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Reintegrating Human Attitudes in the Acceptance of AI-Driven Technology in HR Across Diverse User Interactions

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ABSTRACT

This research delves into the intricate dynamics involved in adopting an artificial intelligence (AI)-driven Skill Management Software (SMS) in Human Resources (HR), with a focus on human-centered acceptance. It underscores the significance of user attitudes and illuminates the distinctions between active and passive use interaction. More specifically, this article argues that the acceptance of using a highly complex technology is not solely shaped by the attitudes toward the system itself, but also the attitudes toward using the system. To this end, the variable Attitude Toward Use (ATTU) was integrated into the Technology Acceptance Model (TAM). An empirical study with N = 286 employees from the DACH region, focusing on the scenario-based adoption of AI-based SMS in HR, was carried out. Structural Equation Modeling demonstrated that integrating ATTU outperforms the original TAM in explaining Behavioral Intention, active and passive user interaction and their nuanced interactions.

KEYWORDS

Technology acceptance; active and passive use; reintegrating attitudes; highly complex technologies; artificial intelligence in human resources

1. Introduction

In the Fourth Industrial Revolution, sophisticated technology is expanding in various fields (Schwab, 2015). Highly complex technologies, like artificial intelligence (AI), often evoke dystopian or utopian perceptions in media and society (Cools et al., 2024). Some technological advancements, such as the recent natural language processing tool ChatGPT, achieved rapid adoption, reaching a million users within days (Hu, 2023). By contrast, others face significant implementation challenges, like autonomous vehicles (Fraedrich & Lenz, 2016).

The Technology Acceptance Model (TAM) serves as a foundational framework for understanding the principles that drive technology adoption. This article offers a challenging perspective on the integration of attitudes in the TAM as the core model of technology acceptance research, reintegrating attitudes with the variable Attitude Toward Use (ATTU) as a critical factor in predicting Behavior Intention (BI). The adaption differentiates between active and passive technology usage, operationalizing attitudes toward the system and its use separately. The efficacy of this adaption is empirically tested in the context of the scenario-based adoption of an AI-based Skill Management Software (SMS) in Human Resources (HR), providing a practical case study that illustrates specific implementation strategies.

2. The role of attitude in the Technology Acceptance Model

The TAM builds upon the Theory of Reasoned Action (Ajzen & Fishbein, 1980) and the Theory of Planned Behavior (Ajzen, 1985) by linking technology use to perceptions of usefulness (PU) and ease

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of use (PEU; Davis, 1985). While the original TAM included Attitude Toward Using (ATT), later revisions proposed removing ATT to clarify the direct influence of system-related beliefs (PU, PEU) on BI and to enable the integration of additional predictors of technology adoption (Venkatesh & Davis, 1996). However, more recent studies underscore the valuable role of ATT within the TAM, with its significance varying across different types of technology (Angela Lee Siew et al., 2017; Djamasbi et al., 2009; Kim et al., 2009; Lau & Woods, 2008; López-Bonilla & López-Bonilla, 2011; Teo, 2008; 2009; Ursavas, 2013; Yang et al., 2021; Yang & Yoo, 2004). Overall, ATT is infrequently included in research studies (Ma & Liu, 2004), as illustrated by meta-analytic reviews of the TAM: "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[T] 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). Despite this gradual divergence from the TAM's foundational focus on attitudes, recent comprehensive meta-analyses demonstrate the construct's meaningful effect sizes (see Table 1). This highlights a gap between the insufficient integration and the proven influence of ATT in technology acceptance.

2.1. The role of attitude in the acceptance of highly complex technology

In the framework "diffusion of innovation theory", the concept of highly complex technology relates to the complexity dimension, which posits that innovations perceived as difficult to understand and use are adopted more slowly (Rogers, 1983). Technologies like AI embody this complexity, eliciting diverse reactions regarding their systems. A 2021 systematic literature review across various industries highlights obstacles like safety and trust issues in AI adoption (Cubric, 2020). Studies on an integrated AI acceptance–avoidance model underscore how positive and negative attitudes toward AI significantly sway the intention to use such technologies (Cao et al., 2021). These include attitudes toward the system, e.g., poor AI decision-making outcomes (Mikalef et al., 2022; Rana et al., 2022), and attitudes toward the use, e.g., fears over diminished job security and potential unemployment (Brougham & Haar, 2018; Ransbotham et al., 2018).

