM.

Future studies should address and extensively examine the role of active and passive usage to understand these complex relationships in more detail. Specifically, it is crucial to investigate whether user groups exhibit different attitudes towards the use of the system while maintaining consistent attitudes toward the system itself. Furthermore, it is necessary to explore the potential differentiation between ATTU and attitudes towards the system. Additionally, it is necessary to investigate the mediating effects of PU and PEU on BI through

ATTU. Moreover, it is essential to examine the behavior-intention gap and align the assumptions of the ATTU-TAM on actual use.

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Appendix

Appendix A

Table 1

Item-Pool

Item	Adaption	Translation	Source	Scale	Number
Using the system improves my performance in my job.	AI-based Skill Management Software improves Talent Management.	KI-basierte Kompetenzmanagementsoftware verbessert das Talentmanagement.	(Venkatesh & Davis, 2000)	PU	A501_01
Using the system in my job increases my productivity.	AI-based Skill Management Software increases the productivity of Talent Management.	KI-basierte Kompetenzmanagementsoftware steigert die Produktivität im Talentmanagement.	(Venkatesh & Davis, 2000)	PU	A501_02
Using the system enhances my effectiveness in my job.	AI-based Skill Management Software enhances effectiveness of Talent Management.	KI-basierte Kompetenzmanagementsoftware verbessert die Effektivität im Talentmanagement.	(Venkatesh & Davis, 2000)	PU	A501_03
I find the system to be useful.	I find AI-based Skill Management Software to be useful for Talent Management.	Ich finde eine auf KI-basierter Kompetenzmanagementsoftware für das Talentmanagement nützlich.	(Venkatesh & Davis, 2000)	PU	A502_01

My interaction with the system is clear and understandable.	The use of AI-based Skill Management Software is clear and understandable.	Die Benutzung einer KI-basierten Kompetenzmanagementsoftware ist klar und verständlich.	(Venkatesh & Davis, 2000)	PEU	A601_01
Interacting with the system does not require a lot of my mental effort.	Using AI-based Skill Management Software does not require a lot of mental effort.	Die Benutzung einer KI-basierten Kompetenzmanagementsoftware erfordert keine große mentale Anstrengung.	(Venkatesh & Davis, 2000)	PEU	A601_02
I find the system to be easy to use.	I find AI-based Skill Management Software easy to use.	Ich finde KI-basierte Kompetenzmanagementsoftware einfach zu verwenden.	(Venkatesh & Davis, 2000)	PEU	A602_01
I find it easy to get the system to do what I want it to do.	AI-based Skill Management Software makes it easy to do what you want to do.	Mit KI-basierter Kompetenzmanagementsoftware ist es einfach zu tun, was man tun möchte.	(Venkatesh & Davis, 2000)	PEU	A602_02

I intend to continue using mobile internet in the future.	I intend to use / advocate using AI-based Skill Management Software in the future.	Ich beabsichtige in der Zukunft KI-basierte Kompetenzmanagementsoftware zu verwenden / zu befürworten.	(Venkatesh et al., 2012)	BI	B301_01
I will always try to use mobile internet in my daily life.	I will try to use / advocate AI-based Skill Management Software in my business life.	Ich werde versuchen, KI-basierte Kompetenzmanagementsoftware in meinem beruflichen Leben zu verwenden / zu befürworten.	(Venkatesh et al., 2012)	BI	B301_02
I plan to continue to use mobile internet frequently.	I plan to use / to advocate AI-based Skill Management Software frequently.	Ich plane, KI-basierte Kompetenzmanagementsoftware häufig zu verwenden / zu befürworten.	(Venkatesh et al., 2012)	BI	B301_03
I plan to use mobile learning in the future.	I plan to continue to use / advocate AI-based Skill Management Software in the future.	Ich beabsichtige weiterhin / ab heute KI-basierte Kompetenzmanagementsoftware zu verwenden / zu befürworten.	(Chao, 2019)	BI	B301_04

Assuming I had access to the mobile learning, I intend to use it.	Assuming I had access to an AI-based Skill Management Software, I intend to use it.	Angenommen ich hätte Zugang zu einer KI-basierten Kompetenzmanagementsoftware, würde ich es nutzen.	(Chao, 2019)	BI	B301_05
Given that I had access to the mobile learning, I predict that I would use it.	Given that I had access to an AI-based Skill Management Software, I predict that I would use it.	Wenn ich Zugang zu einer KI-basierten Kompetenzmanagementsoftware hätte, würde ich es sicher nutzen.	(Chao, 2019)	BI	B301_06
Using an XX is something I would do.	The use / recommendation of AI-based Skill Management Software is something I would do.	Die Nutzung / Empfehlung einer KI-basierten Kompetenzmanagementsoftware ist etwas, was ich tuen würde.	(Davis, 1989)	BI	B301_07
I intend to recommend that other people use the AI product.	I intent to recommend others to use / advocate AI-based Skill Management Software.	Ich werde anderen empfehlen, KI-basierte Kompetenzmanagementsoftware zu nutzen / zu befürworten.	(Rahman et al., 2017)	BI	B301_08

New technologies contribute to a better quality of life.	Neue Technologien tragen zu einer besseren Lebensqualität bei.	(Parasuraman & Colby, 2015)	TR	A701_01
Technology gives me more freedom of mobility.	Neue Technologien ermöglichen mir mehr Mobilität.	(Parasuraman & Colby, 2015)	TR	A701_02
Technology gives people more control over their daily lives.	Neue Technologien geben Menschen mehr Kontrolle über ihr tägliches Leben.	(Parasuraman & Colby, 2015)	TR	A701_03
Technology makes me more productive in my personal life	Neue Technologien machen mich in meinem persönlichen Leben produktiver.	(Parasuraman & Colby, 2015)	TR	A701_04
Other people come to me for advice on new technologies.	Andere Menschen kommen zu mir um Rat in Bezug auf neue Technologien zu bekommen.	(Parasuraman & Colby, 2015)	TR	A702_01

In general, I am among the first in my circle of friends to acquire new technology when it appears.	Im Allgemeinen bin ich unter den ersten in meinem Freundeskreis, der neue Technologie erwirbt, wenn sie erscheint.	(Parasuraman & Colby, 2015)	TR	A702_02
I can usually figure out new high-tech products and services without help from others.	Ich kann gewöhnlich neue Hightech-Produkte und Dienstleistungen ohne Hilfe von anderen verstehen.	(Parasuraman & Colby, 2015)	TR	A702_03
I keep up with the latest technological developments in my areas of interest.	Ich informiere mich über die neuesten technologischen Entwicklungen in meinem Interessensgebiet.	(Parasuraman & Colby, 2015)	TR	A702_04

When I get technical support from a provider of a high-tech product or service, I sometimes feel as if I am being taken advantage of by someone who knows more than I do.	Wenn ich technischen Support von einem Anbieter eines Hightech-Produkts erhalte, habe ich manchmal das Gefühl, von jemandem ausgenutzt zu werden, der mehr weiß als ich.	(Parasuraman & Colby, 2015)	TR	A706_01*
Technical support lines are not helpful because they don't explain things in terms I understand.	Technische Supports sind nicht hilfreich, weil sie Dinge nicht in Begriffen erklären, die ich verstehe.	(Parasuraman & Colby, 2015)	TR	A706_02*

Sometimes, I think that technology systems are not designed for use by ordinary people.	Manchmal denke ich, dass Technologie-Systeme nicht für den Einsatz durch Otto Normalverbraucher entwickelt wurden.	(Parasuraman & Colby, 2015)	TR	A706_03*
There is no such thing as a manual for a high-tech product or service that's written in plain language.	Es gibt keine Bedienungsanleitung für ein Hightech-Produkt, die in einfacher Sprache geschrieben ist.	(Parasuraman & Colby, 2015)	TR	A706_04*
People are too dependent on technology to do things for them.	Die Menschen sind zu sehr von der Technologie abhängig, die Dinge für sie erledigt.	(Parasuraman & Colby, 2015)	TR	A710_01*

Technology lowers the quality of relationships by reducing personal interaction.	Technologie senkt die Qualität von Beziehungen, indem sie die persönliche Interaktion reduziert.	(Parasuraman & Colby, 2015)	TR	A710_02*
I worry that information I make available over the Internet may be misused by others.	Ich befürchte, dass Informationen, die ich zur Verfügung stelle, von anderen missbraucht werden können.	(Parasuraman & Colby, 2015)	TR	A710_03*
Whenever something gets automated, you need to check carefully that the system is not making mistakes.	Jedes Mal, wenn etwas automatisiert wird, muss man sorgfältig prüfen, dass das System keine Fehler macht.	(Parasuraman & Colby, 2015)	TR	A710_04*

