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Stability through human perception: Technology acceptance models' robustness across various interaction perspectives and comparable technologies

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ABSTRACT

Technology acceptance research has traditionally focused on system design and interaction experience integrated into established frameworks like the *Technology Acceptance Model* (TAM; Davis, 1985) and the *Unified Theory of Acceptance and Use of Technology* (UTAUT; Venkatesh et al., 2003). While these models are widely applied to investigate the interaction between humans and technology, critiques have highlighted limitations concerning their generalizability, robustness, and conceptual clarity. This study addresses these challenges by examining the structural strength of TAM and UTAUT across comparable complex technologies and user interaction perspectives: between an active and a passive vignette. Furthermore, it introduces a model integrating *Usage Perception* (UP), incorporating the broader user perception of system usage, as a possible solution to the emerging vulnerability of traditional technology acceptance frameworks.

A controlled laboratory experiment was conducted in a simulated online environment, featuring two functionally developed AI agents that varied in interaction type and user autonomy. This design allowed direct comparison between active and passive interaction user perspectives and comparable complex technologies across a broad and diverse sample of 311 participants.

The results confirm that while some core predictors remained robust, traditional TAM and UTAUT structures showed inconsistency when disaggregated by interaction perspective and technology use case. In contrast, UP-integrated modelling showed greater path stability, theoretical coherence, and consistent predictive power. This paper offers a refined framework to holistically explain technology acceptance in complex AI systems—by integrating the human perception of system usage.

1. Introduction

Technology acceptance research has traditionally centred on the evaluation of system design and interaction experience, with constructs such as *Perceived Usefulness* (PU) and *Perceived Ease of Use* (PEU) forming the basis of established frameworks like the *Technology Acceptance Model* (TAM) and the *Unified Theory of Acceptance and Use of Technology* (UTAUT; Venkatesh & Davis, 2003; Davis, 1985).

While these models have been widely adapted across a broad range of technologies, ongoing discussions point to challenges concerning their generalizability, robustness, and conceptual clarity (Benbasat & Barki, 2007; Blut et al., 2022; Marangunić & Granić, 2014). The growing importance of complex technologies has further highlighted these questions, as comparable complex systems are perceived in diverse contexts and can be experienced through different interaction perspectives (cf. Christ et al., 2016; Guertin-Lahoud et al., 2023; Li et al., 2024; Poushneh & Vasquez-Parraga, 2024). Interaction with a system can be experienced via an active vignette, involving direct engagement with the system, or via a passive vignette in which the interaction is affected by the system usage. These dynamics indicate the need for models that can explain distinct differences while supporting robustness.

This article explores these considerations by examining the structural robustness of TAM and UTAUT across comparable complex technologies and differentiated user perspectives. Further, it introduces Usage Perception (UP) as an additional stabilizing construct within a UP-integrated model. A controlled laboratory experiment with two

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comparable AI agents provides the empirical basis for this investigation, which aims to contribute to a more nuanced understanding of technology acceptance in complexity through integrating the broader human perception of a system's usage.

2. Technology acceptance models' evolution and adaption

Human–Computer Interaction (HCI) has its roots deeply anchored in the cognitive and behavioral sciences (Marangunić & Granić, 2014). Early behavioral models such as the *Theory of Reasoned Action* (Ajzen & Fishbein, 1980) and the *Theory of Planned Behavior* (Ajzen, 1985) introduced key constructs, attitudes, subjective norms, intentions, and perceived behavioral control, which shaped the early understanding of technology adoption. At present, TAM (Davis, 1985) is the most used model for explaining technology acceptance (Lee et al., 2003).

During the decades, this framework was adapted to match different technologies and use cases. To extend TAM, Venkatesh and Davis (2000) introduced TAM2, integrating social influences such as subjective norm and image, as well as cognitive instrumental processes like job relevance and output quality. TAM3 (Venkatesh & Bala, 2008) further extended this foundation by detailing determinants of PEU, introducing factors such as computer self-efficacy, computer anxiety, and perceived enjoyment.

Building on these insights, Venkatesh and Davis (2003) proposed UTAUT, synthesizing constructs from models like TAM (Davis, 1985), the *Innovation Diffusion Theory* (Rogers, 1962), and *Social Cognitive Theory* (Bandura, 1986). UTAUT highlighted performance expectancy, effort expectancy, social influence (SI), and facilitating conditions (FC) as primary determinants of usage behavior, moderated by variables such as gender, age, experience, and voluntariness of use (Venkatesh & Davis, 2003). UTAUT2 (Venkatesh et al., 2012) expanded the model to include hedonic motivation, price value, and habit, explicitly addressing technology adoption in consumer contexts.

While the TAM and UTAUT evolved, interactive systems simultaneously increased in complexity, prompting HCI to expand its analytical lens beyond isolated task–tool interactions toward a more holistic evaluation of user experiences across diverse contexts (Gurcan et al., 2020; Shneiderman & Plaisant, 2010). This shift introduced interdisciplinary influences from computer science, design, and ergonomics into the study of human–technology interaction (Dix, 2017; Shneiderman & Plaisant, 2010). Consequently, the modification of technology acceptance models followed a structured path, typically incorporating four types of additional variables: external predictors, constructs drawn from other theoretical frameworks, contextual factors, and refined measurements of actual technology use (Marangunić & Granić, 2014).

3. Boundaries of technology acceptance models

TAM and UTAUT have established themselves as robust frameworks for predicting technology adoption, with meta-analytic evidence consistently confirming their core structural relationships (Dwivedi et al., 2011, 2020; King & He, 2006). However, despite their enduring relevance, concerns regarding the theoretical clarity and robustness of TAM and UTAUT remain, as both models have been criticized for lacking consistency when applied across varying technology domains (Benbasat & Barki, 2007; Blut et al., 2022; Marangunić & Granić, 2014). While they offer foundational value in modelling technology acceptance, scholars argue that their evolving structure and frequent extensions undermine their conceptual coherence and generalizability (Abdullah & Ward, 2016; Dwivedi et al., 2011, 2020).

The constant evolution and adaptation of TAM across individual environments have led to conceptual blurriness (Benbasat & Barki, 2007; Malatji et al., 2020). Meta-analyses reveal that while general technology beliefs remain stable, the inclusion of contextual variables introduces heterogeneity, challenging the assumption of universal applicability (Marikyan et al., 2023; Doulani, 2019). Moreover, the modification of TAM to incorporate external predictors, factors from other theories, and domain-specific variables (Marangunić & Granić, 2014) has expanded its explanatory power—but at the cost of less cohesive model architecture (Abdullah & Ward, 2016).

Similarly, while UTAUT retains a strong general predictive structure (Dwivedi et al., 2011, 2020), its core relationships are increasingly shown to be moderated by individual factors, including previous experience, cultural background, and technology (Blut et al., 2022; Dwivedi et al. 2011, 2020). Meta-analyses confirm that while general technology beliefs show consistency, the predictive strength of constructs varies significantly across domains (Blut et al., 2022; Doulani, 2019; King & He, 2006).

This research highlights potential limitations and sources of inconsistency in technology acceptance research, particularly in the context of emerging technologies such as AI and differing interaction perspectives between active and passive technology use. Building on the general boundaries and limitations of TAM and UTAUT outlined above, the study contributes to a more nuanced understanding of how interaction mode and emerging technologies shape technology acceptance models.