Specifically, attitudes toward the adoption of AI-based technologies in HR are characterized by a mix of openness and concern (see Dahm & Dregger, 2019). Del Giudice et al. (2023) emphasized that attitudes toward AI in HR involve rational evaluation, emotional, and cognitive dimensions. Laurim et al. (2021) investigated perceived control and trust as critical factors in AI acceptance within recruitment. Iftikhar et al. (2025) showed that applicants with disabilities experience ambivalent feelings, balancing positive and negative emotions about AI recruitment. Overall, Park et al. (2021) identified six burdens that hinder acceptance of AI in HR: emotional, mental, bias-related, manipulation, privacy, and social concerns. In a literature review, Bärmann (2022) revealed that trust in the context of AI in HR is multifaceted; a system not only needs to be trustworthy in itself (e.g., decision-making) but also handled in a trustworthy manner (by HR managers). Finally, distinctions between active and passive technology use of AI in HR have been explored, revealing that job applicants experience AI's influence passively, as not making an active use decision, which can intensify concerns like privacy (Ochmann & Laumer, 2020).

2.2. Adapting the TAM

Despite its foundational role in guiding concepts, the original framework and empirical investigations, the significance of attitudes regarding highly complex technologies is often overlooked. Practical adaptions and theoretical developments of the TAM imply operationalizing attitudes regarding the system design by

Table 1. Effect sizes attitude in the Technology Acceptance Model.

Relationship	Feng et al. (2021)	Yousafzai et al. (2007b)
PU → ATT	0.53*	0.39*
PEU → ATT	0.45*	0.33*
ATT → BI	0.56*	0.43*

PU: Perceived Usefulness; PEU: Perceived Ease of Use; BI: Behavior Intention; ATT: Attitude.
*$p > 0.05$.
Own presentation.

introducing variables such as computer anxiety as external predictors (Mikalef et al., 2022; Rana et al., 2022; Venkatesh & Bala, 2008). However, even attitudes toward the use of a system, namely the impact or passive influence, are operationalized similarly in terms of the system design (see Abdullah & Ward, 2016; Baroni et al., 2022; Dahm & Dregger, 2019; Rosli et al., 2022; Yousafzai et al., 2007a). Subsequently, the operationalization and application of models, inadequately account for the interplay of attitudes toward the system design and its use, similarly the distinction between active and passive use perspectives.

Considering these observations, we propose an adaption to the established TAM, reintegrating attitudes by including ATTU in the overall model (see Figure 1). This adaption simultaneously encapsulates an individual's evaluative affect regarding the system usage, allowing effective differentiation between attitudes toward actively interacting with the system itself (System Design: PU, PEU) and the passive effect of the utilization thereof (ATTU).

As a use-case scenario to investigate the adaption of a highly complex AI-driven technology, this study aims to empirically assess the theoretical adaptions presented by examining the acceptance of an AI-based SMS within the HR. AI-based SMS analyzes Big Data to optimize employee skill mapping, enabling precise job matching, talent management, and data-driven career development (Ward et al., 2021). It exemplifies a highly complex technology that is subjected to both active and passive forms of use. The distinction between active and passive use becomes particularly evident as AI-based SMS is identified by recent studies as functioning in an augmented capacity (Dahm & Dregger, 2019), indicating that its deployment and effectiveness are significantly shaped by the manner of its application. HR professionals encounter active use scenarios, such as leveraging the system for data-driven decision-making processes. Conversely, employees experience the technology's impact passively through the system's recommendations on career progression opportunities via a dashboard or a decision.

2.3. Research questions

This research seeks to validate this model via a use-case analysis and comparative model evaluation. The investigation centers on the deployment of AI-based SMS in HR, addressing the perspectives of both active (HR) and passive (non-HR) users.