The system is deceptive.	The use of AI-based Skill Management Software is deceptive.	Die Verwendung einer KI-basierten Kompetenzmanagemementsoftware ist irreführend.	(Jean et al., 2000)	T	A801_01*
The system behaves in an underhanded manner.	The use of AI-based Skill management Software behaves in an underhanded manner.	Die Verwendung einer KI-basierten Kompetenzmanagemementsoftware ist unaufrichtig.	(Jean et al., 2000)	T	A801_02*
I am suspicious of the system´s intent, action, or output.	I am suspicious of the use of AI-based Skill Management Software in terms of intent, action or output.	Ich bin misstrauisch bezüglich der Verwendung einer KI-basierten Kompetenzmanagementsoftware hinsichtlich Absicht, Handlung oder Ausgang.	(Jean et al., 2000)	T	A802_02*
I am wary of the system.	If AI-based Skill Management Software is used, I am wary.	Wenn eine KI-basierte Kompetenzmanagementsoftware verwendet wird, bin ich vorsichtig.	(Jean et al., 2000)	T	A802_04*
The system´s action will have a harmful or injurious outcome.	The use of AI-based Skill Management Software will have a harmful or injurious outcome.	Die Verwendung einer KI-basierten Kompetenzmanagemementsoftware wird zu einem schädlichen oder gefärhrlichen Ergebnis führen.	(Jean et al., 2000)	T	A801_03*

I am confident in the system.	I have confidence in the use of AI-based Skill Management Software.	Ich habe Vertrauen in die Verwendung einer KI-basierten Kompetenzmanagementsoftware.	(Jean et al., 2000)	T	A802_01
The system provides security.	The use of AI-based Skill Management Software provides security.	Die Verwendung einer KI-basierten Kompetenzmanagement-Software bietet Sicherheit.	(Jean et al., 2000)	T	A801_04
The system has integrity.	The use of AI-based Skill Management Software has integrity.	Die Verwendung einer KI-basierten Kompetenzmanagement-Software ist anständig.	(Jean et al., 2000)	T	A801_05
The system is dependable.	The use of AI-based Skill Management Software is dependable.	Die Verwendung einer KI-basierten Kompetenzmanagement-Software ist zuverlässig.	(Jean et al., 2000)	T	A801_06
The system is reliable.	The use of AI-based Skill Management Software is reliable.	Die Verwendung einer KI-basierten Kompetenzmanagemementsoftware ist verlässlich.	(Jean et al., 2000)	T	A801_07

I can trust the system.	If AI-based Skill Management Software is used, I can trust the system.	Wenn eine KI-basierte Kompetenzmanagementsoftware verwendet wird, kann ich dieser vertrauen.	(Jean et al., 2000)	T	A802_03
I am familiar with the system.	I am familiar with the use of AI-based Skill Management Software.	Ich bin vertraut mit der Verwendung einer KI-basierten Kompetenzmanagementsoftware.	(Jean et al., 2000)	T	A802_05
	The usage of an AI-based Skill Management Software values my work.	Der Einsatz einer KI-basierten Kompetenzmanagementsoftware schätzt meine Arbeit wert.	According to Jacobshagen et al. (2008)	AP	A901_01
	The usage of an AI- based Skill Management Software value my person.	Der Einsatz einer KI-basierten Kompetenzmanagementsoftware schätzt meine Person wert.	According to Jacobshagen et al. (2008)	AP	A901_02
	The usage of an AI- based Skill Management Software value my abilities.	Der Einsatz einer KI-basierten Kompetenzmanagementsoftware schätzt meine Fähigkeiten wert.	According to Jacobshagen et al. (2008)	AP	A901_03

	The usage of an AI-based Skill Management Software promotes fairer decisions in Talent Management.	Der Einsatz einer KI-basierten Kompetenzmanagementsoftware fördert gerechtere Entscheidungen im Talentmanagement.	According to Adams and Freedman (1976); Greenberg (1986); Hughes et al. (2019).	F	B101_01
	The usage of an AI-based Skill Management Software leads to fairer decisions in Talent Management.	Der Einsatz einer KI-basierten Kompetenzmanagementsoftware führt zu gerechteren Entscheidungen im Talentmanagement.	According to Adams and Freedman (1976); Greenberg (1986); Hughes et al. (2019).	F	B101_02
	The usage of an AI-based Skill Management Software promotes equity in Talent Management.	Der Einsatz einer KI-basierten Kompetenzmanagementsoftware fördert die Gerechtigkeit im Talentmanagement.	According to Adams and Freedman (1976); Greenberg (1986); Hughes et al. (2019).	F	B101_03
Unpleasant / pleasant		Unangenehm / Angenehm	(Van der Laan et al., 1997)	ATTU	B201_01
Undesirable / desirable		Unerwünscht / Erwünscht	(Van der Laan et al., 1997)	ATTU	B201_02
Irritating / Likeabel		Irritierend / Sympathisch	(Van der Laan et al., 1997)	ATTU	B201_03
Good / Bad		Schlecht / Gut	(Van der Laan et al., 1997)	ATTU	B201_04

Wise / Foolish	Ungeschickt / Klug	(Davis, 1989)	ATTU	B201_05
Favourable / Unfavourbale	Unvorteilhaft / Vorteilhaft	(Davis, 1989)	ATTU	B201_06
Beneficial / Harmful	Schädlich / Wohltätig	(Davis, 1989)	ATTU	B201_07
Positive / Negative	Negativ / Positiv	(Davis, 1989)	ATTU	B201_08

Note. *Item reversed. Own presentation.

Table 2

Implicit Association Test-Indicators

Positive	Negative	Skill Management	AI-based SMS
Angenehm	Unangenehm	Talentmanagement	KI basiertes Talentmanagement
Erwünscht	Unerwünscht	Entscheidungen durch Personaler	KI gestützte Entscheidungen
Sympathisch	Irritierend	Kompetenzmanagement	KI basiertes Kompetenzmanagement
Gut	Schlecht	Karriereentwicklung	KI gestützt Karrierepfade
Klug	Törichte	Aus- und Weiterbildungen	Automatisierte Aus- und Weiterbildungsempfehlungen

Vorteilhaft	Unvorteilhaft	Interne Nachbesetzung	Automatisierte Nachbesetzungsempfehlungen
Wohltätig	Schädlich	Datensammlung, Datenanalyse und Datenauswertung	Automatisierte Erstellung/ Aktualisierung von Kompetenzprofilen
Positiv	Negativ	Kompetenzprofile	Automatisierte Datensammlung, Datenanalyse und Datenauswertung

Note. Own presentation.

Table 3

Item-Parcels

Parcel	Items
parcel1_BI	B301_02, B301_05
parcel2_BI	B301_01, B301_06
parcel3_BI	B301_04, B301_07
parcel3_BI	B301_03, B301_08
parcel1_ATTU	B201_08, B201_05
parcel2_ATTU	B201_04, B201_07
parcel3_ATTU	B201_01, B201_03
parcel4_ATTU	B201_02, B201_06
parcel1_T	A802_01, A801_01, A802_05
parcel2_T	A802_03, A801_05, A801_02
parcel3_T	A801_07, A802_02, A802_04
parcel4_T	A801_06, A801_04, A801_03
parcel1_TR	A701_04, A702_01, A706_04, A706_01
parcel2_TR	A701_01, A701_02, A706_03, A710_04
parcel3_TR	A702_04, A702_03, A710_02, A710_03

parcel4_TR	A702_02, A701_03, A710_01, A706_02

Note. Own presentation.

Table 4

Correlation Matrix, Descriptive Statistics, Among Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
PU (1)	1.00 ***	.54 ***	.49 ***	.70 ***	.52 ***	.65 ***	.71 ***	.69 ***	-.20 **	.44 ***
PEU (2)	.54 ***	1.00 ***	.39 ***	.54 ***	.49 ***	.55 ***	.57 ***	.53 ***	-.06	.47 ***
TR (3)	.49 ***	.39 ***	1.00 ***	.61 ***	.43 ***	.50 ***	.59 ***	.58 ***	-.09	.46 ***
T (4)	.70 ***	.54 ***	.61 ***	1.00 ***	.63 ***	.71 ***	.85 ***	.75 ***	-.09	.42 ***
AP (5)	.52 ***	.49 ***	.43 ***	.63 ***	1.00 ***	.68 ***	.65 ***	.61 ***	-.12	.46 ***
F (6)	.65 ***	.55 ***	.50 ***	.71 ***	.68 ***	1.00 ***	.73 ***	.66 ***	-.17 *	.40 ***
ATTU (7)	.71 ***	.57 ***	.59 ***	.85 ***	.65 ***	.73 ***	1.00 ***	.80 ***	-.12	.45 ***
BI (8)	.69 ***	.53 ***	.58 ***	.75 ***	.61 ***	.66 ***	.80 ***	1.00 ***	-.21 ***	.57 ***
Age (9)	-.20 ***	-.06	-.09	-.09	-.12 *	-.17 ***	-.12. *	-.21 ***	1.00 ***	-.18 ***
Expert_Scale (10)	0.44 ***	0.47 ***	0.46 ***	0.42 ***	0.46 ***	0.40 ***	0.45 ***	0.57 ***	-0.18 ***	1.00 ***

Mean	3.7	3.44	3.21	3.23	3.04	3.44	3.44	3.26	42.64	2.75
SD	.77	.71	.53	.65	1.03	.94	.88	.99	9.35	1.04

Note. *p < .05, **p < .01, ***p < .001. Own presentation.