3.1. *In the context of emergent technologies*

In the context of increasingly complex and emergent technologies, it becomes necessary to adapt the foundational principles of technology acceptance to better capture and explain the full scope of human–technology interaction, especially in facets. Technology acceptance models seem to be not only domain-sensitive, but also context-sensitive in complex applications, incorporating both interaction with the system and perception of the system. In healthcare technology systems, Taufiq-Hail et al. (2023) found that traditional predictors were often outweighed by user concerns over data privacy and security. Further, Li et al. (2023) highlight how system-related attitudes, PU, and trust collectively shape users' evaluations of AI-based chatbots. In parallel, positive attitudes have proven critical for the acceptance of automated vehicles (Kaye et al., 2021; Li et al., 2024) and socially assistive robots, where system design directly influences user responses (Liang & Nejat, 2022).

A broader meta-analysis on e-government acceptance revealed that constructs such as trust and system availability could outperform conventional indicators, thereby questioning generalizability across sectors (Doulani, 2019). These insights are echoed in the meta-analytic review by Marikyan et al. (2023), who demonstrate that predictors like trust, experience, and perceived risk vary considerably across application domains—including banking, healthcare, and education technology—highlighting the increasing contextual dependency of acceptance models.

Furthermore, recent research has underscored the essential role of perceptual and attitudinal evaluations in the acceptance of AI systems. Specifically, Alkhwaldi et al. (2025) demonstrate that within AI-powered FinTech applications examined through an extended UTAUT framework, users' expectations of AI performance critically shape their attitudes and subsequent adoption intentions. This pattern is consistent across AI adoption research grounded in both UTAUT and TAM, where system design and performance perceptions influence user attitudes, which in turn drive adoption intentions (Hussian & Nethravathi, 2024; Shen et al., 2025).

3.2. *Across interaction perspectives*

As technological complexity increases, the nature of the experience and the entire structure of user engagement appear more layered. Specifically, active and passive user interaction perspectives appear as defining features in emerged systems. On the one hand, active use, where users exert control and directly interact with the system, often leads to greater emotional involvement, heightened enjoyment, and stronger feelings of competence and agency (Christ et al., 2016;

Guertin-Lahoud et al., 2023; Poushneh & Vasquez-Parraga, 2024). However, this immersive engagement may also elevate psychological pressure and stress, as shown in score-based active VR scenarios where self-efficacy declined due to performance anxiety (Shchory et al., 2024). On the other hand, passive use, characterized by less user control and more system-guided processes, tends to facilitate emotional regulation and build self-efficacy and trust. This pattern has been observed especially in sensitive contexts such as healthcare and automated driving, where comfort, perceived safety, and reduced cognitive demands are paramount (Alsyouf et al., 2023; Helgath et al., 2018; Rödel et al., 2014). Notably, even in passive use contexts, users display meaningful levels of psychological engagement and behavioral commitment (Deng & Yuan, 2020). These differences are visible across different domains and influence patterns of technology acceptance.

4. Stability and explainability: understanding the role of Usage Perception

Technology acceptance research has revolved around the evaluation of system design and interaction experience, including constructs such as PU and PEU within defined frameworks like TAM or UTAUT. This research focuses on TAM and UTAUT as foundational technology acceptance models, as they are central to the discussion on the exclusion and integration of attitudes and remain the most frequently and dominantly applied frameworks (Angela Lee Siew et al., 2017; Marangunić & Granić, 2014; Venkatesh & Davis, 1996). Furthermore, the core structures of both models have been extended and adapted to account for differences, leading to critiques on generalizability, robustness, and clarity, which supports the general assumption of this paper.

With the rise of complex technologies, and particularly the differentiation between active and passive interaction perspectives, individual examination appears to be even more important. This underscores the need for a technology acceptance framework that explicitly incorporates the contextual impact of highly complex technologies, differentiates between active and passive modes of use, and remains stable in explaining these effects. We argue that limitations inherent in traditional technology acceptance models contribute to inconsistency when accounting for these variations. This paper presents a possible solution to address this fine line between explainability and generalizability, mitigating the inconsistency through the addition of Usage Perception (UP) in a UP-integrated technology acceptance model.

The inconsistency of technology acceptance models does not solely arise from the diversity of technology domains. Especially across complex technologies, acceptance remains even more sensitive regarding their contextual implementation. As a general difference between technologies is comprehensible, inconsistency across comparable but context-variant complex technologies would raise challenges.

H1. Technology acceptance models exhibit inconsistency across comparable technologies.

H1a. In TAM

H1b. In UTAUT

As autonomous and adaptive systems reshape the boundaries of control and influence, individuals are no longer simply users in the traditional sense, but are also affected by systems without direct engagement. This duality introduces a new layer of complexity in the changing nature of user–system interaction. Whether a system is used actively or passively alters the evaluative process and influences the explanatory consistency of traditional constructs.

H2. Technology acceptance models exhibit inconsistency across different interaction perspectives.

H2a. In TAM

H2b. In UTAUT

Considering these reflections, we extend the technology acceptance framework by introducing UP as a stabilizing variable. Rooted in attitudinal theory and conceptualized as an explicit cognitive representation of the overall system, UP captures a holistic evaluation that transcends the specific technology and its general use. Its inclusion addresses the growing ambivalence users feel when encountering complex technologies, where attitudes become more diffuse, context-sensitive, and shaped by indirect exposure (see Section 3.1). The extension of the technology acceptance framework through the inclusion of UP has been examined in a prior study, which provides a comprehensive theoretical justification of its position within the TAM, its distinction from related constructs, its measurement, and its overall conceptual contribution (Schittko et al., 2025).

In general, the adaptation draws from the original role of Attitude Toward Use (ATTU) in early TAM variants, which served as a motivational bridge between beliefs and intention (Davis, 1985; Sharp, 2007). While streamlined models like TAM-R sought to eliminate ATTU to reduce unexplained variance (Venkatesh & Davis, 1996), subsequent empirical findings revealed that reintroducing ATT significantly improved explanatory depth (Hoong et al., 2017; Or, 2024). By introducing UP as an explicit attitudinal evaluation, we build on this stabilizing function parallel that offers a more perception-oriented external predictor.

UP reflects an explicit attitude toward the overall perception of a system's usage and its broader impact, extending beyond evaluations of system design. In contrast to constructs such as PU (Davis, 1985), which focuses on usability-related assessments, or behavioral intention (BI; Venkatesh & Davis, 2003), which captures intentions for continued use, UP addresses how users perceive the implications and consequences of engaging with the system.

H3. UP-integrated modelling provides a stable technology acceptance model while maintaining comparable explanatory power across comparable technologies.

H3a. In TAM

H3b. In UTAUT

H4. UP-integrated modelling provides a stable technology acceptance model while maintaining comparable explanatory power across different interaction perspectives.

H4a. In TAM

H4b. In UTAUT

To maintain comparability while addressing inconsistency, UP is integrated into the TAM as an additional variable directly influencing BI, while preserving the model's traditional pathways through PU and PEU on BI (see Fig. 1). A comparable modelling logic is applied to UTAUT, where UP is added alongside core constructs, and variables such as SI and FC are treated as moderators of system design evaluation. For conceptual clarity and model closeness, we adopt the original version of TAM and the core structure of UTAUT, excluding its default moderators, to better isolate the effect of UP across both frameworks. In the UP-integrated TAM model, the pathway between PEU and PU is included as covariance. Performance Expectancy is referred as PU, while Effort Expectancy is referred to as PEU.

