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Abstract

Purpose- This study examines how users' experiences of AI inclusion, reflected in feelings of belonging and authenticity during human-AI interaction, are associated with user satisfaction and interactional justice.

Design/methodology/approach- The study assesses the proposed relationships between the constructs using two separately analyzed datasets: 219 Amazon Alexa users and 577 ChatGPT users. Regression analysis was used to assess the proposed relationships within each dataset.. Additionally, the study adopts Latent Profile Analysis (LPA) to identify distinct AI user profiles.

Findings- The findings indicate that AI inclusion dimensions (i.e., belonging and authenticity) are positively associated with user satisfaction and interactional justice. The results of LPA reveal different user profiles based on inclusion, satisfaction, and justice scores.

Research limitations/implications- While this study assesses AI inclusion in the contexts of Amazon Alexa and ChatGPT, future research may explore AI inclusion in other AI systems and employ longitudinal or experimental methodologies. Previous research has largely approached AI inclusion through access, participation, or design-oriented perspective, whereas this study examines AI inclusion from a micro-level experiential perspective.

Practical implications- The findings of this study have several implications for AI developers, organizations, policy makers, society, and education by showing that AI systems should be designed not only for functional performance but also to foster users' feelings of belonging and authenticity. Hence, users' emotional experiences should be treated as an important dimension of AI evaluation and governance.

Originality- This study advances research on AI and inclusion by conceptualizing AI inclusion as users' felt experience during human-AI interactions rather than access to, participation in, or governance of AI systems. It defines AI inclusion as a micro-level experiential construct and highlights its importance for understanding user satisfaction and interactional justice.

Keywords: *AI Inclusion, Human-AI interaction, User Satisfaction, Interactional Justice, Latent Profile Analysis*

1. Introduction

Inclusion has attracted significant attention in Information Systems (IS) research as digital technologies increasingly shape social, organizational, and policy contexts. Prior research has provided valuable insights into inclusion by focusing on issues such as digital access, participation, and the limited representation of women and marginalized groups in the use and development of technology (Tarafdar et al., 2023; Tanyel et al., 2025; Tielman et al., 2024). These perspectives have contributed to a deeper understanding of individuals' ability to access, participate and use digital technologies. Yet, there has been limited focus on whether users feel included when interacting with AI systems.

This gap warrants attention because AI systems operate differently from traditional digital technologies. Rather than functioning only as passive systems, AI systems increasingly engage users through adaptive, interactive, and socially rich interactions. Such interactions can influence whether users feel understood, respected, accepted, or able to express themselves freely (Flavian et al., 2024). For instance, users may have technical access to an AI system, yet still experience psychological exclusion, such as feeling judged or unable to freely express themselves. Therefore, understanding inclusion in AI contexts requires moving beyond technology access and participation perspectives to studying inclusion as a felt experience during interactions with AI systems.

Recent studies have started to extend digital inclusion discussions into the AI context. Much of the existing research on AI inclusion examines macro-level perspectives, focusing on issues such as access, infrastructure, governance, and algorithmic bias (Sarkar, 2025; Soldatic et al., 2025). Although previous research has yielded important insights, it does not comprehensively address users' psychological and relational experiences during interactions with AI systems. This perspective is essential because users may have access to AI systems but still feel excluded if the interaction does not promote authentic self-expression and sense of belonging .

Hence, in this study we conceptualize AI inclusion as the extent to which interactions with AI systems foster users' sense of being accepted, valued, understood, and free to express their authentic selves. AI inclusion comprises two key aspects: belonging and authenticity. Belonging refers to the perception of having a strong, stable interpersonal relationship with AI technologies. For instance, when AI systems show concern, support and care during interaction it gives users a sense of belongingness. On the other hand, authenticity refers to the feeling where users freely express themselves when interacting with AI systems. For instance, when AI systems show empathy, ensure confidentiality, and use a non-judgmental tone, users feel accepted and heard rather than corrected or judged, fostering a sense of authenticity.

Given the experiential nature of AI inclusion, interactional justice and user satisfaction emerge as two relevant outcomes. Unlike behavioral outcomes such as adoption or continued use which are impacted by task requirements, instrumental benefits, and organizational constraints (Venkatesh et al., 2003), interactional justice and user satisfaction directly capture users' subjective evaluations of how they are treated by the AI system during interaction. Interactional justice refers to the degree to which users perceive respect, fairness, and dignity in their interaction with AI systems (Bacile, 2020). User satisfaction refers to the user's affective evaluation of the interaction itself, rather than system performance alone. These outcomes help assess whether interactions with AI systems meet users' experiential and psychological expectations.

Based on the above arguments, this study addresses three research questions. First, how can AI inclusion be conceptualized in the human-AI interaction? Second, how is AI inclusion associated with user satisfaction and interactional justice? Third, do users exhibit different AI inclusion profiles within different AI interaction contexts? To address these questions, we evaluate our research model using two separately analysed samples comprising 219 Amazon Alexa users and 577 ChatGPT users. By assessing AI inclusion across a voice-based AI system and a conversational AI system, the study provides insights into how users experience belonging and authenticity within different forms of human-AI interaction.