Appendix B

Figure 1

Questionnaire

JOHANNES KEPLER UNIVERSITÄT LINZ

AI-HR → base　　27.05.2023, 16:12

Korrekturfahne

Bitte beachten Sie, dass Filter und Platzhalter in der Druckansicht prinzipbedingt nicht funktionieren. Fragen, die mittels PHP-Code eingebunden sind, werden nur eingeschränkt wiedergegeben.

Bitte beachten Sie folgende Unterschiede zum tatsächlichen Fragebogen:

- Filter können prinzipbedingt nicht funktionieren,
- Fragen im PHP-Code werden nur angezeigt, wenn die Kennung statisch vorliegt,
- die Anzeige der Fragen kann abweichen, weil die Frage-Kennungen eingeblendet werden, und
- Platzhalter und andere dynamische Elemente können prinzipbedingt nicht dargestellt werden.

☑ Kennungen & Notizen
☑ Filter
☐ Variablen
☑ PHP-Code
☐ HTML-Elemente
☐ JavaScript
Tabelle (Download)
Seite drucken / PDF

Tipp: Stellen Sie in den Druck-Einstellungen Ihres Browser ein, dass dieser auch Hintergrundbilder druckt, damit auch Schieberegler und benutzerdefinierte Eingabefelder korrekt gedruckt bzw. in ein PDF übernommen werden.

Seite 01

A101
Sehr geehrte(r) Teilnehmer*in...

Sehr geehrte Teilnehmer*innen,

vielen Dank für das Interesse an meiner Studie. Am Institut für Arbeits- und Organisationspsychologie der Johannes Kepler Universität Linz erforsche ich im Rahmen meiner Masterarbeit die Anwendung von künstlicher Intelligenz (KI) im Arbeitsumfeld. Hierzu werden Ihnen in den nächsten 20 Minuten anhand eines Anwendungsbeispiels Fragen gestellt. Zur Beantwortung dieser benötigen Sie keinerlei Vorwissen.

Die Teilnahme an der Studie ist freiwillig und anonym. Genauere Informationen finden Sie in der anschließenden Einverständniserklärung.

Beachten Sie, dass die Beantwortung aller Fragen notwendig ist, um Ihre Ergebnisse verwenden zu können. Füllen Sie die Fragen nach bestem Wissen und Gewissen aus. Sollten Sie sich unsicher sein, entscheiden Sie sich bitte trotzdem für eine Ausprägung. Beantworten Sie den Fragebogen in ruhiger Atmosphäre, konzentriert und möglichst an einem Stück. Der Fragebogen ist zur Nutzung am Computer optimiert. Die Verwendung eines mobilen Endgerätes ist grundsätzlich möglich.
Vielen Dank!

Bei weiteren Fragen zum Forschungsgegenstand, der Studie oder Datenschutzrichtlinien wenden Sie sich bitte an Marvin Schittko unter folgenden Kontaktdaten:

Marvin S. Schittko, B.Sc
Johannes Kepler Universität Linz
Institut für Psychologie
Abteilung für Arbeits-, Organisations- und Medienpsychologie
Altenbergerstraße 69
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Seite 02

A102
Consent

Bitte erklären Sie sich mit der Teilnahme an dieser Studie einverstanden.

Freiwilligkeit. Ihre Teilnahme an dieser Untersuchung ist freiwillig. Es steht Ihnen zu jedem Zeitpunkt dieser Studie frei, Ihre Teilnahme abzubrechen, ohne dass Ihnen daraus Nachteile entstehen.

Anonymität. Ihre Daten sind vertraulich, werden nur in anonymisierter Form ausgewertet und nicht an Dritte weitergegeben. Demographische Angaben wie Alter oder Geschlecht lassen keinen eindeutigen Schluss auf Ihre Person zu.

Fragen. Falls Sie noch Fragen zu dieser Studie haben sollten, wenden Sie sich bitte an den Studienleiter unter angegebenen Kontaktdaten.

Hiermit bestätige ich, dass ich mindestens 18 Jahre alt bin sowie die Einverständniserklärung gelesen und verstanden habe.

○ Nein (nicht an der Studie teilnehmen)
○ Ja

Seite 03

A205
**Bitte beantworten Sie einig...

Bitte beantworten Sie einige Fragen zu Ihren demografischen Daten.

A201
DM1

Wie alt sind Sie?

Alter: ____ Jahre

A202
DM2

Welchem Geschlecht fühlen Sie sich zugehörig?

[Bitte auswählen]

A209
DM8

Was ist Ihre höchste abgeschlossene Ausbildung?

[Bitte auswählen]

Seite 04

Sind Sie momentan erwerbstätig? — A208 DM7

- Ja
- Nein

Waren Sie in den letzten sechs Monaten in einem Anstellungsverhältnis beschäftigt? — A203 DM3

- Ja
- Nein

Wie viele Stunden arbeiten Sie wöchentlich? — A206 DM5

Arbeitszeit: [   ] Stunden

In welchem Land arbeiten Sie? — A211 DM10

[Bitte auswählen]

In welcher Unternehmensgröße sind Sie beschäftigt? — A212 DM11

[Bitte auswählen]

Wie lange sind Sie in Ihrem aktuellen Unternehmen tätig? — A207 DM6

[Bitte auswählen]

Sind Sie in einer Funktion des Human Resource Management / Personalmanagement tätig? — A204 DM4

- Ja
- Nein

Seite 05

Um diesen Fragebogen beantworten zu können, lesen Sie bitte anschließende Definitionen genau durch. — A308 ** Um diesen Fragebogen beant…

Talent Management:
Umfasst die Entwicklung und Förderung von Mitarbeitenden innerhalb des Unternehmens, sowie die Besetzung von Jobs und benötigter Kompetenzen.

Künstliche Intelligenz:
Überbegriff für Software, die versucht, menschliches Lernen und Denken nachzuahmen.

Machine Learning und Deep Learning:
Algorithmen, die selbständig Daten sammeln, aus diesen lernen und anhand dessen Vorhersagen treffen.
Algorithmen = Maschinelles Handeln

Seite 06

Im Folgenden wird Ihnen ein Anwendungsbeispiel zur Funktionsweise einer künstlichen Intelligenz im Human Resource (HR) / Personalmanagement vorgestellt. Bitte lesen Sie dieses aufmerksam durch und beantworten Sie die anschließenden Fragen gewissenhaft. — A301 Im Folgenden wird Ihnen ein A…

A302 Die Software „Developi" ermög…

Das Unternehmen „Altero" möchte das interne Talent Management modernisieren. Hierfür wird die durch künstliche Intelligenz (KI) gestützte Kompetenzmanagementsoftware „Developi" eingeführt.

„Developi" basiert auf einem gut funktionierenden, getesteten Algorithmus. Dieser sammelt mittels Machine Learning automatisiert interne und externe Daten, lernt aus diesen und erstellt dank Deep Learning meist treffsichere Vorhersagen.

„Developi" ist eine unterstützende Anwendung. So entscheidet die künstliche Intelligenz nicht selbstständig, es werden lediglich Daten und Analysen bereitgestellt. Diese unterstützen Human Resource Manager*innen bei der Entscheidungsfindung.

Alle Daten und Analysen werden sicher verwahrt, unterliegen strengster Datenschutzbestimmungen und können von den jeweiligen Mitarbeiter*innen transparent eingesehen werden.

„Developi" kann unterschiedlich eingesetzt werden. Anschließend finden Sie vier Anwendungsbeispiele:

A) Die Software vergleicht stetig die im Unternehmen vorhandenen, auf den jeweiligen Positionen verteilten Kompetenzen. Diese werden mit aktuellen internen und externen Daten verglichen. So können Vorhersagen über die in Zukunft benötigten Kompetenzen getroffen werden.

B) In der Personalentwicklung kann die Software für alle Mitarbeiter*innen individualisierte Weiterentwicklungsmöglichkeit aufzeigen. Es werden mögliche Kompetenzdefizite ausgeglichen, Kompetenzen aufgefrischt oder neue Kompetenzen entwickelt. So können Mitarbeiter*innen auf zukünftige Aufgaben im Unternehmen vorbereitet werden.

C) In der Nachbesetzung offener Stellen findet „Developi" automatisch die in der Stelle benötigten Kompetenzen und empfiehlt passende interne Profile von Mitarbeiter*innen.

D) Zudem gibt es die Möglichkeit für Mitarbeiter*innen Karrierepfade selbstständig einzusehen und zu Ihrem Kompetenzprofil passende Stellen, beziehungsweise geeignete Weiterentwicklungsmöglichkeiten zu entdecken.