5. Methodology

This study was conducted as a controlled experiment in a simulated online laboratory, designed to emulate realistic yet standardized conditions for human–AI interaction. The core aim was to evaluate users' interaction with two comparable AI agents varying in interaction types and use cases. Furthermore, levels of user autonomy were manipulated to represent active and passive interaction perspectives. In the active interaction perspective, participants retained full autonomy over the AI's

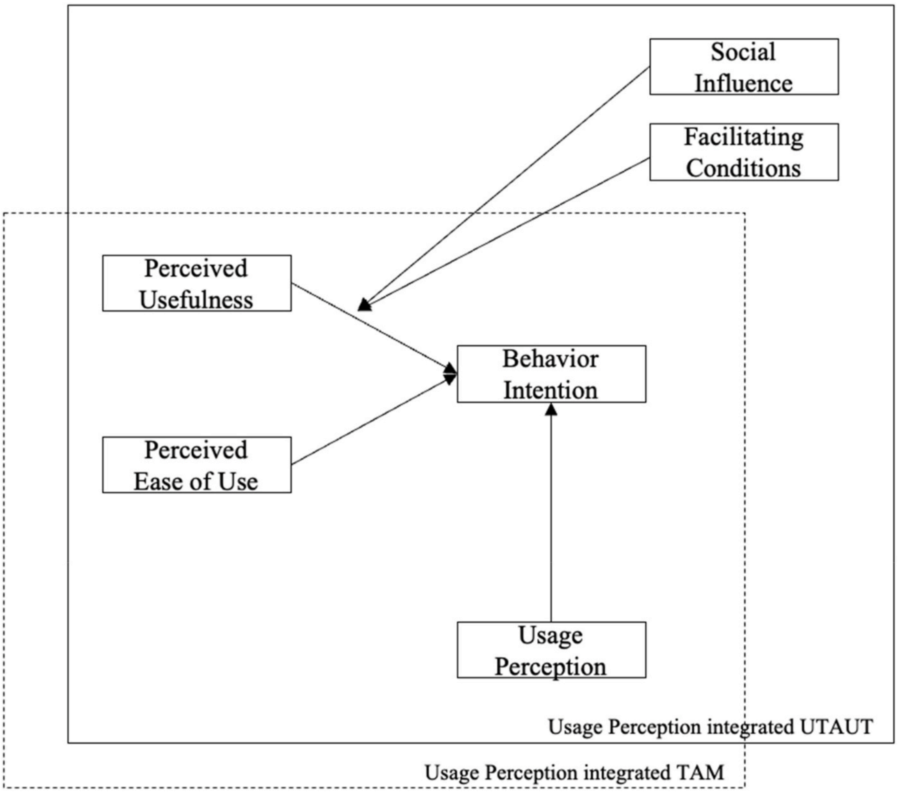
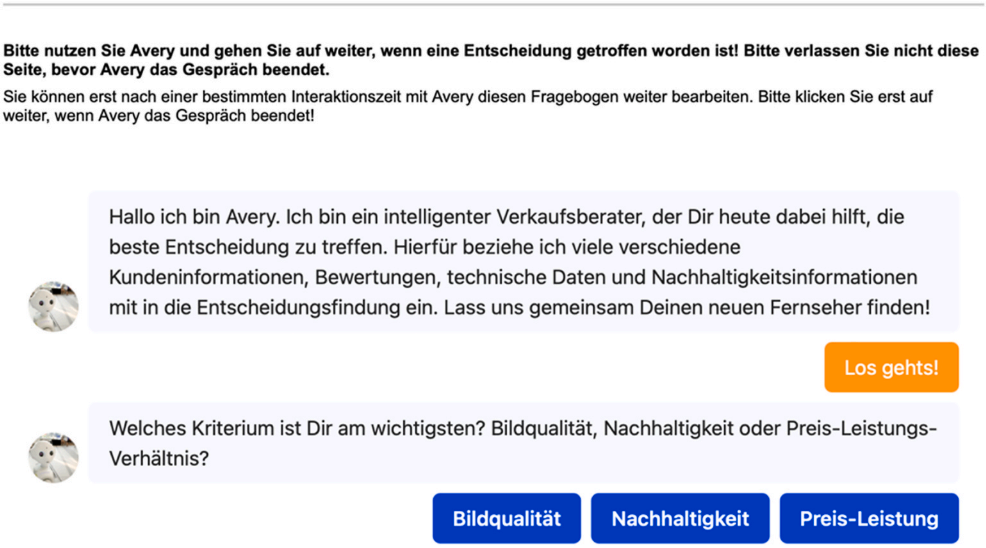


Fig. 1. *Usage Perception–Integrated Modelling*
Note. Figure as hypothesized.

final decision by selecting one explicitly presented option from several alternatives. In the passive interaction perspective, participants had no control over the AI's decision, as the system executed it automatically without user autonomy following the interaction. To achieve this, two self-developed, functional AI agents were created and embedded into the experimental platform. These agents served as the experimental stimuli and formed the foundation for a structured yet personalized interaction experience.

The first AI system, Avery, operated as a conversational text-based chatbot. Avery was introduced to participants as an innovative AI agent developed for automated purchase recommendations in online retail. The system assumed the role of a digital customer advisor, simulating real-world decision-making processes in e-commerce. Using a combination of usage data, technical specifications, customer reviews, and personal preferences, Avery provided support in identifying the optimal and most sustainable product for a given use case. During the experiment, participants were guided through a scenario in which they intended to purchase a new television via an online shop. The chatbot facilitated the purchase decision through interactive dialogue and dynamic recommendation updates. The system was described to



Bitte nutzen Sie Avery und gehen Sie auf weiter, wenn eine Entscheidung getroffen worden ist! Bitte verlassen Sie nicht diese Seite, bevor Avery das Gespräch beendet.

Sie können erst nach einer bestimmten Interaktionszeit mit Avery diesen Fragebogen weiter bearbeiten. Bitte klicken Sie erst auf weiter, wenn Avery das Gespräch beendet!

Hallo ich bin Avery. Ich bin ein intelligenter Verkaufsberater, der Dir heute dabei hilft, die beste Entscheidung zu treffen. Hierfür beziehe ich viele verschiedene Kundeninformationen, Bewertungen, technische Daten und Nachhaltigkeitsinformationen mit in die Entscheidungsfindung ein. Lass uns gemeinsam Deinen neuen Fernseher finden!

Welches Kriterium ist Dir am wichtigsten? Bildqualität, Nachhaltigkeit oder Preis-Leistungs-Verhältnis?

Fig. 2. *AI Agent Avery*
Note. Participant view.

participants as being under development and requiring user testing, thereby enhancing ecological validity and engagement. A screenshot of the Avery AI can be viewed in Fig. 2.

The second AI system, Mika, represented a multimodal avatar chat-based learning assistant. Mika was portrayed as a cutting-edge AI agent designed for automated training and education. Through individualized video-based instruction using a humanoid avatar, Mika supported both teaching and learning activities and conducted performance evaluations. Participants interacted with Mika through a pre-programmed educational session, during which the avatar delivered structured content, allowed user guidance through learning phases, and simulated responsive feedback mechanisms, interacting via text chat. As with Avery, the system was framed as a prototype under development, emphasizing the user's role in contributing to its evaluation. A screenshot of the Mika AI can be viewed in Fig. 3.