2.Theoretical Background

2.1 Inclusion

Inclusion has been defined and operationalized from different perspectives across research domains. Inclusion, from an organizational perspective, is defined by Miller (1998) as "the extent to which diverse individuals are allowed to participate and are enabled to contribute fully" (p. 151). Pelled et al. (1999) defined inclusion as "the degree to which an employee is accepted and treated as an insider by others in a work system". Further, Roberson (2006) defined it as "the removal of obstacles to the full participation and contribution of employees in organizations" (p. 217). This perspective emphasizes the participatory dimension of inclusion, where users have opportunities to participate and contribute and are recognized as legitimate system members.

Inclusion has also been defined from an individual perspective. For instance, Lirio et al. (2008) described it as existing "when individuals feel a sense of belonging and inclusive behaviors such as eliciting and valuing contributions from all employees are part of the daily life in the organization" (p. 443). Further, Avery et al. (2008) stated that inclusion is "the extent to which employees believe their organizations engage in efforts to involve all employees in the mission and operation of the organization with respect to their individual talents" (p. 6).This individual-level perspective emphasizes that inclusion encompasses not only participation and access, but also whether individuals feel accepted, valued, and able to express their authentic selves.

To address this gap, Jansen et al. (2014) offered a comprehensive definition of inclusion as a two-dimensional construct consisting of belonging and authenticity. They argued that individuals should feel their authentic self, respected, and supported, which they described as perceived authenticity. They defined belongingness as the need to form and maintain strong, stable interpersonal relationships. Based on this argument, they defined inclusion as "the degree to which individuals experience treatment from the group that satisfies their need for belongingness and uniqueness" (Jansen et al, 2014). Later, these dimensions were adopted by other researchers to measure inclusion. Therefore, belonging and authenticity provide a valuable perspective for understanding inclusion as a personal experience. Belonging indicates whether users feel valued and accepted, while authenticity concerns their ability to express themselves openly. This distinction is essential for the present study, as users may access AI systems yet do not feel understood and accepted during interactions.

2.2 Inclusion in IS

A large body of IS research has examined inclusion in terms of access, representation, and structural inequalities in the development, deployment and use of information technologies (Trauth, 2017). To get deeper insight on inclusion, Tanyel et al. (2025) synthesized the IS inclusion literature and identified four prominent research themes related to ICT access and use among marginalized communities, identity-based inclusion disparities based on gender, ethnicity, income, age, and disabilities, women's representation in the IS profession, and the role of digital technologies in supporting organizational inclusion (Gorbacheva et al., 2018; Tarafdar et al., 2023; Tanyel et al., 2025; Tielman et al., 2024). A related stream of IS research highlights the role of design in enabling or constraining inclusion and emphasizes addressing digital inequalities across the development, adoption, use, and maintenance of digital technologies (DiMaggio et al., 2004).

Furthermore, (DiMaggio et al., (2004) highlighted the role of system design in enabling inclusion and emphasized addressing digital inequalities across different stages of digital innovation including adoption, use, and maintenance However, others cautioned that that inclusive design does not guarantee inclusive user experience as users may experience inclusion and exclusion simultaneously within the same IS platform (Curto-Millet & Canibano, 2023). For instance, social media platforms may promote identity formation, academic growth, and self-care awareness leading to the inclusion of minorities but they may also amplify social exclusion by perpetuating existing racial, ethnic, gender and economic inequalities (Gonzalez and Deng, 2023). This suggests that inclusion cannot be understood only through the lens of inclusive design, it must also be assessed through users' lived experiences with AI technologies.

Hence, the IS literature suggests that access, participation, representation, and inclusive design are important but not sufficient to fully explain inclusion in AI contexts. The deeply personal nature of inclusion experiences necessitates a closer exploration of the micro-level

dimensions of inclusion that shape users' direct interactions with AI technologies that are particularly designed to facilitate more human-like interactions. Studies have shown that users often perceive advanced technologies such as ChatGPT and voice-based virtual assistants as human counterparts (Hubert et al., 2024), underscoring the importance of users, emotional and experiential dimensions in shaping AI inclusion (Hubert et al., 2024). Therefore, exploring AI inclusion requires moving beyond whether users can access and use technology to whether users feel accepted, respected, and able to express themselves authentically during their interactions with AI systems.

2.3 AI Inclusion

AI is no longer limited to handling routine tasks but is increasingly embedded in conversational and social rich interactions with users. As this trend continues, there is a stronger need to understand whether users feel included while engaging with AI systems. The Computers as Social Actors (CASA) theory proposed by Reeves and Nass (1996) posits that individuals often interact with computers as if they were social beings, applying human social norms such as empathy, politeness, and trust. In the context of AI inclusion, this perspective suggests that users may perceive AI systems not merely as tools but as interactional agents that shape whether they feel accepted and valued, and able to express themselves freely. Hence, AI should not only be functionally accessible but also experientially inclusive.

With the growing attention to the social and ethical implications of digital technologies, several related constructs have emerged, including digital inclusion, responsible AI and trust in AI often used interchangeably. Although these constructs are connected, they capture different aspects of the social, ethical, and experiential relationships between users and digital technologies. For instance, digital inclusion focuses primarily on the conditions of access and participation that enable people to use digital technologies (Tarafdar et al., 2023). For example, providing affordable internet access and assistive technologies for users with disabilities reflects digital inclusion. Responsible AI, on the other hand, refers to governance mechanisms and organizational accountability to design and deploy AI to ensure that the AI is equitable, fair, ethical, and generally "good" for all those affected by it (Stahl and Wright, 2018; Ghallab, 2019; Rakova et al., 2021). For example, auditing AI hiring systems for bias or mandating explainability in automated decision-making systems. Further, trust in AI reflects users' confidence that AI systems will perform tasks accurately, fairly, and reliably (Glikson & Woolley, 2020). For instance, managers may trust an AI predictive system if they believe it provides reliable and accurate advice. Trust in AI does not necessarily mean the manager feels included by the AI predictive system. Though they may trust the system's output while still feeling the system does not understand their way of thinking, respect their decision, and appreciate their efforts.