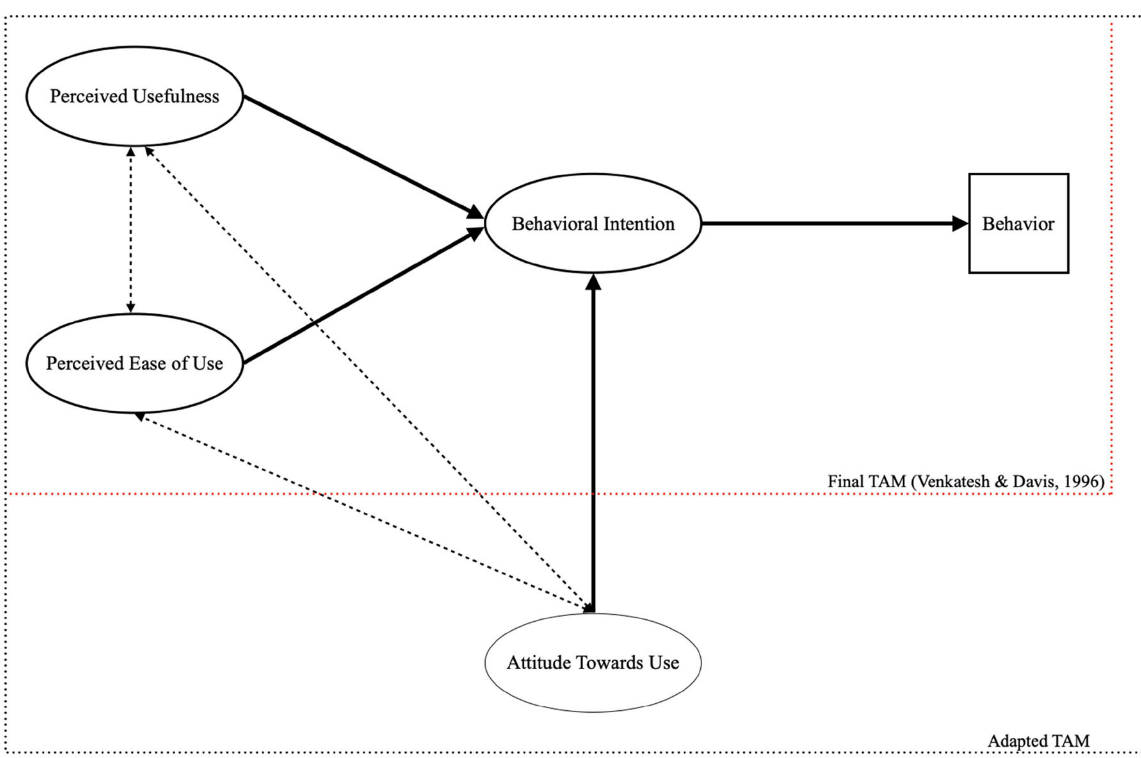

Figure 1. Adapted Technology Acceptance Model. Dashed lines represent investigated covariances.

H1: ATTU has a positive effect on BI, both, among (a) active and (b) passive users.

H2: The adapted TAM can better explain BI than the final TAM, both for (a) active and (b) passive users.

H3: The adapted TAM can better explain the collected data than the classic TAM, even if ATTU is included as an external predictor.

3. Methodology

The study recruited participants for an online survey designed to examine the acceptance of an AI-based SMS in HR across the DACH region (Germany, Austria, and Switzerland). It achieved initial participation with $n = 386$ completing the survey. Samples that did not meet the inclusion criteria were removed. Specifically, 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 due to possible interference with the concept of an AI-based SMS. 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; the response time was significantly shorter than the average and expected response time based on the questionnaire's pretest; more than 90% of the five-point scaled items were answered with the highest value (5), lowest value (1), or middle value (3). Post-data cleansing, the analysis was conducted on a final sample of $n = 286$ respondents. The study employed Post hoc Monte Carlo simulations for each primary model and related group comparisons to ensure the sample size, as well as cut-off values, were adequate.

Demographically, the sample was diverse: 54.9% were not in HR roles (passive users). The total sample had an average age of $M = 42.66$ years ($SD = 9.33$), spanning from 22 to 60 years. The gender split was 55.6% male and 44.4% female. Educational achievements varied, with 55.6% holding a degree, 38.8% having completed vocational training, and 5.6% having only primary education. A majority were employed in Germany (78.0%), followed by Austria (17.5%) and Switzerland (2.8%). The average workweek was $M = 39.61$ hr ($SD = 5.65$), and 55.2% worked in companies with more than 250 employees. A significant portion (44.4%) had been with their current employer for over 10 years. Preregistration, data, supplements and statistics can be found in an online repository (https://osf.io/m7u4z/?view_only=ce74cab9606c4747b85a57fd920d7add).

3.1. Measurement

The survey began with an introduction that clarified the study's goals, instructions for respondents, privacy assurances, and provided contact details for further inquiries. This section also gathered essential demographic and basic information, such as age, gender, educational background, employment status, weekly working hours, location of the workplace, size of the employer, and the grouping question regarding the HR affiliation. Additionally, fundamental concepts related to Talent Management, AI, Machine Learning, and Deep Learning were introduced. In front, the study presented participants with a hypothetical scenario involving AI-based SMS in HR settings (see Supplementary Appendix A, Table A1), designed to mirror an enhanced, credible system as discussed in prior studies (Dahm & Dregger, 2019). Followed by questions targeting the study's latent variables (PEU, PU, ATTU, and BI). The questionnaire items, derived from existing research and tailored to this specific context, were initially drafted in English, then translated into German, and subsequently retranslated to ensure accuracy.