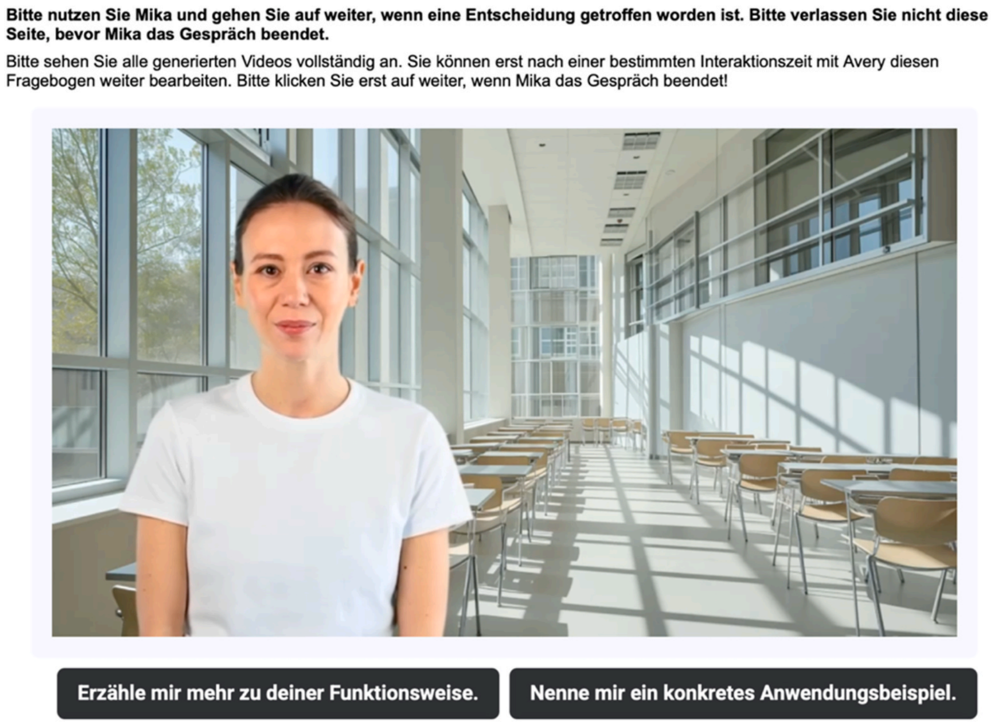
Each participant interacted with both AI agents, Avery and Mika, in a counterbalanced order, with a minimum interaction duration of 3 min per system. The sequence of exposure was randomized to control for order effects. Additionally, participants were randomly assigned to one of two experimental manipulation conditions: an active user group and a passive user group for each interaction. In the active condition, participants maintained agency throughout the interaction and made the final task decision themselves, guided by the data and recommendations provided by the AI. In the passive condition, participants followed a fixed interaction path and received identical information, but the final decision was made autonomously by the AI system, without user input. Importantly, the outcome options of each task were framed in a neutral manner, ensuring that both alternatives were equally plausible and valid. This ensured that user experience and perception were shaped by the interaction process rather than by the outcome desirability itself.

Despite the individualized nature of the interaction, both AI agents were programmed to deliver structurally comparable experiences across all participants with controlled interaction paths and system design. Following each interaction, participants were directed to complete a structured questionnaire measuring key constructs related to technology acceptance. These included standardized items from TAM and UTAUT, along with the presented adaption of UP.

Participants were recruited through a professional panel provider that enabled structured sampling across the German population, as well as through a university's internal recruitment. Individuals who did not provide informed consent to the privacy policy were immediately excluded. Following this, data quality screening was conducted: Participants were removed if their response time was more than 33 % shorter than the average completion time based on a pretest benchmark, or if they exhibited straight-answering behavior, defined as selecting the same extreme (1 or 6) or central value (3 or 4) for more than 90 % of the 6-point Likert items. After these exclusion criteria were applied, the final sample consisted of 311 participants. All details of the study—including preregistration, data, and supplements—can be found in an online repository (https://osf.io/z46py/).

5.1. Sample

The sample (N = 311) represented a demographically diverse group across age, gender, education, and income levels. Participants reported their age within predefined brackets. The largest age group was 25–34 years (n = 88, 28.3 %), followed by 55–65 years (n = 63, 20.3 %), 18–24 years (n = 60, 19.3 %), 35–44 years (n = 58, 18.6 %), and 45–54 years (n = 42, 13.5 %). No participants reported being over 65 years of age. In terms of gender, 57.6 % of participants identified as female (n = 179), 41.8 % as male (n = 130), and .6 % as diverse (n = 2). Educational attainment was distributed as follows: 29.3 % (n = 91) reported completing vocational training, 24.4 % (n = 76) held a high school diploma, 18.6 % (n = 58) had earned a bachelor's degree, and 13.8 % (n = 43) held a master's degree. Additionally, 7.7 % (n = 24) had completed secondary school, 3.2 % (n = 10) lower secondary education, and 2.9 % (n = 9) held a master craftsman qualification. The monthly net incomes reported by participants also reflected a broad range: 30.9 % (n = 96) earned less than €1000; 20.9 % (n = 65) earned between €1000 and €1999; 25.1 % (n = 78) earned between €2000 and €2999; and 16.4 % (n = 51) earned between €3000 and €4999. Higher income brackets were also represented: 3.9 % (n = 12) earned between €5000



Bitte nutzen Sie Mika und gehen Sie auf weiter, wenn eine Entscheidung getroffen worden ist. Bitte verlassen Sie nicht diese Seite, bevor Mika das Gespräch beendet.

Bitte sehen Sie alle generierten Videos vollständig an. Sie können erst nach einer bestimmten Interaktionszeit mit Avery diesen Fragebogen weiter bearbeiten. Bitte klicken Sie erst auf weiter, wenn Mika das Gespräch beendet!

Fig. 3. *AI Agent Mika*
Note. Participant view.

and €7499; 1.6 % (n = 5) between €7500 and €9999; and 1.3 % (n = 4) reported incomes above €10,000.

5.2. Measurement

All questionnaire items were adapted from established scales and tailored to the experimental context of the AI-based system. The survey employed 6-point Likert-type scales (−3 = strongly disagree to +3 = strongly agree), as well as semantic differential formats using six-point bipolar adjective pairs.

Performance expectancy (e.g., "XX helps me achieve goals faster") was measured using four items assessing the perceived usefulness of the system in supporting goal attainment and personal productivity. The scale demonstrated excellent internal consistency, Cronbach's α = .93, ω = .93, and average variance extracted (*AVE*) = .78. For clarity, performance expectancy is referred to as PU in this paper.

Effort expectancy (e.g., "I find XX easy to use") was assessed with four items evaluating users' perceived ease of use and clarity of interaction. This scale too demonstrated excellent internal consistency, α = .92, ω = .92, *AVE* = .74. For clarity, effort expectancy is referred to as PEU in this paper.

Social influence (e.g., "People whose opinions I value think I should use XX") was measured with three items targeting perceived social norms and the influence of others. This scale again demonstrated excellent internal consistency, α = .95, ω = .95, *AVE* = .86.

Facilitating conditions (e.g., "I have the necessary resources to use XX") were captured using four items assessing technical compatibility, access to support, and user resources. This scale demonstrated good internal consistency, α = .81, ω = .82, *AVE* = .54.

Behavioral intention (e.g., "I intend to continue using XX") was assessed using three items reflecting the users' future usage plans. This scale demonstrated excellent internal consistency, α = .95, ω = .95, *AVE* = .86. All those scales were adapted from UTAUT (Venkatesh & Davis, 2003).

UP was assessed as an explicit attitude toward the overall perception of a system, operationalized through eight semantic differential items that primarily capture the cognitive representation of the technology (e.g., harmful–beneficial). This scale was originally developed and tested in previous research (Schittko et al., 2025), and it demonstrated excellent internal consistency, α = .90, ω = .90, *AVE* = .55.