Seite 07

Bitte beantworten Sie die angezeigten Verständnisfragen bezüglich des vorgestellten Anwendungsbeispiels. — A307 Bitte beantworten Sie die ang…

Die Daten und Analysen, die „Developi" sammelt, werden sicher verwahrt und sind für die jeweiligen Mitarbeiter*innen transparent einsehbar. — A303 VF1

- Richtig
- Falsch

„Developi" trifft selbständig Personalentscheidungen. — A304 VF2

- Richtig
- Falsch

„Developi" basiert auf einem schlecht funktionierenden machine learning Algorithmus. — A305 VF3

- Richtig
- Falsch

Seite 08

Wird in Ihrem Arbeitsumfeld aktuell ein vergleichbares System angewendet? — A306 VF4

[Bitte auswählen]

Bitte bewerten Sie folgende Aussagen: — A210 DM9

	stimme gar nicht zu	stimme eher nicht zu	unent- schieden	stimme eher zu	stimme voll zu
Ich bin Expert*in in KI gestützter Software.	○	○	○	○	○
Ich informiere mich intensiv über künstliche Intelligenz.	○	○	○	○	○
Ich nutze KI gestütze Software.	○	○	○	○	○
Ich besitze ein Grundverständnis von künstlicher Intelligenz.	○	○	○	○	○

Seite 09

Auf den nachfolgenden Seiten werden Ihnen unterschiedliche Aussagen präsentiert. Kreuzen Sie auf der beiliegenden Skala diejenige Ausprägung an, die am besten auf Sie zutrifft. Sollten Sie sich unsicher sein, entscheiden Sie sich bitte trotzdem für eine Option. Versuchen Sie, alle Abstufungen der Skala in Betracht zu ziehen.

A503
**Auf den nachfolgenden Seite...

KI basierte Kompetenzmanagementsoftware...

A501
PU1

	stimme gar nicht zu	stimme eher nicht zu	unent-schieden	stimme eher zu	stimme voll zu
verbessert das Talentmanagement.					
steigert die Produktivität im Talentmanagement.					
verbessert die Effektivität im Talentmanagement.					

Bitte bewerten Sie folgende Aussage:

A502
PU2

	stimme gar nicht zu	stimme eher nicht zu	unent-schieden	stimme eher zu	stimme voll zu
Ich finde eine auf KI basierte Kompetenzmanagementsoftware für das Talentmanagement nützlich.					

Seite 10

Die Benutzung einer KI basierten Kompetenzmanagementsoftware...

A601
PEU1

	stimme gar nicht zu	stimme eher nicht zu	unent-schieden	stimme eher zu	stimme voll zu
ist klar und verständlich.					
erfordert keine großen mentalen Anstrengungen.					

Bitte bewerten Sie folgende Aussagen:

A602
PEU2

	stimme gar nicht zu	stimme eher nicht zu	unent-schieden	stimme eher zu	stimme voll zu
Ich finde KI basierte Kompetenzmanagementsoftware einfach zu verwenden.					
Mit KI basierter Kompetenzmanagementsoftware ist es einfach zu tun, was man tun möchte.					

Seite 11

Neue Technologien...

A701
TRO1

	stimme gar nicht zu	stimme eher nicht zu	unent-schieden	stimme eher zu	stimme voll zu
tragen zu einer besseren Lebensqualität bei.					
ermöglichen mir mehr Mobilität.					
geben Menschen mehr Kontrolle über ihr tägliches Leben.					
machen mich in meinem persönlichen Leben produktiver.					

Seite 12

Bitte bewerten Sie folgende Aussagen:

A702
TRI1

	stimme gar nicht zu	stimme eher nicht zu	unent-schieden	stimme eher zu	stimme voll zu
Andere Menschen kommen zu mir, um Rat in Bezug auf neue Technologien zu bekommen.					
Im Allgemeinen bin ich unter den Ersten in meinem Freundeskreis, der neue Technologie erwirbt, wenn sie erscheint.					
Ich kann gewöhnlich neue Hightechprodukte ohne Hilfe von anderen verstehen.					
Ich informiere mich über die neuesten technologischen Entwicklungen in meinem Interessensgebiet.					

Seite 13

Bitte bewerten Sie folgende Aussagen:

A706
TRD1

	stimme gar nicht zu	stimme eher nicht zu	unent-schieden	stimme eher zu	stimme voll zu
Wenn ich technischen Support von einem Anbieter eines Hightechprodukts erhalte, habe ich manchmal das Gefühl, von jemandem ausgenutzt zu werden, der mehr weiß als ich.					
Technische Supports sind nicht hilfreich, weil sie Dinge nicht in Begriffen erklären, die ich verstehe.					
Manchmal denke ich, dass Technologien nicht für den Einsatz durch Otto Normalverbrauchende entwickelt wurden.					
Es gibt keine Bedienungsanleitung für ein Hightechprodukt, die in einfacher Sprache geschrieben ist.					

Seite 14

Bitte bewerten Sie folgende Aussagen:

A710
TRIN1

	stimme gar nicht zu	stimme eher nicht zu	unent-schieden	stimme eher zu	stimme voll zu
Die Menschen sind zu sehr von der Technologie abhängig, die Dinge für sie erledigt.					
Technologie senkt die Qualität von Beziehungen, indem sie den persönlichen Kontakt reduziert.					
Ich befürchte, dass Informationen, die ich über das Internet zur Verfügung stelle, von anderen missbraucht werden können.					
Jedes Mal, wenn etwas automatisiert wird, muss man sorgfältig prüfen, dass das System keine Fehler macht.					

Seite 15

Die Verwendung einer KI basierten Kompetenzmanagemementsoftware...

A801
TT1

	stimme gar nicht zu	stimme eher nicht zu	unent-schieden	stimme eher zu	stimme voll zu
ist unaufrichtig.	○	○	○	○	○
bietet Sicherheit.	○	○	○	○	○
ist verlässlich.	○	○	○	○	○
ist irreführend.	○	○	○	○	○
ist anständig.	○	○	○	○	○
wird zu einem schädlichen oder gefärhrlichen Ergebnis führen.	○	○	○	○	○
ist zuverlässig.	○	○	○	○	○

Seite 16

Bitte bewerten Sie folgende Aussagen:

A802
TT4

	stimme gar nicht zu	stimme eher nicht zu	unent-schieden	stimme eher zu	stimme voll zu
Ich habe Vertrauen in die Verwendung einer KI basierten Kompetenzmanagementsoftware.	○	○	○	○	○
Ich bin misstrauisch bezüglich der Verwendung einer KI basierten Kompetenzmanagementsoftware hinsichtlich Absicht, Handlung oder Ausgang.	○	○	○	○	○
Wenn eine KI basierte Kompetenzmanagementsoftware verwendet wird, kann ich dieser vertrauen.	○	○	○	○	○
Wenn eine KI basierte Kompetenzmanagementsoftware verwendet wird, bin ich vorsichtig.	○	○	○	○	○
Ich bin vertraut mit der Verwendung einer KI basierten Kompetenzmanagementsoftware.	○	○	○	○	○

Seite 17

Wenn eine KI basierte Kompetenzmanagementsoftware im Unternehmen verwendet wird, ...

A901
AP1

	stimme gar nicht zu	stimme eher nicht zu	unent-schieden	stimme eher zu	stimme voll zu
schätzt das meine Arbeit wert.	○	○	○	○	○
schätzt das meine Person wert.	○	○	○	○	○
schätzt das meine Fähigkeiten wert.	○	○	○	○	○

Seite 18

Die Verwendung einer KI basierten Kompetenzmanagementsoftware...

B101
F1

	stimme gar nicht zu	stimme eher nicht zu	unent-schieden	stimme eher zu	stimme voll zu
fördert gerechtere Entscheidungen im Talentmanagement.	○	○	○	○	○
führt zu gerechteren Entscheidungen im Talentmanagement.	○	○	○	○	○
fördert die Gerechtigkeit im Talentmanagement.	○	○	○	○	○

Seite 19

Bitte beurteilen Sie die folgende Aussage anhand der angezeigten Gegensatzpaare. Kreuzen Sie auf jeder Zeile eine Ausprägung an.

A902
** Bitte beurteilen Sie die A...

Ich beurteile die Verwendung einer KI basierten Kompetenzmanagementsoftware als...