The survey primarily utilized five-point Likert scales, with options ranging from 1 = strongly disagree to 5 = strongly agree. The constructs of PEU (e.g., The use of AI-based SMS is clear and understandable) and Perceived Usefulness (e.g., AI-based SMS improves Talent Management) were measured with items adapted from Venkatesh and Davis (2000), demonstrating high internal consistency ($\alpha = 0.80$ and 0.91) and moderate convergent validity (Average Variance Extracted (AVE) = 0.52 and 0.70). Attitude Toward Using Technology was assessed through an eight-item semantic differential scale (e.g., Unpleasant/pleasant), based on Davis (1989) and Van Der Laan et al. (1997), which showed excellent reliability ($\alpha = 0.95$) and strong convergent validity ($AVE = 0.84$). Behavioral Intention (e.g., I intend to use/advocate using AI-based SMS in the future) was evaluated using an extended eight-item scale from a variety of sources, including Venkatesh et al. (2012), Davis et al. (1989), and Chao (2019), with outstanding internal consistency ($\alpha = 0.97$) and robust convergent validity ($AVE = 0.88$). Item scales can be found in the Supplementary Appendix A (see Supplementary Appendix A, Table A2). The chi-squared difference test across all latent variables indicated significant distinctions, affirming the discriminant validity of the measurements (see Supplementary Appendix B, Tables B1 and B2). The measurement invariance test across different groups achieved partial measurement invariance, permitting the comparison of critical variables across groups (see Supplementary Appendix B, Table B3).

3.2. Analysis

All statistical analyses were performed in R (R Core Team, 2023), utilizing a suite of packages. All data and analysis code are available on request. A test for multivariate normality showed deviations from normal distribution for both ATTU and BI, indicating the necessity for robust statistical methods. A post hoc power analysis, leveraging Monte Carlo simulations, established that a minimum of $N = 222$ participants is necessary to achieve adequate power ($\beta \geq 0.80$) for detecting the hypothesized effects within the models ($\alpha = 0.05$). This analysis considered factor loadings of 0.80, a standard variance of $s^2 = 0.20$ for manifest items, and $s^2 = 1$ for latent constructs. Effect sizes were anticipated as small ($d = 0.30$) for PEU to BI, PU and BI, and as medium ($d = 0.60$) for ATTU to BI. Items for BI and ATTU were grouped into four parcels (see Supplementary Appendix C, Table C1).

Models were established using Structural Equation Models (SEMs; 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). 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), 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 with the cut-off values >0.90 = Excellent, >0.80 = Good, >0.70 = Acceptable, >0.60 = Questionable, >0.50 = Poor, and <0.50 = Unacceptable (Gliem & Gliem, 2003). The convergent validity using AVE should exceed >0.50 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 were 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 0.98 for a close fit, $CFI \leq 0.95$ for a reasonable fit, $RMSEA \leq 0.05$ for a close fit, $RMSEA \leq 0.08$ for a reasonable fit, $SRMR \leq 0.08$; Browne & Cudeck, 1992; 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. 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, 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 (Kwan & Chan, 2011; Urban & Mayerl, 2013). Afterward, model restrictions and group comparisons were carried out.

The study explored two models: the original TAM (MOD1) and the proposed TAM adoption (MOD2), along with two variations of MOD2 imposing specific restrictions. MOD2_R1 zeroed the regression between ATTU and BI, creating a nested model with covariances of ATTU with PU and PEU, describing a model where ATTU is influencing PU and PEU. MOD2_R2 eliminated covariances between ATTU and both PEU and PU, forming a non-nested model comparable to MOD1 but matching MOD2 in the variable count. These adjustments allowed for a detailed comparison between the models, particularly in assessing the impact of ATTU on BI and the interrelations with PU and PEU. A visualization of the models can be found in the Supplementary Appendix (see Supplementary Appendix, Figure A1).