5.3. Analysis

All statistical analyses were conducted using R (R Core Team, 2025). Prior to modelling, assumptions for multivariate analysis were evaluated. Multivariate normality was tested using Mardia's test, which indicated significant deviations from normality in both skewness (Mardia skewness = 592.06, $p < .001$) and kurtosis (Mardia kurtosis = 11.84, $p < .001$). Univariate normality was assessed using the Shapiro–Wilk test across all constructs. The results revealed significant departures from normality for all variables: PU (W = .92, $p < .001$), PEU (W = .90, $p < .001$), SI (W = .95, $p < .001$), FC (W = .94, $p < .001$), UP (W = .96, $p < .001$), and BI (W = .95, $p < .001$). Descriptive statistics confirmed left-skewed distributions and excess kurtosis in several constructs, particularly PEU (skew = −1.12, kurtosis = 1.31) and FC (skew = −.92, kurtosis = 1.14). These two variables were selected for further inspection and treated for outliers through z-standardization. Participants whose standardized scores exceeded ±3 standard deviations were excluded from the dataset. Visual inspection of histograms confirmed the deviation from normality and supported the decision to exclude extreme values to improve distributional characteristics and reduce the influence of kurtosis on subsequent modelling. A Mahalanobis distance analysis was conducted to detect multivariate outliers, and a variance inflation factor analysis was performed to assess multicollinearity among predictors; no significant outliers or multicollinearity issues were identified. Consequently, estimation was conducted using robust maximum likelihood, and missing data were treated with full information maximum likelihood.

To validate the measurement model, a confirmatory factor analysis was performed. The model included the latent variables PU, PEU, SI, FC, BI, and UP. Items with loads below .60 were dropped. The internal consistency of each scale was evaluated using Cronbach's alpha, interpreted according to established thresholds: values above .90 were considered excellent, above .80 good, above .70 acceptable, above .60 questionable, above .50 poor, and below .50 unacceptable (Gliem & Gliem, 2003). Convergent validity was assessed through *AVE*, with values greater than .50 deemed adequate (Fornell & Larcker, 1981).

Model fit for structural models was assessed using multiple indices. The comparative fit index (*CFI*) was interpreted as indicating a close fit at values ≥ .98 and a reasonable fit at values ≥ .95. For the root mean square error of approximation (*RMSEA*), values ≤ .05 were considered indicative of close fit and values ≤ .08 as acceptable. The standardized root mean square residual (*SRMR*) was deemed acceptable at values ≤ .08 (Browne & Cudeck, 1992; Hu & Bentler, 1999; Kline, 2023). Modification indices with values ≥ 10 were examined to identify areas of localized misfit. Model modifications were implemented only if theoretically justified and restricted to within-construct covariances. Adjustments were conducted iteratively, one at a time, until the best-fitting model was achieved without compromising parsimony (Urban & Mayerl, 2013). All models were evaluated based on global fit indices, path coefficients, and explained variance (R^2).

Hypothesis 1 (H1) examines the structural inconsistency of technology acceptance models across comparable technologies. For H1a, the TAM was tested using multi-group Structural Equation Model (SEM), with "technology" (Avery vs. Mika) as the grouping variable. For H1b applied the same multi-group approach to the UTAUT framework.

Hypothesis 2 (H2) transfers this inconsistency analysis to the interaction perspective level. Again, the TAM (H2a) and UTAUT (H2b) models were estimated, but this time across the active and passive interaction scenarios. The grouping variable "group" (active vs. passive) allowed the models between these interaction perspectives.

Hypothesis 3 (H3) introduces a UP-integrated modelling approach across comparable technologies. Two baseline models TAM and UTAUT by including the latent variable UP and re-estimated them in the full sample. For H3a, the UP-integrated TAM model using a multi-group SEM, with "technology" (Avery vs. Mika) as the grouping variable. H3b applied the same multi-group approach to the UP-integrated UTAUT model.

Hypothesis 4 (H4) introduces a UP-integrated modelling approach across interaction perspectives. Two baseline models (TAM and UTAUT by including the latent variable UP and re-estimated the models in the full sample. For H4a, the UP-integrated TAM model using a multi-group SEM, with "group" (active vs. passive) as the grouping variable. H3b applied the same multi-group approach to the UP-integrated UTAUT model.

6. Results

6.1. Standard TAM and UTAUT modelling

A SEM based on the traditional TAM structure. The model showed good fit to the data, $\chi^2(41) = 114.68$, $p < .001$, with scaled fit indices indicating acceptable fit: CFI = .985, TLI = .979, RMSEA = .054 (90 % CI [.044, .064], p = .259), and SRMR = .030. All standardized factor loadings were statistically significant ($p < .001$), ranging from .831 to .968. BI was significantly predicted by PU (β = .819, $p < .001$) and negatively by PEU (β = −.117, p = .001). PU was in turn predicted by PEU (β = .607, $p < .001$). The explained variance (R^2) was .568 for BI.

The classic UTAUT model demonstrated good fit, $\chi^2(109) = 234.55$, $p < .001$, with scaled CFI = .986, TLI = .983, RMSEA = .048 (90 % CI [.039, .056]), and SRMR = .034; BI was significantly predicted by PU (β = .357, $p < .001$), SI (β = .569, $p < .001$), and FC (β = .113, p = .024) and negatively by PEU ($\beta = -.159$, $p = .002$), with an explained variance of $R^2 = .699$.

6.1.1. H1: Technology acceptance models exhibit inconsistency across comparable technologies

6.1.1.1. H1a: across TAM. A multi-group SEM tested TAM across comparable technologies (Technology A vs. Technology M). The model demonstrated acceptable fit, scaled chi-square difference, $\chi^2(82) = 159.23$, $p < .001$, with a scaled CFI = .985, TLI = .980, RMSEA = .062 (90 % CI [.047, .077]), and SRMR = .037.

In Group 1 (Technology Avery), PEU significantly predicted PU ($\beta = .531$, $p < .001$), and PU significantly predicted BI ($\beta = .780$, $p < .001$). The direct effect of PEU on BI was not significant ($\beta = -.108$, $p = .056$). The R^2 was .530 for BI.

In Group 2 (Technology Mika), PEU significantly predicted PU ($\beta = .533$, $p < .001$), and PU significantly predicted BI ($\beta = .790$, $p < .001$). The direct path from PEU to BI was also significant ($\beta = -.106$, $p = .033$). The R^2 was .546 for BI. Thus, H1a is confirmed, supported by the divergent role of PEU.

6.1.1.2. H1b: across UTAUT. A multi-group SEM tested UTAUT across comparable technologies (Technology Avery vs. Technology Mika). The scaled chi-square test was $\chi^2(218) = 359.86$, $p < .001$, and the model demonstrated acceptable fit based on scaled indices: CFI = .980, TLI = .975, RMSEA = .046 (90 % CI [.038, .054]), and SRMR = .041.

For Avery, BI was significantly predicted by PU ($\beta = .310$, $p < .001$) and SI ($\beta = .540$, $p < .001$). PEU ($\beta = -.120$, $p = .140$) and FC ($\beta = .120$, $p = .113$) did not reach significance. The R^2 for BI in this group was .647.

For Mika, BI was significantly predicted by PU ($\beta = .370$, $p < .001$) and SI ($\beta = .610$, $p < .001$) and negatively by PEU ($\beta = -.200$, $p = .005$). FC was not significant ($\beta = .110$, $p = .108$). The R^2 for BI in this group was .744. Thus, H1b is confirmed, supported by the divergent roles of PEU and FC, different strengths of effects, and the overall deviance of explained variance.

6.1.2. H2: Technology acceptance models exhibit inconsistency across different interaction perspectives

6.1.2.1. H2a: In TAM. A multi-group SEM tested TAM across different interaction perspectives (active vs. passive users). The scaled chi-square test of model fit was statistically significant, $\chi^2(82) = 169.83$, $p < .001$. The model showed acceptable fit based on the scaled indices: CFI = .980, TLI = .973, RMSEA = .059 (90 % CI [.048, .070]), SRMR = .037.

For active users, PU also significantly predicted BI ($\beta = .842$, SE = .054, $p < .001$). PEU negatively predicted BI ($\beta = -.150$, SE = .077, $p = .004$) and positively predicted PU ($\beta = .549$, SE = .081, $p < .001$). The R^2 for BI in this group was .592.