Another stream of research on AI systems has applied concepts like anthropomorphism, social presence and rapport to explain human-AI interaction (Pradeepa et al. 2024; Lee et al., 2024;

Fatima et al., 2024). Anthropomorphism refers to perceiving AI systems to exhibit humanlike characteristics such as intentions, motivations, (Epley et al., 2007). Similarly, social presence reflects the extent to which an AI system is perceived to be psychologically present during interaction (Pradeepa et al. 2024; Lee et al., 2024). Further, rapport reflects a harmonious interaction characterized by positivity and attentiveness (Lee et al., 2024; Fatima et al., 2024). Although these constructs are related to AI inclusion, they are different conceptually. An AI system may appear human-like, psychologically and socially present, and maintain a warm and courteous conversation, yet users may still feel excluded if they do not feel accepted, valued or able to express freely.

In contrast, AI inclusion shifts attention from access, system performance, governance mechanisms, trust, human-like behaviour, social presence to users' psychological and social experiences during interaction with AI systems. For instance, the user may experience AI inclusion when an AI-based conversational system responds in a supportive and non-judgmental way that makes them feel understood.

Drawing on prior inclusion literature and the belonging-authenticity distinction advanced by Jansen et al. (2014), we define AI inclusion as the extent to which interactions with the AI system foster a sense of belonging and authenticity. AI inclusion comprises two key dimensions: belonging and authenticity. The first dimension, belonging, refers to users' felt sense of being accepted and valued during interaction with AI systems (Antonsich, 2010). Belonging involves an individual's perception of being appreciated and well-regarded in an interaction (Wass et al., 2023). In the context of AI, this may emerge when users perceive that the system recognizes their needs, responds supportively, or provides caring responses. For instance, a user might feel that Amazon Alexa supports a sense of belonging when it remembers past interactions and warns them against bad weather, unlocked doors and windows. Similarly, users may perceive ChatGPT as supportive when it offers encouragement during challenging situations, thereby fulfilling their emotional needs. Hence, during interactions with the AI system, users may feel valued and cared for, thereby fostering a sense of belonging. The second dimension, authenticity, refers to users' felt ability to express their thoughts, preferences, emotions, and identity freely during interaction with AI systems (Kernis & Goldman, 2006). For instance, users may feel that ChatGPT allows them to communicate as they would in daily life, openly expressing their personal feelings.

Recent studies have begun to use terms such as inclusive AI, and AI inclusivity, but they generally explored inclusion at the macro, policy, and design level. For instance, Martin and Richter (2024) conceptualize Inclusive in terms of access, equity and impact, focusing on creating inclusive system design, reducing AI bias, and leveraging AI to foster broader societal inclusion. Similarly, other researchers emphasized participation, accessibility and affordability, disabilities, and the experiences of culturally and linguistically diverse groups such as migrants and people with disabilities, in discussions of digital and AI inclusion (Soldatic et al. 2025; Gonzalez-Jimenez and Costa Pinto, 2024). Further, Sarkar (2025) raised the issue of the AI inclusivity gap and defined it as the unequal ability of populations, institutions, and regions to engage in the creation,

governance, and usage of AI systems. This work focuses on issues related to unequal socio-technical- infrastructural algorithmic literacy, and institutional access. While the authors advanced digital inclusion research by extending it to the AI systems, they predominantly conceptualized AI inclusion from an access and participation-oriented perspective. However, literature suggests that despite having access and participation, users may still not experience inclusion (Curto-Millet & Canibano, 2023), particularly during human-AI interaction if they do not feel accepted, valued, or able to express their authentic selves. Hence, unlike prior work that primarily extends digital inclusion into the AI context, our conceptualization of AI inclusion focuses on users' psychological experiences while interacting with AI systems.

Accordingly, we draw on Jansen et al.'s conceptualization of inclusion as a felt experience of belonging and authenticity to define AI inclusion at the level of human-AI interaction.

2.4 User satisfaction

User satisfaction is defined as the perceptions of the service or product received relative to expectations of what should have been provided (Hu et al., 2017). User satisfaction occurs when the actual performance of a product or service is equal to or more than the expectations of the user (Bhattacherjee, 2001). In the context of IS, user satisfaction reflects an emotional response that arises during interaction and usage of the IS. Positive affect enhances satisfaction by stimulating a sense of willingness to engage with the system, whereas negative affect decreases satisfaction and reduces users' willingness to continue using the system.

Previous IS research has defined user satisfaction as a result of instrumental evaluation, emphasizing system functionality and efficiency (DeLone & McLean, 1992). Although these evaluations are essential for assessing system success, they mainly capture goal-oriented judgments rather than users' experiential perceptions during interaction. In AI contexts where systems increasingly engage in socially rich interactions, users may view systems as functionally effective but experientially exclusive. Thus, user satisfaction may be shaped not only by system functional effectiveness but also by users experience during interaction with AI systems. This motivates the need to consider experiential conditions that shape user satisfaction in human-AI interactions.