B201
ATU1

Unangenehm	○	○	○	○	○	Angenehm
Erwünscht	○	○	○	○	○	Unerwünscht
Irritierend	○	○	○	○	○	Sympathisch
Gut	○	○	○	○	○	Schlecht
Ungeschickt	○	○	○	○	○	Klug
Unvorteilhaft	○	○	○	○	○	Vorteilhaft
Schädlich	○	○	○	○	○	Wohltätig
Negativ	○	○	○	○	○	Positiv

Seite 20

Bitte bewerten Sie folgende Aussagen:

B301
BI1

	stimme gar nicht zu	stimme eher nicht zu	unent-schieden	stimme eher zu	stimme voll zu
Ich beabsichtige in der Zukunft KI basierte Kompetenzmanagementsoftware zu verwenden / zu befürworten.	○	○	○	○	○
Ich werde versuchen, KI basierte Kompetenzmanagementsoftware in meinem beruflichen Leben zu verwenden / zu befürworten.	○	○	○	○	○
Ich plane, KI basierte Kompetenzmanagementsoftware häufig zu verwenden / zu befürworten.	○	○	○	○	○
Ich beabsichtige weiterhin / ab heute KI basierte Kompetenzmanagementsoftware zu verwenden / zu befürworten.	○	○	○	○	○
Angenommen ich hätte Zugang zu einer KI basierten Kompetenzmanagementsoftware, würde ich es nutzen.	○	○	○	○	○
Wenn ich Zugang zu einer KI gestützten Kompetenzmanagementsoftware hätte, würde ich es sicher nutzen.	○	○	○	○	○
Die Nutzung / Empfehlung einer KI gestützten Kompetenzmanagementsoftware ist etwas, was ich tun würde.	○	○	○	○	○
Ich werde anderen empfehlen eine KI basierte Kompetenzmanagementsoftware zu nutzen / zu befürworten.	○	○	○	○	○

Seite 21

Gleich haben Sie es geschafft! Zum Abschluss noch ein kurzes Spiel.

In dieser Aufgabe dürfen Sie verschiedene Begriffe unterschiedlichen Kategorien möglichst schnell zuordnen!
(Dauer: ca. 5min)

A403
TIAT1

E | I

A401
IAT1

KI basiertes Talentmanagement | **Talentmanagement**

Legen Sie Ihre Mittel- oder Zeigefinger auf die Tasten **E** und **I**. Wörter werden nacheinander in der Mitte des Bildschirms erscheinen. Die Wörter passen jeweils zu einer der Kategorien, die Sie am oberen Bildschirmrand sehen können. Wenn das Wort zur linken Kategorie gehört, drücken Sie bitte die Taste **E**, wenn es zur rechten Kategorie gehört, die Taste **I**. Jedes Wort gehört nur zu einer Kategorie.

Nach einer korrekten Zuordnung erscheint automatisch das nächste Wort. Wenn Sie einen Fehler machen, erscheint ein rotes **X**. Korrigieren Sie den Fehler, indem Sie die andere Taste drücken.

Während dieser Zuordnungsaufgabe wird die Zeit gemessen. **REAGIEREN SIE SO SCHNELL SIE KÖNNEN** und machen Sie dabei so wenig Fehler wie möglich. Wenn Sie zu langsam reagieren oder zu viele Fehler machen, wird das Ergebnis ungültig sein. Die Aufgabe wird ca. fünf Minuten dauern.

Bitte die **Leertaste** drücken, um anzufangen.

Seite 22

Vielen Dank für Ihre Teilnahme an meiner Studie und die Unterstützung der damit verbundenen Forschung!

B601
Vielen Dank für Ihre Teilnahm...

Haben Sie etwaige Anregungen?

B603
AR1

Bei weiteren Fragen zum Forschungsgegenstand, der Studie oder Datenschutzrichtlinien wenden Sie sich bitte an Marvin Schittko unter folgenden Kontaktdaten:

B602
Bei weiteren Fragen zum Forsc...

Marvin S. Schittko, B.Sc
Johannes Kepler Universität Linz
Institut für Psychologie
Abteilung für Arbeits-, Organisations- und Medienpsychologie
Altenbergerstraße 69
4040 Linz
marvin.schittko@partner.jku.at

Letzte Seite

Der Fragebogen ist beendet.

B.Sc. Marvin Schittko, Johannes Kepler Universität Linz – 2023

Note. Exported from SoSci Survey (https://www.soscisurvey.de).

Appendix C

Table 1

Factor Loadings, MOD1

	BI	PEU	PU	*Std. Variance*	α	*AVE*
parcel1_B	.940			.117***		
parcel2_B	.964			.070***		

parcel3_B	.932			.132***		
parcel4_B	.901			.189***		
A601_01		.676		.543***		
A601_02		.532		.717***		
A602_01		.848		.281***		
A602_02		.785		.385***		
A501_01			.853	.272***		
A501_02			.808	.347***		
A501_03			.872	.239***		
A502_01			.853	.273***		

Note. ***p < .001. Own presentation.

Table 2

Covariances, MOD1

	BI	**PEU**	**PU**	***Std. Variance***	**α**	***AVE***
BI	1.00			1.00	.967	.874
PEU	.610	1.00		1.00	.802	.519
PU	.739	.649	1.00	1.00	.910	.717

Note. Own presentation.

Table 3

Factor Loadings, MOD2

	BI	**PEU**	**PU**	**ATTU**	***Std. Variance***	**α**	***AVE***
parcel1_BI	.941				.115***		
parcel2_BI	.961				.077***		
parcel3_BI	.935				.127***		

parcel4_BI	.904				.182***
A601_01		.686			.529***
A601_02		.528			.722***
A602_01		.842			.290***
A602_02		.784			.386***
A501_01			.857		.265***
A501_02			.774		.401***
A501_03			.851		.275***
A502_01			.867		.248***
parcel1_ATTU				.916	.160***
parcel2_ATTU				.907	.178***
parcel3_ATTU				.935	.126***
parcel4_ATTU				.915	.163***

Note. ***p < .001. Own presentation.

Table 4

Covariances, MOD2

	BI	**PEU**	**PU**	**ATTU**	***Std. Variance***	**α**	***AVE***
BI	1.00				1.00	.967	.875
PEU	.612	1.00			1.00	.802	.518
PU	.751	.655	1.00		1.00	.910	.702
ATTU	.829	.663	.770	1.00	1.00	.952	.843

Note. Own presentation.

Table 5

Factor Loadings, MOD3

	BI	PEU	PU	ATTU	AP	F	T	TR	*Std. Variance*	α	*AVE*
parcel 1_BI	.920								.154 **		
parcel 2_BI	.942								.113 ***		
parcel 3_BI	.954								.091 ***		
parcel 4_BI	.924								.147 ***		
A601_01		.691							.522 ***		
A601_02		.526							.723 ***		
A602_01		.833							.307 ***		
A602_02		.790							.377 ***		
A501_01			.852						.275 ***		
A501_02			.804						.354 ***		
A501_03			.873						.239 ***		
A502_01			.856						.267 ***		
parcel 1_ATTU				.910					.172 ***	.967	.874
parcel 2_ATTU				.909					.173 ***	.802	.519
parcel 3_ATTU				.937					.122 ***	.910	.717

parcel 4_ATTU	.915					.163***
B101_01		.899				.191***
B101_02		.911				.171***
B101_03		.924				.147***
A901_01			.919			.155***
A901_02			.862			.257***
A901_03			.909			.173***
parcel 1_T				.841		.293***
parcel 2_T				.854		.272***
parcel 3_T				.824		.321***
parcel 4_T				.855		.269***
Parcel 1_TR					.758	.425***
Parcel 2_TR					.729	.468***
Parcel 3_TR					.752	.435***
Parcel 4_TR					.839	.296***

Note. ***p < .001. Own presentation.

Table 6:

Covariances, MOD3

	BI	PEU	PU	ATTU	AP	F	T	TR	*Std. Variance*	α	*AVE*
BI	1.00								1.00	.967	.873
PEU	.622	1.00							1.00	.802	.518
PU	.736	.653	1.00						1.00	.910	.717
ATTU	.834	.667	.757	1.00					1.00	.951	.842
AP	.704	.617	.698	.770	1.00				1.00	.935	.830
F	.647	.566	.566	.683	.728	1.00			1.00	.924	.804
T	.798	.648	.779	.910	.769	.681	1.00		1.00	.908	.711
TR	.637	.493	.554	.646	.563	.484	.684	1.00	1.00	.852	.594

Note. Own presentation.

Appendix D

Table 1

Measurement Invariance Test

	Df	*AIC*	*BIC*	X^2	X^2 diff.	*p*
fit.configural	750	14210	15087	1263.3		
fit.loadings	772	14186	14982	1283.1	19.232	.630
fit.intercepts	794	14177	14893	1318.6	34.661	.042
fit.means	802	14207	14893	1363.8	45.901	< .001

Note. Own presentation.

Table 2

Discriminant Validity MOD1

Variables	X^2 diff.	*Df* diff.	*p*
BI ~~ PEU	119.89	1	< .001

BI ~~ PU	74.15	1	< .001
PEU ~~ PU	49.41	1	< .001

Note. Own presentation.