For passive users, PU significantly predicted BI ($\beta = .749$, SE = .059, $p < .001$), while PEU did not ($\beta = -.070$, SE = .083, $p = .194$). PEU significantly predicted PU ($\beta = .535$, SE = .091, $p < .001$). The latent factor BI showed an R^2 of .510. Thus, H2a is confirmed, supported by the divergent role of PEU.

6.1.2.2. H2b: In the UTAUT. A multi-group SEM tested UTAUT across different interaction perspectives (active vs. passive users). The model demonstrated acceptable fit, with a scaled chi-square of $\chi^2(218) = 360.91$, $p < .001$. Scaled fit indices confirmed the adequacy of the model: CFI = .980, TLI = .975, RMSEA = .046 (90 % CI [.039, .054], $p = .778$), and SRMR = .040.

For active users, BI was significantly predicted by PU ($\beta = .432$, SE = .076, $p < .001$) and SI ($\beta = .536$, SE = .071, $p < .001$) and negatively by PEU ($\beta = -.222$, SE = .115, $p = .005$). FC was not significant ($\beta = .120$, $p = .132$). The R^2 for BI in this group was .728.

For passive users, PU ($\beta = .275$, SE = .075, $p < .001$) and SI ($\beta = .603$, SE = .061, $p < .001$) significantly predicted BI. PEU and FC did not reach significance ($\beta = -.104$, $p = .122$; $\beta = .116$, $p = .069$). The explained variance (R^2) for BI was .682. Thus, H2b is confirmed, supported by the divergent roles of PEU and FC and the different strengths of effects. A condensed view of the results can be viewed in Table 1.

6.2. Usage Perception–integrated modelling

A UP-integrated TAM model. The model demonstrated acceptable fit: scaled $\chi^2(129) = 274.55$, $p < .001$. Scaled fit indices indicated reasonable model adequacy: CFI = .979, TLI = .975, RMSEA = .051 (90 % CI [.043, .060], $p = .393$ for close fit), and SRMR = .034. All factor loadings were statistically significant ($p < .001$), with standardized values ranging from .632 to .966. BI was significantly predicted by PU ($\beta = .623$, $p < .001$) and UP ($\beta = .258$, $p < .001$) and negatively by PEU ($\beta = -.161$, $p < .001$). The model explained 57.3 % of the variance in BI ($R^2 = .573$).

A UP-integrated UTAUT model. The model demonstrated acceptable fit, $\chi^2(994) = 2798.78$, $p < .001$, with scaled fit indices indicating good model adequacy: CFI = .955, TLI = .949, RMSEA = .055 (90 % CI [.052, .057], $p = .001$), and SRMR = .046; all factor loadings were statistically significant ($p < .001$), ranging from .631 to .964; BI was significantly predicted by PU ($\beta = .912$, $p < .001$), UP ($\beta = .197$, $p < .001$), and the interaction of SI × PU ($\beta = .299$, $p < .001$), while PEU ($\beta = -.262$, $p < .001$) negatively predicted BI, and the interaction of FC × PU was not significant ($\beta = -.015$, $p = .640$); the R^2 for BI was .679.

6.2.1. H3: Usage Perception–integrated modelling provides a stable technology acceptance model while maintaining comparable explanatory power across comparable technologies

6.2.1.1. H3a: In TAM. A UP-integrated TAM model was estimated across two technology groups (Technology Avery vs. Technology Mika) using a multi-group SEM. The model demonstrated acceptable fit: $\chi^2(258) = 392.98$, $p < .001$. Scaled fit indices supported model adequacy: CFI = .979, TLI = .975, RMSEA = .041 (90 % CI [.034, .048], $p = .981$ for close fit), and SRMR = .037. For Avery, all factor loadings were significant ($p < .001$), with standardized values ranging from .621 to .960. BI was significantly predicted by PU ($\beta = .604$, $p < .001$) and UP ($\beta = .302$, $p < .001$) and negatively by PEU ($\beta = -.186$, $p = .001$). The R^2 for BI was .572. For Mika, all factor loadings were significant ($p < .001$), with standardized values ranging from .647 to .969. BI was significantly predicted by PU ($\beta = .609$, $p < .001$) and UP ($\beta = .248$, $p = .003$) and negatively by PEU ($\beta = -.145$, $p = .007$). The R^2 for BI was .566. Thus, H3a is confirmed.

6.2.1.2. H3b: In UTAUT. A UP-integrated UTAUT model was estimated for the Avery technology group. The model showed acceptable fit, $\chi^2(788) = 1835.39$, $p < .001$, with scaled fit indices indicating good

Table 1
TAM and UTAUT across comparable technologies and interaction perspectives.

Model	BI-PU	BI-PEU	PU-PEU	BI-SI	BI-FC	R^2
TAM	.82*	−.12*	.39*			.56
TAM Avery	.78*	−.11	.53*			.53
TAM Mika	.79*	−.11*	.53*			.55
TAM Active	.84*	−.15*	.55*			.60
TAM Passive	.75*	−.07	.54*			.51
UTAUT	.36*	−.16*		.57*	.11*	.70
UTAUT Avery	.31*	−.12		.54*	.12	.65
UTAUT Mika	.37*	−.20*		.61*	.11	.75
UTAUT Active	.43*	−.22*		.54*	.12	.73
UTAUT Passive	.28*	−.10		.60*	.12	.68

Note. *$p > .05$. Own presentation. Perceived uUsefulness (PU), Perceived Ease of Use (PEU), Behavior Intention (BI), Social Influence (SI), Facilitating Conditions (FC).

adequacy: CFI = .949, TLI = .941, RMSEA = .066 (90 % CI [.062, .070], $p < .001$), and SRMR = .042. All factor loadings were statistically significant ($p < .001$), ranging from .643 to .969. BI was significantly predicted by PU ($\beta = .828$, $p < .001$), UP ($\beta = .232$, $p = .003$), and the interaction of SI × PU ($\beta = .316$, $p < .001$) and was negatively predicted by PEU ($\beta = -.241$, $p < .001$); the interaction of FC × PU was not significant ($\beta = -.008$, $p = .853$). The R^2 for BI was .676.

A UP-integrated UTAUT model was estimated for the Mika technology group. The model showed acceptable fit, $\chi^2(788) = 1759.88$, $p < .001$, with scaled indices indicating good adequacy: CFI = .944, TLI = .936, RMSEA = .063 (90 % CI [.060, .067], $p < .001$), and SRMR = .044. All factor loadings were statistically significant ($p < .001$), with standardized values ranging from .621 to .959. BI was significantly predicted by PU ($\beta = .906$, $p < .001$), UP ($\beta = .246$, $p = .001$), and the interaction of SI × PU ($\beta = .283$, $p < .001$) and was negatively predicted by PEU ($\beta = -.294$, $p < .001$); the interaction of FC × PU was not significant ($\beta = -.008$, $p = .859$). The R^2 for BI was .664. Thus, H3b is confirmed.

6.2.2. *H4: Usage Perception–integrated modelling provides a stable technology acceptance model while maintaining comparable explanatory power across different interaction perspectives*

6.2.2.1. H4a: In TAM. A multi-group SEM using a UP-integrated TAM structure across active and passive interaction perspectives. The model demonstrated good fit, with a scaled chi-square of $\chi^2(258) = 450.33$, $p < .001$. Scaled fit indices supported model adequacy: CFI = .971, TLI = .965, RMSEA = .049 (90 % CI [.043, .056], $p = .548$), and SRMR = .038. The robust RMSEA was .056 (90 % CI [.047, .065]). All factor loadings were statistically significant ($p < .001$), with standardized values ranging from .598 to .964 across both groups. For active users, BI was predicted positively by PU ($\beta = .691$, $p < .001$) and UP ($\beta = .240$, $p = .002$) and negatively by PEU ($\beta = -.211$, $p < .001$). The R^2 for BI was .614. For passive users, BI was predicted positively by PU ($\beta = .560$, $p < .001$) and UP ($\beta = .273$, $p < .001$) and negatively by PEU ($\beta = -.110$, $p = .039$). The R^2 for BI was .539. Thus, H4a is confirmed.