Comparative analysis between the TAM and the adapted TAM models for both active and passive users employed a dummy variable to identify HR department affiliation, facilitating group comparisons. All analyses were first performed with the full sample and secondly with group comparisons. The study further examined measurement invariance across groups through a sequence of increasingly constrained models, analyzed using chi-square difference tests, to ensure a thorough and precise evaluation of the models' applicability and robustness across different user groups. 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 $N = 286$ samples was simulated. Further cut-off indices for the AIC and BIC values were determined (Pornprasertmanit et al., 2013, 2021; Vrieze, 2012). A chi-squared difference test to compare nested models was conducted (Werner & Schermelleh-Engel, 2010) and a Vuong test (Vuong, 1989) to compare non-nested models.

4. Results

A correlation matrix with all relevant variables, means and standard deviations can be found in the Supplementary Appendix (see Supplementary Appendix C, Table C2). Descriptive analyses revealed variability across key constructs with participants averaging a PU score of $M = 3.69$ ($SD = 0.77$), where active users scored slightly higher ($M = 3.89$, $SD = 0.77$) compared to passive users ($M = 3.53$, $SD = 0.73$). PEU scores averaged $M = 3.43$ ($SD = 0.71$), with active users again reporting higher ($M = 3.64$, $SD = 0.69$) than counterparts ($M = 3.27$, $SD = 0.67$). BI scores averaged $M = 3.26$ ($SD = 0.99$), with active users showing higher averages ($M = 3.61$, $SD = 0.92$) compared to passive users ($M = 2.97$, $SD = 0.95$). ATTU scores were similarly distributed, averaging $M = 3.44$ ($SD = 0.88$), with active users scoring higher ($M = 3.68$, $SD = 0.88$) than passive users ($M = 3.24$, $SD = 0.83$).

4.1. Structural Equation Models

Confirmatory factor analysis validated each model's measurement model, showing significant item loadings on their latent variables without Heywood Cases, as error variances remained between 0 and 1 (see Supplementary Appendix D).

4.1.1. MOD1

MOD1 reflects the basic TAM based on Venkatesh and Davis (1996). Fit indices for the structural model showed strong data alignment: ($\chi^2[50,286] = 80.20$, $p = 0.004$), $CFI = 0.99$, $AIC = 6351.26$, $BIC = 6497.50$, $RMSEA = 0.05$, and $SRMR = 0.04$. All relationships between independent and dependent variables were classified as linear. Regression analysis revealed 58% of BI variance ($R^2 = 0.58$) with PEU ($\beta = 0.23$, $p = 0.005$) and PU ($\beta = 0.60$, $p < 0.001$) significantly affecting BI, and PEU-PU covariance ($\beta = 0.65$, $p < 0.001$). Group comparisons showed 66% BI variance for active users ($R^2 = 0.66$) vs. 45% for passive users ($R^2 = 0.45$).

4.1.2. MOD2

MOD2 reflects the adapted TAM, including ATTU (see Figure 2). Structural model evaluation showed a close fit: ($\chi^2[95,286] = 170.721$, $p < 0.001$), $CFI = 0.98$, $AIC = 7920.62$, $BIC = 8129.01$, $RMSEA = 0.06$, and $SRMR = 0.04$. Linear relationships were confirmed between variables. Regression revealed 72% of BI variance explained ($R^2 = 0.72$), with PEU not significantly affecting BI ($\beta = 0.05$, $p = 0.489$), PU having a small positive impact ($\beta = 0.26$, $p = 0.001$), and ATTU a medium positive effect ($\beta = 0.60$, $p < 0.001$). Significant medium covariances were observed: PEU with PU ($\beta = 0.66$, $p < 0.001$), ATTU with PU ($\beta = 0.77$, $p < 0.001$), and PEU with ATTU ($\beta = 0.66$, $p < 0.001$).

Group analyses for MOD2 indicated the latent variables accounted for 78% of BI variance for active ($R^2 = 0.78$) and 63% for passive users ($R^2 = 0.63$). For active users, PEU's effect on BI was non-significant ($\beta = 0.09$, $p = 0.342$), whereas PU ($\beta = 0.31$, $p = 0.025$) and ATTU ($\beta = 0.56$, $p < 0.001$) significantly predicted BI. Passive users' analysis showed PEU's non-significant prediction ($\beta = -.04$, $p = 0.675$) and significant contributions from PU ($\beta = 0.24$, $p < 0.05$) and ATTU ($\beta = 0.63$, $p < 0.001$). Both PEU ($\beta = 0.65$, $p < 0.001$) and ATTU ($\beta = 0.80$, $p < 0.001$) showed a significant medium covariance with PU for the active users group. PEU showed a significant medium covariance with ATTU ($\beta = 0.62$, $p < 0.001$) for the group of active users. Both PEU ($\beta = 0.61$, $p < 0.001$) and ATTU ($\beta = 0.72$, $p < 0.001$) showed a significant medium covariance with PU for the passive users group. PEU showed a significant medium covariance with ATTU ($\beta = 0.66$, $p < 0.001$) for the passive users group.