Table 3

Discriminant Validity MOD2

Variables	**X^2 diff.**	***Df* diff.**	***p***
BI ~~ PEU	127.585	1	< .001
BI ~~ PU	48.625	1	< .001
BI ~~ ATTU	17.979	1	< .001
PEU ~~ PU	42.733	1	< .001
PEU ~~ ATTU	60.386	1	< .001
PU ~~ ATTU	95.353	1	< .001

Note. Own presentation.

Table 4

Discriminant Validity MOD3

Variables	**X^2 diff.**	***Df* diff.**	***p***
BI ~~ PEU	94.473	1	< .001
BI ~~ PU	72.877	1	< .001
BI ~~ ATTU	13.695	1	< .001
BI ~~ AP	75.357	1	< .001
BI ~~ F	163.252	1	< .001
BI ~~ T	21.726	1	< .001
BI ~~ TR	133.985	1	< .001
PEU ~~ PU	448.507	1	< .001
PEU ~~ ATTU	53.287	1	< .001

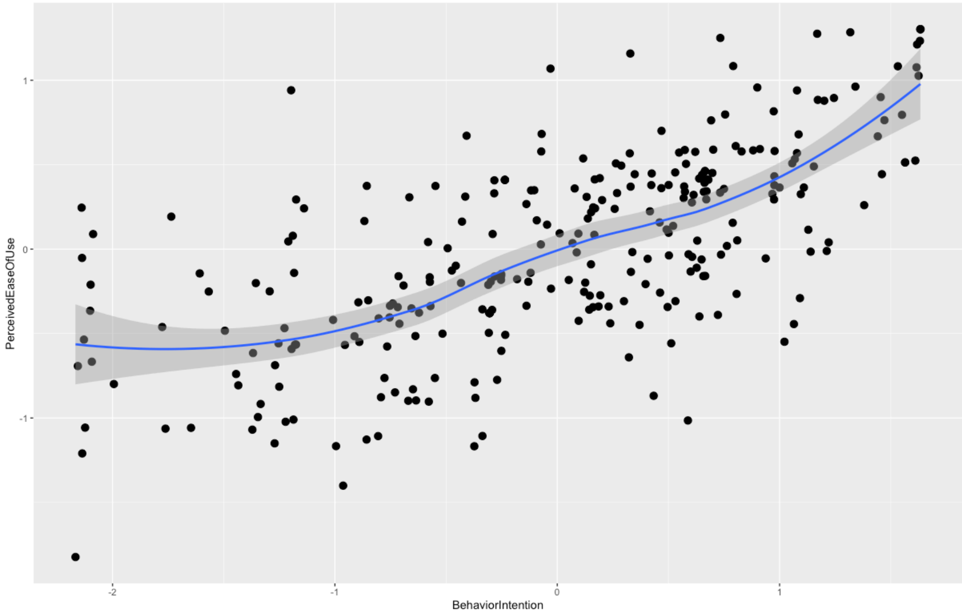
PEU ~~ AP	71.375	1	< .001
PEU ~~ F	288.968	1	< .001
PEU ~~ T	56.060	1	< .001
PEU ~~ TR	197.117	1	< .001
PU ~~ ATTU	268.304	1	< .001
PU ~~ AP	58.972	1	< .001
PU ~~ F	195.972	1	< .001
PU ~~ T	24.202	1	< .001
PU ~~ TR	364.169	1	< .001
ATTU ~~ AP	26.075	1	< .001
ATTU ~~ F	86.639	1	< .001
ATTU ~~ T	-0.0000	1	1.000
ATTU ~~ TR	94.758	1	< .001
AP ~~ F	39.246	1	< .001
AP ~~ T	18.936	1	< .001
AP ~~ TR	155.961	1	< .001
F ~~ T	90.794	1	< .001
F ~~ TR	213.154	1	< .001
T ~~ TR	50.248	1	< .001

Note. Own presentation.

Appendix E

Figure 1

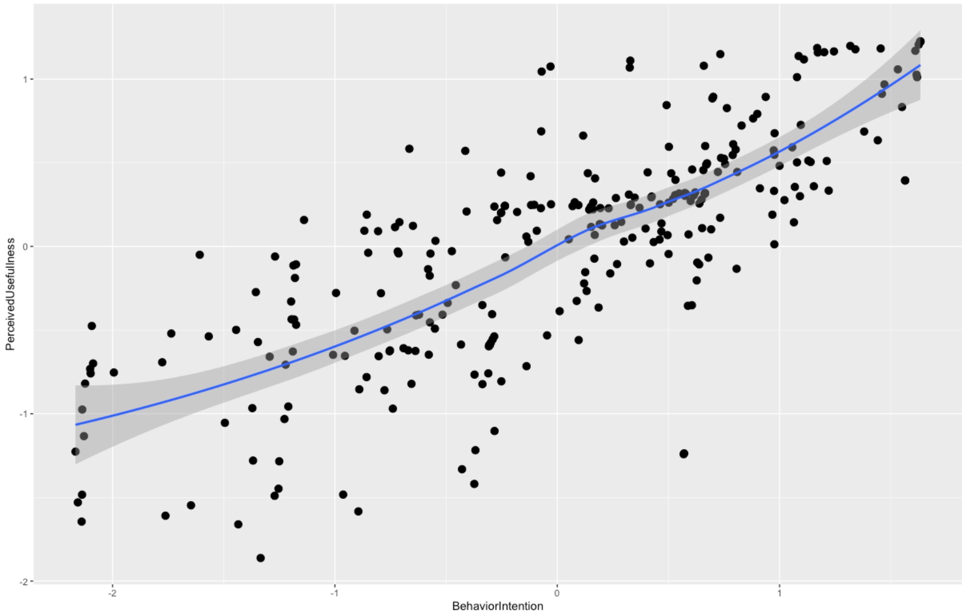
Linearity MOD1 PEU ~ BI



Note. Exported from R Core Team (2023), with ggplot2 (Wickham, 2016).

Figure 2

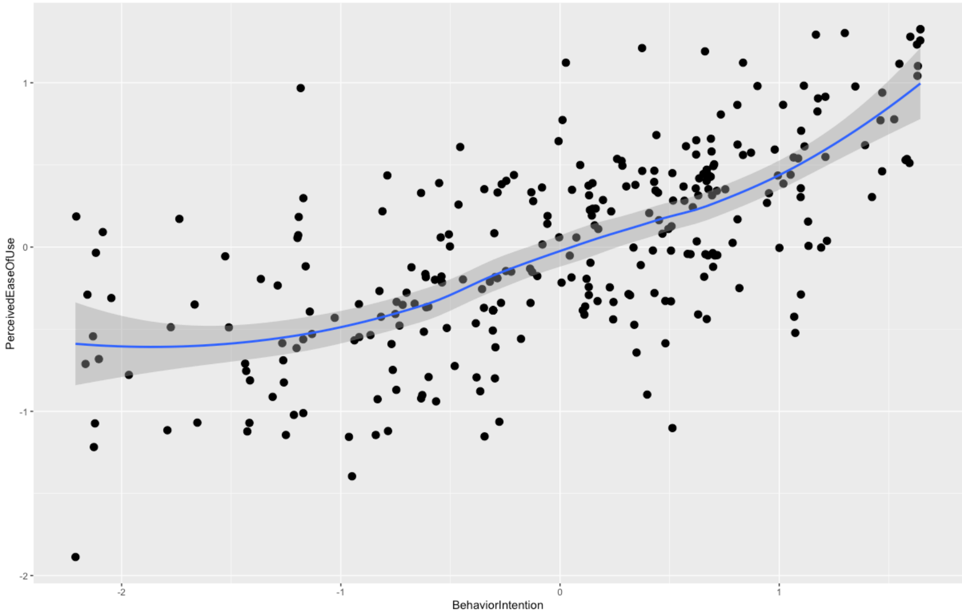
Linearity MOD1 PU ~ BI



Note. Exported from R Core Team (2023), with ggplot2 (Wickham, 2016).

Figure 3

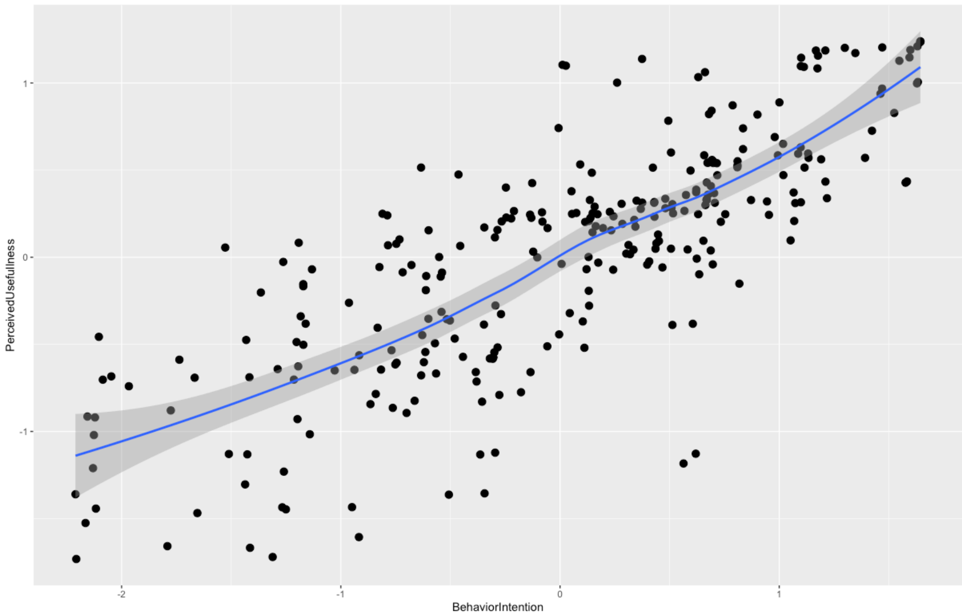
Linearity MOD2 PEU ~ BI



Note. Exported from R Core Team (2023), with ggplot2 (Wickham, 2016).