2.5 Interactional Justice

Interactional justice refers to the quality of communication between the source and the recipient, encompassing elements such as politeness, honesty, and respect (Bies & Moag, 1986; Tyler & Bies, 1990). It involves different actions manifesting social sensitivity, such as treating workers with respect and justice by listening to their concerns, providing sufficient explanations for actions, and showing empathy for others' plight (Skarlicki & Folger, 1997). Such fair treatment communicates to individuals that they are valued members of the group or organization. The IS literature on interactional justice has mainly emphasized on the role of IS platform designs in

promoting interactional justice. For instance, Baygi et al. (2021) highlighted that equitable design in labor platforms improves individual agency and mitigates perceived injustice. Although system design plays a critical role in addressing injustice, human-AI interaction introduces an additional layer of user emotional engagement with the system. This emotional dimension may shape how fairness and respect are perceived during user-AI interactions. Hence, exploring how AI inclusion might contribute to fostering interactional justice in AI systems would make a significant contribution to IS literature.

3.Hypotheses Development

We propose that AI inclusion, including its dimensions belonging and authenticity, is positively associated with interactional justice and user satisfaction as depicted in Figure 1.

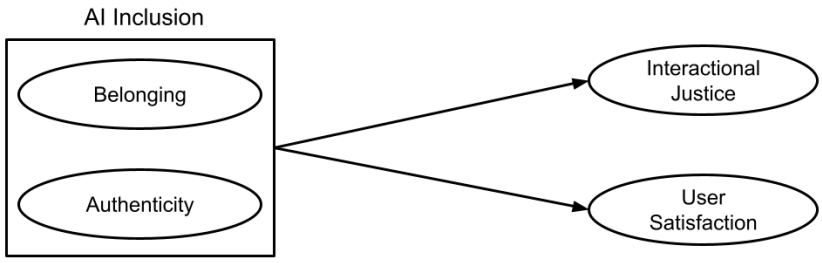


Figure 1: *Research Model*

AI Inclusion and User Satisfaction

We propose that perceived AI inclusion, characterized by belonging and authenticity, is positively associated with user satisfaction. This association is grounded in the social exchange theory that indicates that relationships are sustained through a series of exchanges where individuals anticipate mutual benefits. When users engage with AI systems, they expect the systems to reciprocate in ways that fosters a sense of belonging and authenticity. When AI systems are perceived as inclusive, users are likely to experience higher satisfaction as they expect that an AI system will benefit them. For instance, students reported higher satisfaction with educational platforms that adapted interactions to their learning style (Almufarreh, 2024), fostering a sense of belonging and authenticity. Transparent communication about data usage and feedback mechanisms of these platforms was associated with higher student satisfaction. These findings underscore the importance of inclusive AI systems in fostering user satisfaction; therefore, we propose that:

H1: Perceived AI inclusion (i.e., belonging and authenticity) is positively associated with user satisfaction.

AI Inclusion and Interactional Justice

We also propose that perceived AI Inclusion, characterized by belonging and authenticity, is positively associated with interactional justice. This relationship is grounded on interactional justice theory, which suggests that relationships thrive when there is mutual respect, honesty, empathy and politeness between parties (Tyler & Bies, 1990; Skarlicki & Folger, 1997). AI systems are designed to emulate human-like interaction and adapt to varying contexts by accommodating user needs and preferences (Jiang et al., 2024a). Hence, users feel more engaged and view AI systems as partners that enhance their capabilities and support their goals (Jiang et al., 2024a). When users feel supported, respected and well-treated, they are more likely to develop positive perceptions of the AI system, considering it as fair and supportive. Similarly, when users feel that the system accepts them as they are, without judgment or bias, they are more willing to use it without concerns about discrimination or misjudgment. Therefore, we propose that:

H2: Perceived AI inclusion (i.e., belonging and authenticity) is positively associated with interactional justice.

Distinct AI Usage Profiles

We hypothesize that individuals exhibit distinct AI usage profiles based on their perceived levels of AI inclusion (belonging and authenticity), user satisfaction and interactional justice. Rather than assuming a unidirectional causal relationship, this hypothesis explores users' experiences with AI systems using latent profiles. These user profiles present combinations of emotional perceptions and system evaluative outcomes, reflecting the multifaceted nature of human-AI interactions. To assess this, we draw on person-environment fit theory, which proposes that alignment between an individual and their environment substantially influences key outcomes such as well-being and performance (Chen et al., 2021). The core premise of this theory is that when a person operates in a compatible environment, his/her attitude and behavior tend to be more positive (Pee & Min, 2017). In the AI context, differences in users' emotional perceptions (a sense of belonging and authenticity) and system evaluations (satisfaction and perceived justice) reflect how well the AI system meets users' needs. Identifying user latent profiles that capture these combined experiences enables us to better understand user engagement with AI systems. Therefore, we propose that:

H3: Individuals exhibit distinct AI usage profiles based on their levels of perceived inclusion (i.e., belonging and authenticity), satisfaction, and interactional justice.