In summary, ATTU significantly influenced BI in MOD2, indicating a medium positive effect ($\beta = 0.60$, $p < 0.001$). In active users, ATTU's medium positive impact on BI was evident ($\beta = 0.56$, $p < 0.001$). For passive users, ATTU demonstrated a medium positive effect on BI ($\beta = 0.63$, $p < 0.001$). MOD2 explained an additional 14% variance in BI over MOD1, demonstrating its enhanced explanatory power ($R^2 = 0.72$, $R^2 = 0.58$). For active users, MOD2 accounted for 12% more variance in BI compared to MOD1 ($R^2 = 0.78$, $R^2 = 0.66$). Among passive users, MOD2 explained 18% more BI variance than MOD1, confirming its superior explanatory capacity ($R^2 = 0.63$ vs. $R^2 = 0.45$). This underscores the validity for H1 and H2.

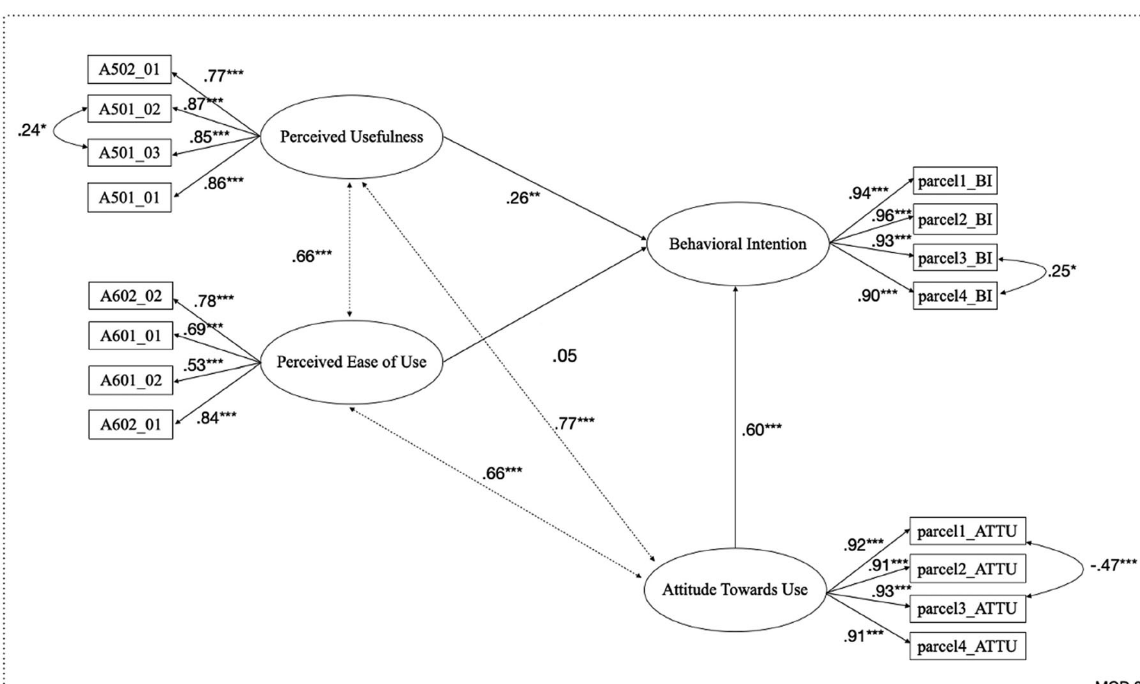

Figure 2. Adapted TAM (MOD2), Structural equation model. $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Dashed lines represent investigated covariances.

4.1.3. MOD2_R1

MOD2_R1 reflects a model where ATTU is treated as an external predictor influencing PU and PEU. MOD2_R1, limiting ATTU's effect on BI to 0, showed poor model fit ($\chi^2[96,286] = 239.31$, $p < 0.001$), $CFI = 0.97$, $AIC = 7992.11$, $BIC = 8196.84$, $RMSEA = 0.08$, and $SRMR = 0.06$, decreasing BI's explained variance to 66% ($R^2 = 0.66$). PEU's impact on BI was non-significant ($\beta = 0.20$, $p = 0.077$), while PU maintained a significant effect ($\beta = 0.67$, $p < 0.001$). Significant covariances were noted between PEU and PU ($\beta = 0.66$, $p < 0.001$), and ATTU and PU ($\beta = 0.81$, $p < 0.001$), with PEU also covarying with ATTU ($\beta = 0.68$, $p < 0.001$).