6.2.2.2. H4b: In UTAUT. A UP-integrated UTAUT model was estimated for passive users. The model demonstrated acceptable fit, $\chi^2(788) = 1819.60$, $p < .001$, with scaled fit indices indicating good model adequacy: CFI = .946, TLI = .938, RMSEA = .065 (90 % CI [.061, .069], $p < .001$), and SRMR = .040. All factor loadings were statistically significant ($p < .001$), ranging from .597 to .967. BI was significantly predicted by PU ($\beta = .879$, $p < .001$), UP ($\beta = .172$, $p = .021$), and the interaction of SI × PU ($\beta = .304$, $p < .001$). PEU negatively predicted BI ($\beta = -.235$, $p < .001$), while the interaction of FC × PU was not significant ($\beta = -.053$, $p = .253$). The R^2 for BI was .651.

A UP-integrated UTAUT model was estimated for active users. The model demonstrated acceptable fit, $\chi^2(994) = 2270.81$, $p < .001$, with scaled fit indices indicating good model adequacy: CFI = .938, TLI = .929, RMSEA = .065 (90 % CI [.061, .069], $p < .001$), and SRMR = .052. All factor loadings were statistically significant ($p < .001$), ranging from .665 to .963. BI was significantly predicted by PU ($\beta = .947$, $p < .001$), UP ($\beta = .224$, $p = .002$), and the interaction of SI × PU ($\beta = .294$, $p < .001$). PEU ($\beta = -.307$, $p < .001$) negatively predicted BI, while the interaction of FC × PU was not significant ($\beta = .015$, $p = .740$). The R^2 for BI was .716. Thus, H4b is confirmed. A condensed view of the results can be found in Table 2.

7. Discussion

This study has examined the structural robustness of traditional technology acceptance models across comparable technological contexts and varying interaction perspectives, supported by research on variation due to technology (cf. Benbasat & Barki, 2007) and context (cf. Abdullah & Ward, 2016; Dwivedi et al., 2020). The findings reveal a critical insight: While core predictors such as PU and SI consistently and significantly predicted BI across all models, subcomponents of the classical framework demonstrated structural inconsistency, in line with the discussion about limitations and boundaries of technology acceptance models (cf. King & He, 2006; Malatji et al., 2020). This can be mitigated by a UP-integrated model accounting for both explainability and stability in the technology acceptance of complex technologies, supported by the arising importance of attitudes in the context of highly complex technologies (cf. Alkhwaldi et al., 2025; Doulani, 2019; Marikyan et al., 2023).

Table 2

Perception-TAM and Perception-UTAUT across comparable technologies and interaction perspectives.

Model	BI-PU	BI-PEU	BI-UP	PUxSI	PUxFC	R^2
TAM	.62*	−.16*	.26*			.57
TAM Avery	.60*	−.19*	.30*			.57
TAM Mika	.61*	−.15*	.25*			.57
TAM Active	.69*	−.11*	.24*			.61
TAM Passive	.56*	−.11*	.27*			.54
UTAUT	.91*	−.26*	.20*	.30*	−.02	.68
UTAUT Avery	.83*	−.24*	.23*	.32*	−.00	.68
UTAUT Mika	.91*	−.30*	.25*	.28*	−.00	.66
UTAUT Active	.95*	−.31*	.22*	.29*	−.02	.72
UTAUT Passive	.88*	−.24*	.17*	.30*	−.05	.65

Note. *$p > .05$. Own presentation. Perceived uUsefulness (PU), Perceived Ease of Use (PEU), Behavior Intention (BI), Social Influence (SI), Facilitating Conditions (FC), Perception-TAM (P-TAM), Perception-UTAUT (P-UTAUT).

7.1. *Inconsistency of classical TAM and UTAUT structures*

Across both TAM and UTAUT, PU consistently emerged as a strong and robust predictor of BI. In the overall models, PU significantly predicted BI in both the classic TAM ($\beta = .819$, $p < .001$) and UTAUT ($\beta = .357$, $p < .001$), with high explanatory power ($R^2 = .568$ for TAM; $R^2 = .699$ for UTAUT). This pattern was mirrored in all subgroup comparisons, across interaction perspectives and technologies, underscoring PU's central and generalizable role in technology acceptance theory.

Similarly, SI, a key component of the UTAUT model, demonstrated structural robustness across all contexts. It significantly predicted BI in the overall UTAUT model ($\beta = .569$, $p < .001$), as well as in all subgroups, including active ($\beta = .536$, $p < .001$) and passive ($\beta = .603$, $p < .001$) interaction perspectives, and across technologies (Avery: $\beta = .540$; Mika: $\beta = .610$; both $p < .001$).

However, PEU and FC paint a more complex picture. In the overall TAM model, PEU significantly predicted both PU ($\beta = .607$, $p < .001$) and BI ($\beta = -.117$, $p = .001$); in UTAUT too, PEU ($\beta = -.159$, $p = .002$) and FC ($\beta = .113$, $p = .024$) were significant. Yet, in subgroup analyses, these effects became inconsistent: PEU was significant only for passive users and for one technology (Mika), and FC failed to reach significance in all disaggregated models, whether by interaction perspective or technology. These discrepancies provide direct empirical support for H1 and H2, indicating that classical models tend to overgeneralize, whereas a differentiated picture emerges once UP is considered, resulting in a more stable model overall. This finding aligns with the broader discussion on the consistency, explanatory power, and adaptability of technology acceptance models (cf. Dwivedi et al., 2011; Dwivedi et al., 2020; King & He, 2006). Moreover, it reflects the growing emphasis on attitudinal mechanisms in the evaluation of emerging technologies, particularly in the context of AI systems, where users' perceptions and attitudes play an increasingly central role in shaping acceptance (cf. Alkhwaldi et al., 2025; Hussian & Nethravathi, 2024; Shen et al., 2025).

7.2. *Stabilizing effects of Usage Perception–integrated models*

The introduction of UP into both the TAM and UTAUT structures substantially improved model stability across all levels of comparison. The UP-integrated TAM model showed that all predictors—PU, PEU, and UP—significantly influenced BI, and this pattern remained consistent across both interaction perspectives and comparable technologies. In contrast to the variability observed in the classical models, the inclusion of UP contributed to greater path stability and theoretical coherence across subgroups.

Crucially, UP emerged as a robust and consistent predictor of BI across all comparisons. In the overall UTAUT model, UP significantly predicted BI ($\beta = .197$, $p < .001$) and maintained significance across both interaction perspectives and technologies. Similarly, in the UP-integrated TAM, UP also predicted BI consistently across all subgroups (e.g., active: $\beta = .240$, $p = .002$; passive: $\beta = .273$, $p < .001$; A: $\beta = .302$, $p < .001$; M: $\beta = .248$, $p = .003$). This consistency reinforces UP's unique theoretical role as a context-insensitive construct that captures attitudinal responses reliably.