4. Method

We conducted two studies using two widely adopted AI tools: Amazon Alexa and ChatGPT. Alexa is a voice-based, task-oriented tool for everyday activities, whereas ChatGPT serves as a text-based generative conversational AI designed for extended dialogue. Together, these AI tools represent two dominant classes of AI: virtual assistants and generative AI. This approach enables the examination of AI inclusion across different classes of AI technologies rather than focusing on a single application. Recent research in human-computer interaction (HCI) shows that interaction modality shapes user experiences and influences their relationships with AI tools (Zheng, 2022). Unlike Alexa, ChatGPT enables richer text-based interaction, while Alexa relies on voice-based engagement. Although AI inclusion is conceptualized in both contexts through belonging and authenticity, its expression may vary by interaction mode. Thus, the findings in this study are interpreted within each AI system context rather than as direct cross-platform comparisons. A total of 219 Alexa users and 577 ChatGPT users were surveyed to assess AI inclusion. The two datasets were analyzed separately and were not pooled. By using these samples, we can assess AI inclusion in two forms of human-AI interaction, making our conclusions more robust and widely applicable, without making formal cross-sample comparisons between the two systems.

Research Design

We applied two distinct approaches to empirically analyze our data: 1) variable-centered and 2) person-centered. For the variable-centered approach, we utilized multiple linear regression to examine associations between belonging and authenticity, and the outcomes as proposed in Hypotheses 1 and 2. Hypothesis 3, in contrast, was assessed using the person-centered approach to identify user profiles within the population based on common user patterns. Drawing on these two approaches, our work aims to assess relationships between variables and the variations among users.

Measurements

The survey items used in this study were adapted from established scales in prior research. We included a screening question to ensure that only individuals with prior AI interaction participated in the study. We assessed interactional justice using three items adapted from Luo (2007) and user satisfaction using four items adapted from Bhattacherjee (2001). AI inclusion was conceptualized as a higher-order construct encompassing belongingness and authenticity measured using four items each adapted from Jansen et al. (2014).

Because the original scales were not designed with human-AI interaction in mind, we reworked the item wording to fit the Alexa and ChatGPT contexts, while keeping the core constructs intact. Further, two senior IS researchers reviewed the adapted items to assess conceptual clarity. All items were measured on a seven-point Likert scale with values ranging from

"Strongly Disagree" (1) to "Strongly Agree" (7). The control variables age, gender, and education were used to rule out alternative explanations for the results.

5.Results

5.1 Measurement Model Assessment

The reliability, convergent validity, and discriminant validity of the measurement model were assessed for both datasets. Table 1 demonstrates that all Cronbach's alpha values exceeded 0.70, which indicates acceptable internal consistency. Composite reliability (CR) values were also above 0.70, and average variance extracted (AVE) values surpassed 0.50, thereby supporting convergent validity. Discriminant validity was assessed using the Fornell-Larcker criterion. As indicated in Tables 2 and 3, the square root of the average variance extracted (AVE) for each construct exceeded its correlations with other constructs, thereby supporting discriminant validity.

Datasets	**Constructs**	**Cronbach's Alpha**	**CR**	**AVE**
Alexa	Belonging	0.913	0.915	0.729
	Authenticity	0.894	0.896	0.684
	Interactional Justice	0.857	0.859	0.670
	User Satisfaction	0.923	0.925	0.756
ChatGPT	Belonging	0.921	0.924	0.755
	Authenticity	0.940	0.940	0.798
	Interactional Justice	0.879	0.881	0.713
	User Satisfaction	0.944	0.945	0.812

Table 1: Reliability and Convergent Validity Results

Constructs	**Belonging**	**Authenticity**	**Interactional Justice**	**User Satisfaction**
Belonging	**0.854**	0.602	0.539	0.487
Authenticity	0.602	**0.827**	0.467	0.429
Interactional Justice	0.539	0.467	**0.819**	0.512
User Satisfaction	0.487	0.429	0.512	**0.869**
Note. Diagonal values show the square root of AVE for each construct. Off-diagonal values show inter-construct correlations.				

Table 2: Fornell-Larcker Discriminant Validity Results for the Alexa Dataset

Constructs	**Belonging**	**Authenticity**	**Interactional Justice**	**User Satisfaction**
Belonging	**0.869**	0.756	0.682	0.526
Authenticity	0.756	**0.893**	0.677	0.538
Interactional Justice	0.682	0.677	**0.844**	0.519
User Satisfaction	0.526	0.538	0.519	**0.901**

Note. Diagonal values show the square root of AVE for each construct. Off-diagonal values show inter-construct correlations.

Table 3: Fornell-Larcker Discriminant Validity Results for the ChatGPT Dataset

5.2 Study 1

We used CloudResearch to recruit participants and administer the surveys to assess user experience with Amazon Alexa. After excluding inaccurate and overly fast responses, we had a final total of 219 valid responses.

Regression Analysis (Hypotheses 1 & 2)

We conducted multiple linear regression to assess hypotheses 1 and 2. As shown in Table 1, the regression analysis reveals that both belonging (B= 0.21) and authenticity (B= 0.15) demonstrate a strong association with user satisfaction. For interactional justice, the analysis shows that belonging (B= 0.38) and authenticity (B= 0.24) play important roles, with strong positive relationships with interactional justice. Therefore, our hypotheses H1 and H2 are supported. Additionally, the analysis for control variables (age, gender, and education level) is also presented in Table 4.

Dependent Variables	**Independent Variables**	**First-Order Linear Equation**		
		R^2	**B**	**SE**
User Satisfaction	Age	0.27	0.00	0.00
	Gender		0.13	0.10
	Education		-0.02	0.03
	Belonging		0.21***	0.04
	Authenticity		0.15**	0.04
Interactional Justice	Age	0.32	-0.00	0.00
	Gender		0.00	0.15
	Education		-0.00	0.05
	Belonging		0.38***	0.05
	Authenticity		0.24**	0.07
Note: $p < 0.001$ ***, $p < 0.01$ **, $p < 0.05$ *				

Table 4. Predicting Outcomes Among Amazon Alexa Users

5.2.1 Person-Centered Data Analysis and Typology (Hypothesis 3)

To test Hypothesis 3, we conducted LPA to explore different user profiles in our data. Before including profile analyses, we conducted multiple linear regression analyses to validate that profiles significantly explained the variance in the dependent variables (Table 5).