Figure 4

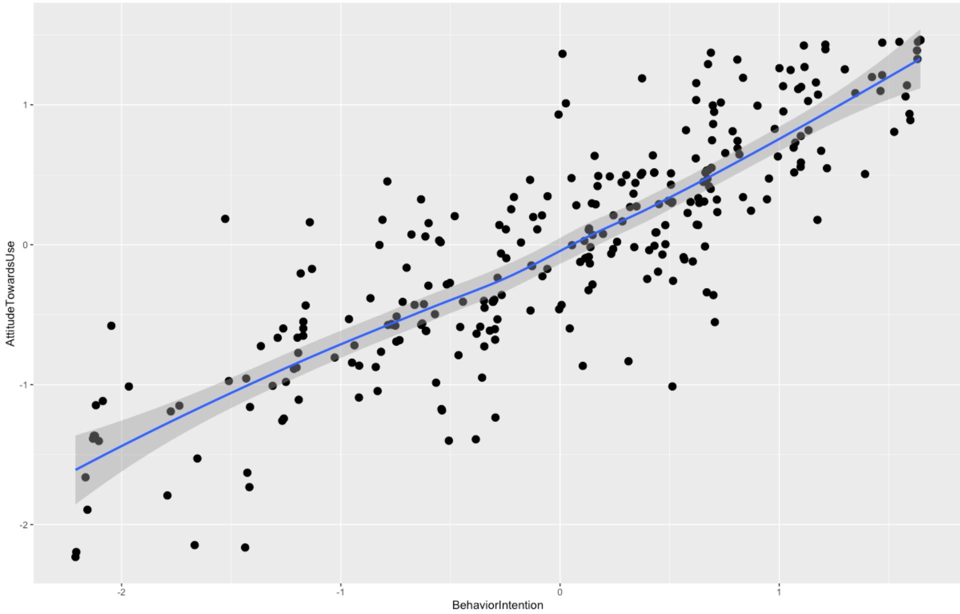
Linearity MOD2 PU ~ BI



Note. Exported from R Core Team (2023), with ggplot2 (Wickham, 2016).

Figure 5

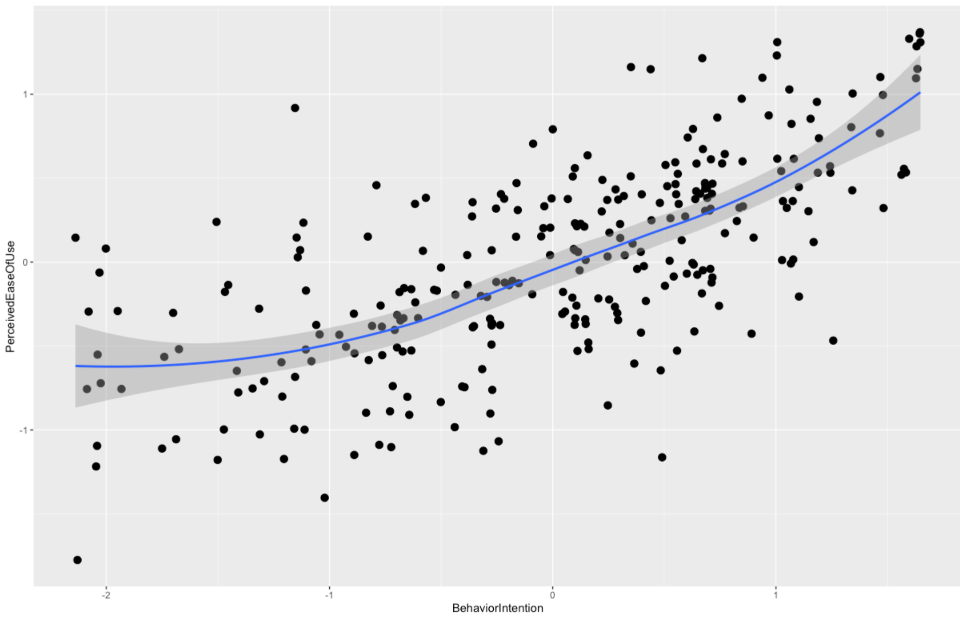
Linearity MOD2 ATTU ~ BI



Note. Exported from R Core Team (2023), with ggplot2 (Wickham, 2016).

Figure 6

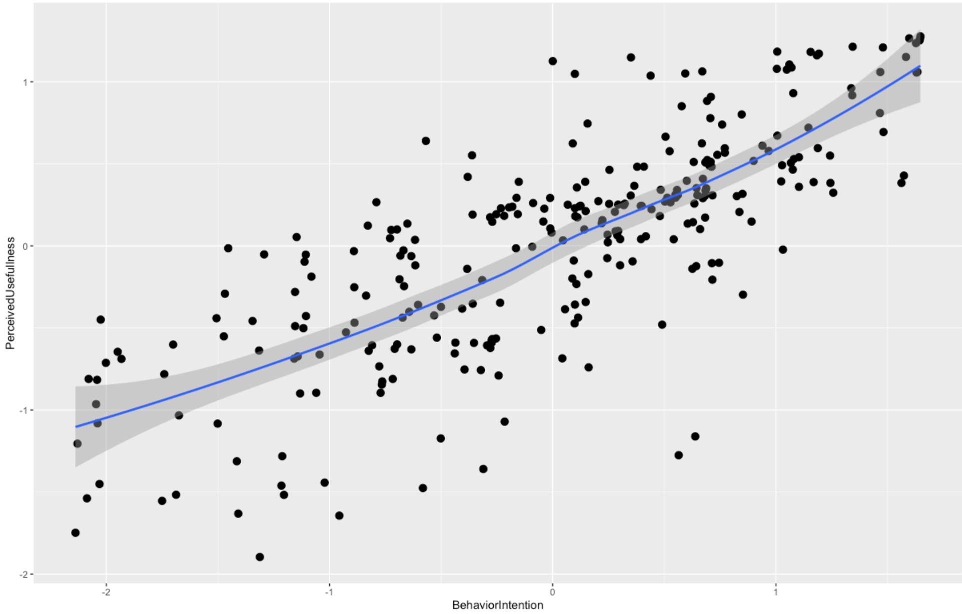
Linearity MOD3 PEU ~ BI



Note. Exported from R Core Team (2023), with ggplot2 (Wickham, 2016).

Figure 7

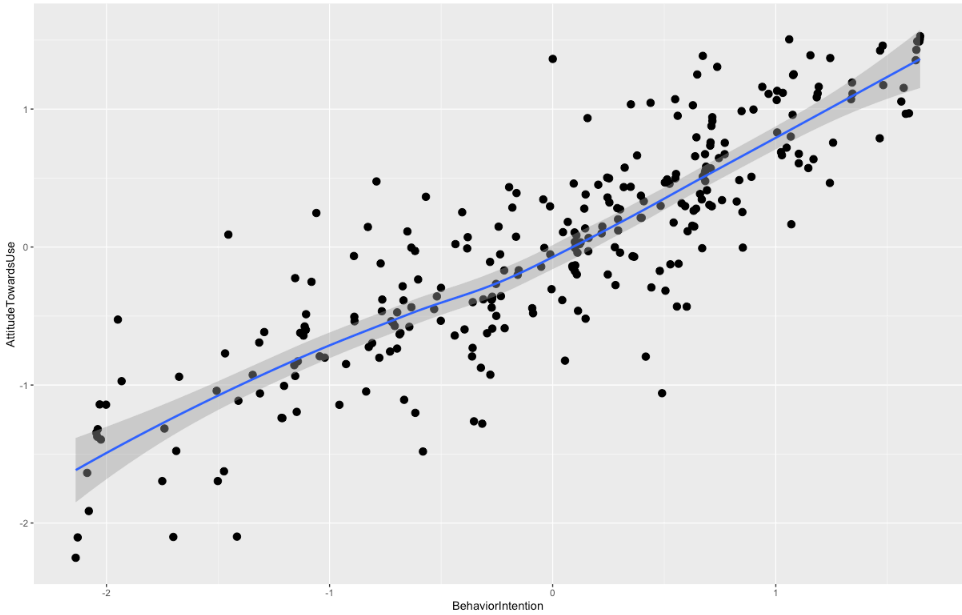
Linearity MOD3 PU ~ BI



Note. Exported from R Core Team (2023), with ggplot2 (Wickham, 2016).