Finally, the UP-integrated models maintained a comparable explanatory power across all configurations. Overall, the UP-integrated UTAUT ($R^2 = .679$) and TAM ($R^2 = .573$) matched or exceeded their classical counterparts (UTAUT: $R^2 = .699$; TAM: $R^2 = .568$). This advantage became clearer in subgroup comparisons. Across interaction perspectives, the UP-integrated UTAUT showed high R^2 (active: .716; passive: .651), with more stable paths than the classical model (active: .728; passive: .682). In TAM, the UP-integrated variant reduced disparities (active: .614; passive: .539) compared to the classical version (active: .592; passive: .510). Across technologies, the UP-integrated TAM yielded consistent R^2 (Avery: .572; Mika: .566), displaying an improvement over the classical TAM (Avery: .530; Mika: .546). Similarly, the UP-integrated UTAUT maintained strong and balanced explanatory power (Avery: .676; Mika: .664), outperforming the classical model in stability. Thus, UP-integrated modelling not only preserves predictive utility, but also resolves structural inconsistency. Overall, the findings provide strong holistic evidence in support of H3 and H4. Although prior research has already emphasized the need to adapt technology acceptance models by incorporating attitudinal measures to adequately explain AI acceptance (cf. Alkhwaldi et al., 2025; Hussian & Nethravathi, 2024; Shen et al., 2025), the present results align closely with and further substantiate this line of argumentation.

7.3. Interaction perspectives and comparable-technology implementation

Interestingly, active versus passive interaction perspectives introduced greater structural variability than technology type alone, even within stabilized models. For example, in the UP-integrated TAM, the predictive strength of PU on BI increased from $\beta = .560$ ($p < .001$) in active users to $\beta = .691$ ($p < .001$) in passive users, while PEU shifted from $\beta = -.110$ ($p = .039$) to $\beta = -.211$ ($p < .001$). Similarly, the UP-integrated UTAUT revealed notable R^2 differences between user groups (active: .716; passive: .651). While technology type also caused inconsistency in the classical TAM—for instance, PEU was significant for Technology M ($\beta = -.106$, $p = .033$), but not for Technology A ($\beta = -.108$, $p = .056$)—the UP-integrated TAM resolved this issue. It yielded consistent effects for PEU (A: $\beta = -.186$, $p = .001$; M: $\beta = -.145$, $p = .007$) and UP, with nearly identical R^2 values for BI (A: .572; M: .566). This supports the interpretation that user interaction perspectives play a stronger role than the technological context regarding variability in acceptance between complex technologies. This finding further underscores that active versus passive interaction perspectives exert a substantial influence on user interaction and acceptance of highly complex technologies, such as virtual reality or autonomous driving, and that these effects extend to AI-based systems as well (cf. Alsyouf et al., 2023; Christ et al., 2016; Guertin-Lahoud et al., 2023; Rödel et al., 2014).

While FC significantly predicted BI in the classic UTAUT model ($\beta = .113$, $p = .024$), this effect was not replicated in any subgroup model, whether based on interaction perspective or technology type. This discrepancy suggests that the observed pooled significance may mask structural heterogeneity in how environmental-support factors influence intention. The UP-integrated UTAUT reframed FC as a moderator rather than a direct predictor, operationalized through an interaction with PU (FC × PU). However, this interaction was not significant in the overall model ($\beta = -.015$, $p = .640$) and remained non-significant in all subgroup analyses (A: $\beta = -.008$, $p = .853$; M: $\beta = -.008$, $p = .859$; passive: $\beta = -.053$, $p = .253$). Null findings support the interpretation that FC plays, in this concrete laboratory environment, a conditional or peripheral role. This could be because contextual implementation variables are not necessary in the specific application example.

7.4. Practical implications

The above insights highlight acceptance framework models that consider not only what technology is used, but also how, by whom, and under what interactional conditions. The integration of UP into this framework marks a possible solution, pushing acceptance theory toward a stable, perception-integrated modelling approach that proves particularly effective across complex technologies and diverse interaction perspectives. This practically opens up the discussion on which role user perception should play in developing new innovations—in favor of holistic, improved, and simplified explainability.

Additionally, a key insight appearing from this research is the distinct impact of active versus passive interaction perspectives. Across all tested models, user role introduced greater structural variability than technology type alone. Even in the UP-integrated TAM, the predictive effects of core constructs such as PU and PEU systematically differed depending on whether users engaged actively or passively with the system. This highlights that user role is not a secondary contextual factor, but a central determinant of technology acceptance. Especially in the design of new complex technologies, different user groups and interaction perspectives should be considered.

Further, UP-integrated modelling offers more than structural stabilization. Specifically, it uncovers the influence of interaction mode and technology perception on how constructs like PU, PEU, and UP shape BI. In practice, this means that even small changes in the interaction and perception of a technology can change the overall acceptance of comparable technologies, especially if it is complex and affected by different user perspectives. Thus, we advocate for a sensible innovation development process for complex technologies which captures the synergies among the system, user, context, usage, and specific end product.

7.5. Limitations

First, this study was conducted in a simulated online laboratory environment, which, although enabling controlled manipulation of conditions, may limit ecological validity. In addition, we employed forced interaction with the technology which was tightly aligned with the experimental objectives. As a result, the use case and usage context were predefined rather than emerging from participants' intrinsic motivation, which limits the ecological validity with respect to natural AI use. To ensure experimental control, interaction time was constrained by a minimum duration—a condition that does not fully reflect realistic technology engagement. Moreover, the AI's responses and interaction paths were restricted to a specific use case, effectively constituting a highly controlled interaction environment. Finally, as the study was confined to a single usage context, it does not include an examination of how interactions with complex technologies evolve over time.

Second, despite the holistic sampling approach, the findings reflect improvements of the proposed model within a single use case context, and thus applicability across broader technologies remains to be demonstrated. The study is founded on an experimental manipulation in which participants were assigned to either an active or a passive interaction vignette. These vignettes differed solely with respect to user autonomy over the system's final decision: In the active vignette, participants were able to make the decision themselves, whereas in the passive vignette, the decision was executed automatically by the AI following the interaction. While this design ensured a stable and well-controlled manipulation, it represents a forced dichotomization and does not fully capture the inherently continuous nature of active and passive interaction with technology.

7.6. Statement of declaration

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. We declare no competing interests.

7.7. Future research

Future research should examine whether the proposed UP-integrated model and active/passive differences also apply across other technology domains. It also remains to be studied how UP changes with increasing technological experience. Finally, the consistent null findings regarding FC suggest that its role may depend on contextual implementation, which should be addressed in an applied setting.

8. Conclusion

Founded on a controlled experimental design with real AI interaction scenarios, this study offers strong insights into the structural robustness of technology acceptance models across user interaction scenarios: between an active and a passive perspective and across complex comparable technologies. The results confirm that while core predictors such as PU and SI consistently and robustly predict BI across all models, the TAM and UTAUT frameworks exhibit structural inconsistency when disaggregated by interaction perspective or comparable technology types. In contrast, the UP-integrated models, augmented by UP, exhibited greater path stability, theoretical coherence, and consistent predictive power across all subgroup comparisons.

This primary finding reveals an additional angle of technology acceptance models, advocating for modelling that is sensitive to interaction perspective. Furthermore, the study highlights that in complex technologies, even across comparable technology types, traditional acceptance models show disharmonies. The broader human perception of a complex technology emerges as a particularly reliable and stabilizing predictor of BI, reinforcing its theoretical value. Moreover, it can account for explainability across both interaction perspectives and comparable technologies. Overall, UP-integrated modelling accounts for increasing technological complexity, while reducing model complexity.

CRediT authorship contribution statement

Marvin Schittko: Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Patrick Planing:** Writing – review & editing, Validation, Resources. **Patrick Müller:** Writing – review & editing, Supervision, Resources, Funding acquisition.

Declaration of generative AI and AI-assisted technologies in the writing process

In the process of drafting this document, the author utilized ChatGPT (2025) 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.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

All data are transparent in an online repository cited.

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