The multiple linear regression analysis presented in Table 2 shows an increase in the explanatory power of the user satisfaction model with an R^2 value of 0.33 (compared to 0.27 in Table 4). The adjusted R^2 also improved to 0.25 from 0.31, demonstrating that the model including the profile predictor explains a higher proportion of the variance in user satisfaction. The authenticity predictor remained positively significant with a minor decrease in the coefficient to 0.12. The decrease in the value of authenticity might indicate that the profile value captured some of the variance that was previously attributed to authenticity. However, belonging became non-significant which indicates that the variance captured by belonging is now accounted for by the profile variable. This suggests that the effect of belonging on user satisfaction is depicted now by user profiles. Furthermore, the inclusion of profile as a predictor yielded a significantly positive coefficient (B = 0.16), indicating that moving from one profile to another (i.e., profile 1 to profile 2) is associated with an increase in user satisfaction.

The analysis of interactional justice (Table 2) shows $R^2 = 0.41$, an improvement from 0.32 (Table 4). The adjusted R^2 increased from 0.31 to 0.39, meaning that the model better explains the variance in interactional justice after adding the profile predictor. In addition, the coefficients of belonging and authenticity showed decreases, 0.14 and 0.18, respectively, both remaining significant. This suggests that the variance in interactional justice explained previously by belonging and authenticity is now accounted for by the profile variable. The profile had a positive and significant coefficient (B = 1.18), suggesting that moving between profiles is associated with an increase in interactional justice.

Dependent Variables	**Independent Variables**	**First-Order Linear Equation**		
		R^2	**B**	**SE**
User Satisfaction	Age	0.33	0.00	0.00
	Gender		0.14	0.09
	Education		-0.02	0.03
	Belonging		0.09	0.04
	Authenticity		0.12**	0.04
	Profiles		0.61***	0.13
Interactional Justice	Age	0.41	-0.00	0.00
	Gender		0.02	0.00
	Education		-0.01	0.05

	Belonging		0.14*	0.07
	Authenticity		0.18**	0.06
	Profiles		1.18***	0.19
Note: $p < 0.001$ ***, $p < 0.01$ **, $p < 0.05$ *				

Table 5. Predicting Outcomes and Profiles Among Amazon Alexa Users

5.2.2 Latent Profile Analysis

Latent Profile Analysis (LPA) is a person-centered technique used in this study to identify hidden subgroups of users based on their responses to belonging, authenticity, satisfaction, and interactional justice. Each profile represents a distinct user type, reflecting a unique behavioral pattern from the data.

Table 6 shows the fit statistics for the possible latent profile structure. Lower values of the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and adjusted BIC (ABIC) indicate better model fit. As shown in Table 6, the two-profile model showed the best fit. Therefore, the 2-class solution was considered the best fit to the data.

Models	**Log-Likelihood**	**AIC**	**BIC**	**ABIC**
1 Class	-1492	3012.60	3061.79	3061.79
2 Class	**-1420**	**2898.79**	**3000.68**	**3000.69**
3 Class	-1406	2900.79	3055.38	3055.43
4 Class	-1385	2887.83	3095	3095.22

Table 6. Model Fit Indices for the Amazon Alexa Dataset

Table 7 reports profile sample percentage, means, and standard deviation (SD) for the variables in the two profiles. The graph in Figure 2 depicts the mean values of these variables. Profile 1 includes 112 participants (45.15%). This profile also illustrates relatively lower mean scores of all variables, indicating a weaker collective perception of AI inclusion and interactional justice from participants' perspective. For this reason, we called this profile "reserved users".

Profile 2 includes 136 participants (54.84%). This profile shows higher scores in all variables, indicating strong perceptions of belonging, authenticity, user satisfaction, and interactional justice. Therefore, this profile was named "engaged users", indicating that they display a more positive and engaged perception of the system than reserved users

The Alexa study identified two user profiles that show clear differences in how users experience AI inclusion. This suggests that for voice-based AI tools, functional usefulness may compensate for the lack of psychological inclusion.

Profiles	% of Sample	Belonging Mean (SD)	Authenticity Mean (SD)	User Satisfaction Mean (SD)	Interactional Justice Mean (SD)
1	45.16%	3.11 (0.13)	4.25 (0.14)	5.38 (0.09)	3.59 (0.13)
2	54.84%	5.19 (0.08)	5.53 (0.06)	6.34 (0.05)	5.32 (0.08)