4.1.4. MOD2_R2

MODR2_R2 reflects the basic TAM based on Venkatesh and Davis (1996). MOD2_R2, setting the regression of ATTU on BI and covariances with PEU to 0, also indicated a poor fit ($\chi^2[98,286] = 475.55$, $p < 0.001$), $CFI = 0.91$, $AIC = 8268.07$, $BIC = 8465.49$, $RMSEA = 0.12$, and $SRMR = 0.34$, explaining 59% of BI variance ($R^2 = 0.59$). PEU modestly predicted BI ($\beta = 0.21$, $p = 0.011$), while PU showed a stronger effect ($\beta = 0.61$, $p < 0.001$), and a significant covariance with PEU ($\beta = 0.65$, $p < 0.001$) was observed.

4.2. Model comparisons

A Monte Carlo simulation was utilized to determine cut-off indices for comparing nested and non-nested models, assuming factor loadings of 0.80 and standard variances for manifest items and latent constructs of $s^2 = 0.20$ and $s^2 = 1$, respectively. The simulation, based on a non-normal dataset of $N = 286$ with skewness of two and kurtosis of minus one, ran 1000 iterations on MOD2 and its variations. It established cut-off indices between MOD2 and MOD2_R1 at $AIC = 37.02$ and $BIC = 33.37$, and between MOD2 and MOD2_R2 at $AIC = 61.33$ and $BIC = 50.37$. The chi-squared difference test confirmed a significant model improvement in MOD2 over MOD2_R1 ($\chi^2[1,286] = 11.08$, $p < 0.001$), highlighting the benefit of MOD2's additional parameters. The Vuong test further distinguished MOD2 from MOD2_R2 ($w^2 = 0.73$, $p < 0.001$; $z = 12.21$, $p < 0.001$), endorsing MOD2 as the superior model.

In conclusion, MOD2, incorporating ATTU directly, showed a better data fit than MOD2_R1, where ATTU was an external predictor, as indicated by lower *AIC* and *BIC* values and a significant chi-squared difference ($\chi^2[1, 286] = 11.25$, $p < 0.001$). The *AIC* difference of 71.49 and *BIC* difference of 67.83 showed smaller values for MOD2, suggesting a better fit to the collected data and even exceeding the predicted cut-off indices ($AIC = 37.02$, $BIC = 33.37$). MOD2 outperformed MOD2_R2 in explaining collected data, evidenced by superior model fit indices ($\chi^2[95,286] = 170.34$, $p < 0.001$) and a significant Vuong test result ($w^2 = 0.73$, $p < 0.001$). The *AIC* difference of 347.45 and *BIC* difference of 336.48 showed smaller values for MOD2, suggesting a better fit to the collected data and even exceeding the predicted cut-off indices ($AIC = 61.33$, $BIC = 50.37$). This underlines the validity of H3.

5. Discussion

This study asserts that the acceptance of highly complex technologies is significantly shaped by attitudes toward its use, incorporating perspectives of both active and passive use, with nuanced interactions. The adapted TAM integrates ATTU as a variable. Through empirical analysis of a hypothetical implementation of an AI-based SMS, this investigation delves into these complex interactions, assessing the model performance against various TAM variants via SEMs.

Generally, participants perceived AI-based SMS to be useful, attributing it moderate usability and expressing neutral BI toward usage. Specifically, active users evaluated the software as more useful and user-friendly, exhibiting a higher intention to adopt it. Conversely, passive users viewed the software's usability as neutral and were ambivalent about its usage. The final TAM model adequately explains technology acceptance for AI-based SMS, with PU emerging as a crucial factor. Notably, active users place slightly greater emphasis on PU compared to passive users. These insights confirm the TAM's applicability in investigating a highly complex technology, suggesting a nuanced perception difference between active and passive user perspectives toward technology acceptance.