Figure 8

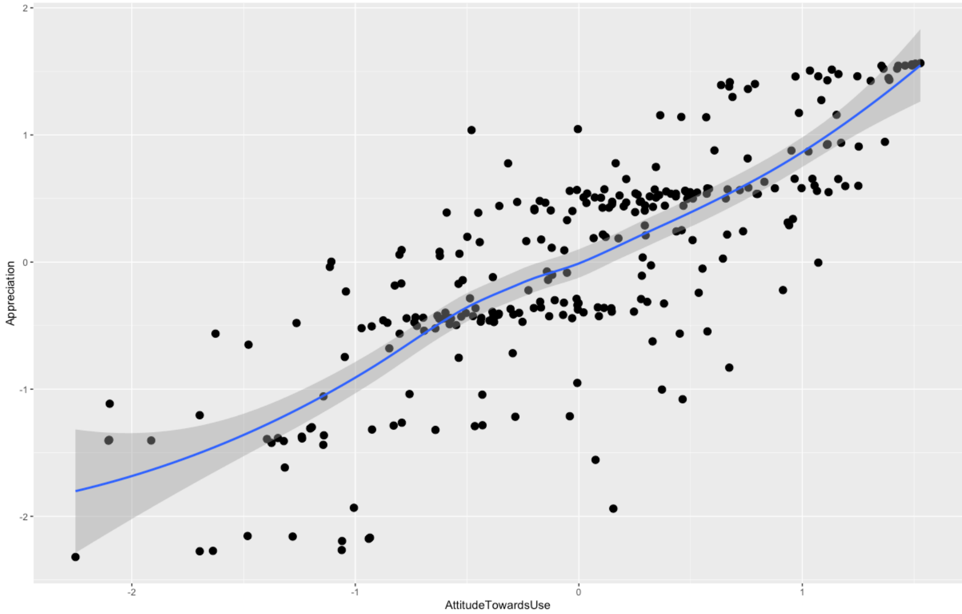
Linearity MOD3 ATTU ~ BI



Note. Exported from R Core Team (2023), with ggplot2 (Wickham, 2016).

Figure 9

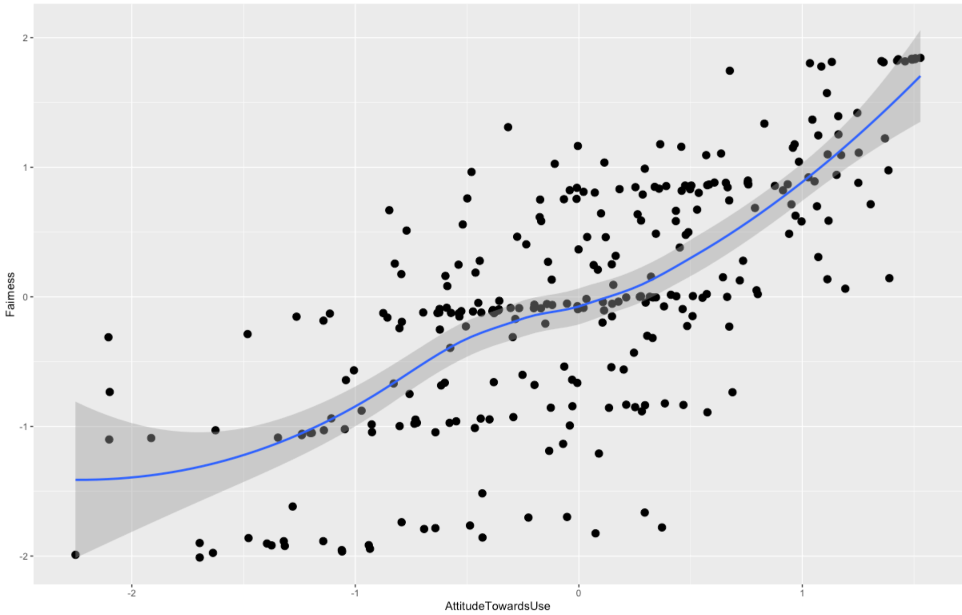
Linearity MOD3 AP ~ BI



Note. Exported from R Core Team (2023), with ggplot2 (Wickham, 2016).

Figure 10

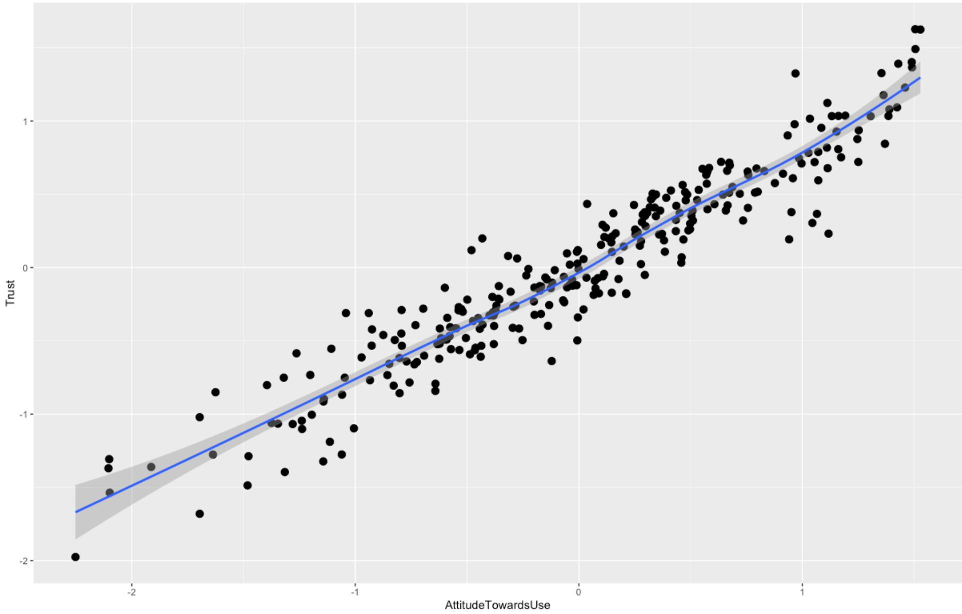
Linearity MOD3 F ~ BI



Note. Exported from R Core Team (2023), with ggplot2 (Wickham, 2016).

Figure 11

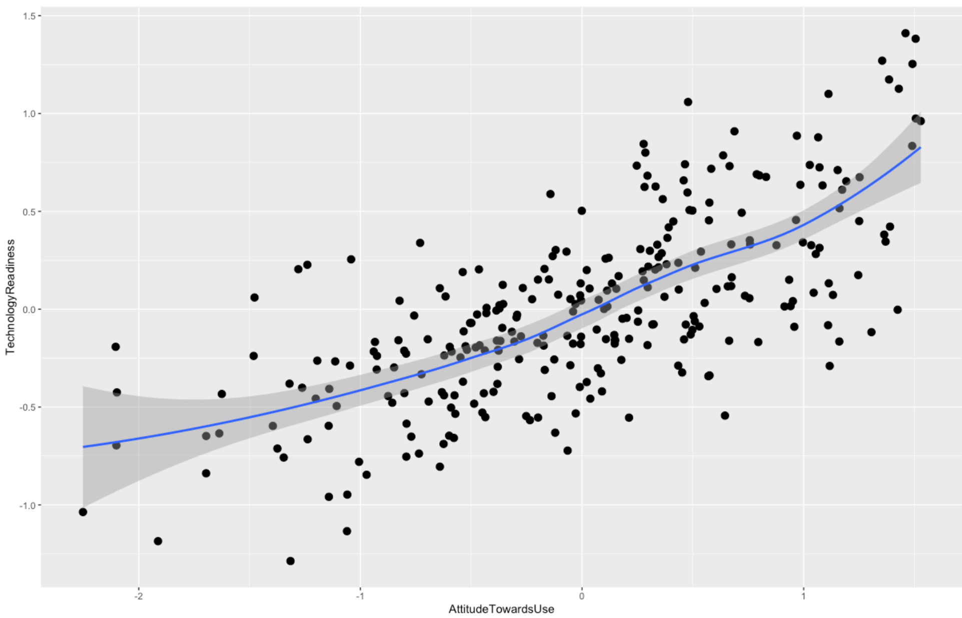
Linearity MOD3 T ~ BI



Note. Exported from R Core Team (2023), with ggplot2 (Wickham, 2016).

Figure 12

Linearity MOD3 TR ~ BI



Note. Exported from R Core Team (2023), with ggplot2 (Wickham, 2016).