Table 7. The Means Values and Standard Deviation (SD) of Variables by Profile

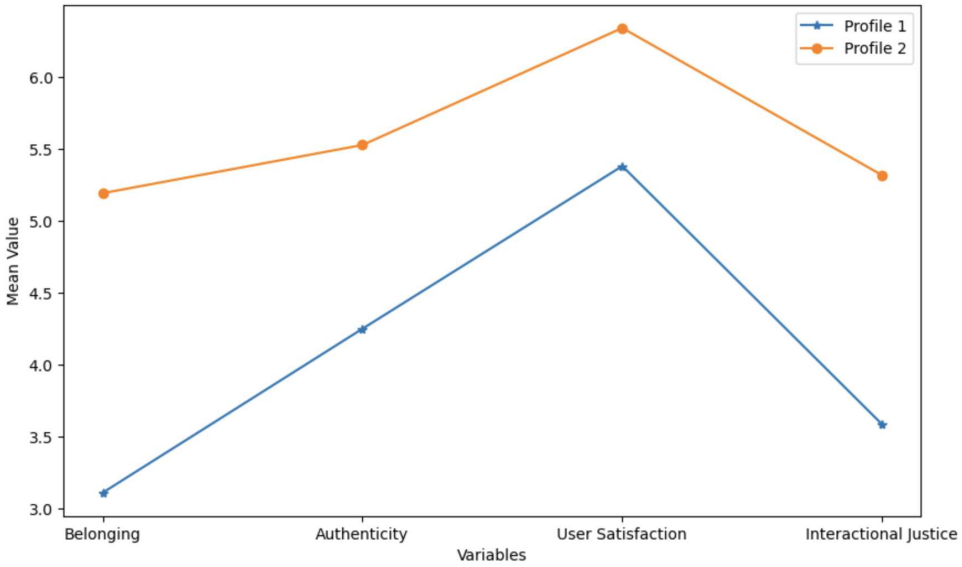


Figure 2. Mean Values of Variables Across Identified Profiles

5.2.3 Validation of Latent Profile Associations with Outcomes

We performed ANOVA to assess differences in the dependent variables between the two profiles. Table 8 shows significant differences between the engaged and reserved user groups (two profiles) for user satisfaction and interactional justice. For user satisfaction, the analysis yielded an F-value of 32.86 ($p = 0.00$), with the engaged users group reporting a mean value of 6.34 ($SD = 0.05$) compared to a mean of 5.38 ($SD = 0.08$) for the reserved users group. Similarly, interactional justice also showed a significant difference, with an F-value of 55.64 ($p = 0.00$). than reserved users ($M= 3.59$, $SD = 0.13$).

Outcomes	F	df	p	M(SD) Engaged Users	M(SD) Reserved Users
User Satisfaction	32.86	1,246	0.00	6.34(0.05)	5.38(0.09)
Interactional justice	55.64	1,246	0.00	5.32(0.08)	3.59(0.13)

Table 8. ANOVA Results for User Satisfaction and Interactional Justice Across Profiles

We also conducted the post-hoc test to see which profiles differ from each other (Table 9). For user satisfaction, results showed a significant difference between profiles 1 and 2, with a mean difference of -0.702, indicating higher satisfaction in profile 2 [CI: -0.9432 to -0.4608]. Similarly, interactional justice was significantly higher in profile 2, with a mean difference of -1.377 [CI: -1.7406 to -1.0134].

Outcomes	Group Comparison	Mean Difference	p-adj	Lower CI	Upper CI	Reject
User Satisfaction	Profile 1 vs 2	-0.702	0.00	-0.9432	-0.4608	True
Interactional Justice	Profile 1 vs 2	-1.377	0.00	-1.7406	-1.0134	True

Table 9. Pairwise Comparison of Outcomes Across Profiles

5.3 Study 2

We conducted another study to further assess our hypothesis. CloudResearch to recruit participants and administer the surveys to assess user experience with ChatGPT. After excluding inaccurate and overly fast responses, we had a final total of 585 valid responses.

5.3.1 Regression Analysis

We conducted multiple linear regression analyses to evaluate our hypothesis. As shown in Table 10, both belonging (B= 0.17) and authenticity (B= 0.22) were positively associated with user satisfaction, with the model explaining 33% of the variance ($R^2 = 0.33$). Both belonging and authenticity were also positively related to interactional justice (B=0.35 for both), with the model explaining 53% of the variance ($R^2 = 0.53$). Therefore, H1 and H2 are supported.

Dependent Variables	Independent Variables	First-Order Linear Equation		
		R^2	B	SE
	Age	0.33	-0.00	0.00
	Gender		-0.17**	0.06

User Satisfaction	Education		0.00	0.02
	Belonging		0.17***	0.03
	Authenticity		0.22***	0.03
Interactional Justice	Age	0.53	-0.00	0.00
	Gender		-0.17**	0.07
	Education		-0.04	0.03
	Belonging		0.35***	0.04
	Authenticity		0.35***	0.04
Note: $p < 0.001$ ***, $p < 0.01$ **, $p < 0.05$ *				

Table 10. Predicting User Satisfaction & Interactional Justice Among ChatGPT Users

5.3.2 Person-Centered Data Analysis and Typology

To test Hypothesis 3, we conducted LPA to explore different user profiles in the sample of ChatGPT users. Before including profile analyses in our study, we conducted multiple linear regression analyses to validate that profiles significantly contributed to explaining the variance in the dependent variables (Table 11). The adjusted R^2 increased marginally from 0.32 to 0.33 (Table 10). While this improvement is marginal, such incremental changes are typical in theory-driven models that prioritize testing conceptual contributions over maximizing predictive performance. Notably, belonging and authenticity remained significant predictors, and the profile variable was also significant, suggesting that profiles explain additional variance beyond the inclusion dimensions.

The analysis of interactional justice in Table 8 also shows an increase in explanatory power, with an R^2 value of 0.62, up from 0.53 in Table 10. The adjusted R^2 increased from 0.52 to 0.61, suggesting that the model better explains the variance in interactional justice after adding the profile predictor. The profile predictor had a negative coefficient (B = -0.29), indicating that moving between profiles is associated with a notable decrease in interactional justice on average.