Model evaluations indicate that the adapted TAM offers the most comprehensive explanation of the collected data, outperforming the final TAM in data fit. This superiority underscores the importance of attitudes toward the system's use, with the adapted TAM elucidating a broader variance in BI across both overall and group-specific models. Notably, ATTU significantly impacts BI, with its effect being more pronounced among passive users. This holds validity even if ATTU is operationalized, actively influencing PEU and PU, directly toward the system design. Research findings accentuate the divergent perceptions of ATTU between HR and non-HR employees in the context of AI-based SMS implementation, reinforcing the premise that active and passive users distinctly navigate their engagement with highly complex technologies concerning their attitudes toward use.

These findings suggest that incorporating human attitudes toward the use of highly complex systems provides actionable insights into the adaption and effective use of AI-driven technologies in HR. By acknowledging the critical role of ATTU in shaping the acceptance of a technology by its users and environment, and by highlighting diverse user perspectives, this research offers valuable guidance for the responsible design of technologies. Such designs should prioritize inclusivity and adaptability to meet the needs of an ever-present and evolving technology environment like HR. Especially in the context of applying an AI-based SMS in HR practical implementation should consider differentiated strategies for active and passive users. With ongoing attitude monitoring and inclusive design to ensure acceptance.

5.1. Limitations

This research is subject to certain constraints, primarily its dependency on a fictional use-case that necessitates participants to employ their imagination, potentially influencing the genuineness of the outcomes. Additionally, the application of the Vuong test in conditions of non-normality represents a non-traditional method, warranting careful consideration. In the process of drafting this document, the author utilized ChatGPT (2023) for assistance in rewriting and rephrasing the manuscript. After employing this tool, the author meticulously reviewed and revised the material as necessary, thereby assuming complete accountability for the publication's content. For our online study conducted in Germany, ethical approval was not required as the study complies with national regulations regarding non-interventional research. According to German law, surveys that do not involve any medical or invasive procedures do not require approval from an ethics committee. Additionally, the study did not involve the collection of sensitive personal data or interventions that would necessitate further ethical oversight. Participants were informed of the voluntary nature of their participation, the anonymity of their responses, and their right to withdraw at any time. On behalf of all authors, the corresponding author states that there is no conflict of interest.

5.2. Further research

This study serves as an initial exploration into the acceptance of highly complex technologies, highlighting the critical need to consider user attitudes toward system use and reintegrating attitudes in the TAM. Future investigations should further explore the dynamics of active versus passive use and their unique influences on technology acceptance relationships. It's imperative to differentiate between attitudes toward use and system attitudes, examining the roles that PU and PEU play in influencing BI among different use perspectives. Moreover, addressing the gap between behavior and intention. Additionally, future research should substantiate the premises of these findings through studies involving real system usage in both laboratory and real-world contexts.

6. Conclusions

This study effectively clarifies the intricate dynamics governing the acceptance of a highly complex technology. It identifies ATTU as a critical determinant of BI, suggesting that a more favorable ATTU enhances overall technology acceptance. This principle holds for both active and passive user groups, with the latter experiencing a more pronounced effect and explained variance. Thus, the ATTU accounts for a significant portion of acceptance across both user categories, offering particularly strong explanatory power for passive users. Differences in ATTU between active and passive users of AI-based SMS are notable, demonstrating that varied interactions with the system foster distinct attitudes toward its usage, thereby affecting technology acceptance relationships in diverse ways. These insights highlight the need for role-specific implementation strategies that address users' varying degrees of involvement and influence their attitude formation accordingly.

Upon comparing the adapted with the conventional TAM, it becomes evident that the adapted version superiorly accounts for the observed data and variations in BI, surpassing even models that frame ATTU in the context of PU and PEU, acting as attitudes toward the system design. This comparison indicates that attitudes toward system usage cannot be effectively inferred solely from system design features (PU, PEU). Importantly, the model yields the highest additional variance in BI among passive users, though it also significantly impacts active users.

Under the line, the findings bolster the foundational premises of the adapted TAM as a fitting model for dissecting the acceptance of sophisticated technologies. It underscores the critical role of reintegrating users' attitudes and illuminates the nuanced distinctions between multidimensional attitudes toward the system facets, as well as different use perspectives and those interactions with the technology. By emphasizing attitudes toward use, this advances our understanding of technology acceptance in ever-present environments such as HR, where AI systems are becoming increasingly integral. The findings provide actionable insights for designing adaptive, human-centered systems that prioritize acceptance and the responsible use by incorporating human attitudes into design and implementation frameworks.

Author contributions

CRediT: **Marvin Schittko**: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft; **Martina Mara**: Supervision, Writing – review & editing; **Barbara Stiglbauer**: Funding acquisition, Project administration, Resources, Supervision, Writing – review & editing.

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