Dependent Variables	**Independent Variables**	**First-Order Linear Equation**		
		R^2	**B**	**SE**
User Satisfaction	Age	0.34	-0.00	0.00
	Gender		-0.16**	0.06
	Education		0.01	0.02

	Belonging		0.18***	0.03
	Authenticity		0.23***	0.03
	Profiles		-0.07**	0.02
Interactional Justice	Age	0.62	-0.00	0.00
	Gender		-0.14*	0.06
	Education		-0.01	0.02
	Belonging		0.39***	0.03
	Authenticity		0.36***	0.03
	Profiles		-0.29***	0.02
Note: $p < 0.001$ ***, $p < 0.01$ **, $p < 0.05$ *				

Table 11. Profiles and User Outcomes Among ChatGPT Users

5.3.3 Latent Profile Analysis

Table 12 shows the fit statistics for the possible latent profile structure. The lower values of AIC, BIC and Adjusted BIC (ABIC) indicate a better fit. As shown in Table 12, the fit indices reached their lowest values at the six-profile solution. Based on these values, the 6-profile solution was deemed the best fit for the data.

Models	**Log-Likelihood**	**AIC**	**BIC**	**ABIC**
1 Class	-3439	6907.83	6968.84	6968.84
2 Class	-3249	6556.42	6682.79	6682.80
3 Class	-3198	6484.14	6675.89	6675.91
4 Class	-3176	6470.68	6727.79	6727.84
5 Class	-2918	5984.95	6307.43	6307.50
6 Class	**-2474**	**5127.08**	**5514.92**	**5515.03**
7 Class	-2461	5130.52	5583.73	5583.88

Table 12. Model Fit Indices for the ChatGPT Dataset

Table 13 displays the percentage of the sample along with the mean and standard deviation (SD) for the key variables across identified profiles. Figure 3 provides a graph visualizing the mean values of these variables. Table 13 presents metrics that offer insights into the perceived AI inclusion (i.e., belonging and authenticity) and interactional justice and levels of satisfaction among participants in each profile.

Profiles	% of Sample	Belonging Mean (SD)	Authenticity Mean (SD)	User Satisfaction Mean (SD)	Interactional Justice Mean (SD)
1	9.35	2.06(0.10)	2.15(0.07)	4.89(0.17)	4.07(0.15)
2	16.63	5.21(0.12)	5.80(0.09)	7.00(0.00)	5.53(0.10)
3	30.32	3.45(0.07)	4.64(0.07)	5.10(0.05)	4.28(0.05)
4	4.33	1.20(0.08)	1.22(0.07)	4.44(0.29)	1.20(0.08)
5	32.75	4.95(0.05)	5.29(0.05)	6.01(0.02)	5.09(0.06)
6	6.58	2.30(0.20)	3.34(0.26)	5.03(0.15)	1.53(0.09)

Table 13. The Means Values and SD of Variables by Profile

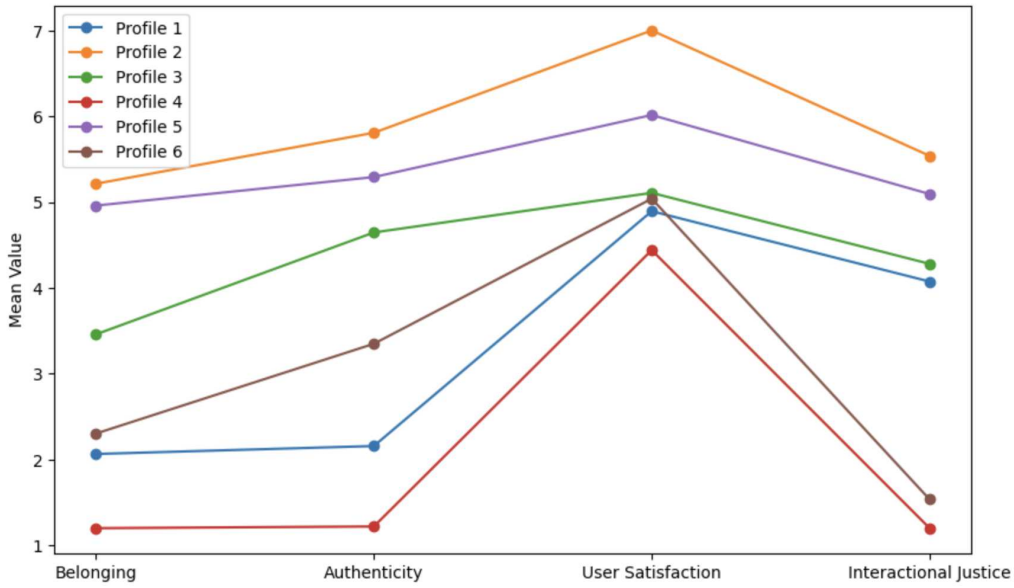


Figure 3. Mean Values of Variables Across Identified Profiles

Although the LPA conducted on the ChatGPT dataset extracted six profiles, the post-hoc comparisons (Table 15) indicate that only three profiles are meaningfully distinct from one another. Each profile represents a unique user experience with ChatGPT. In contrast to variable-based techniques like regression analysis, which examine relationships between variables averaged across the entire sample, LPA is a person-centered approach that identifies hidden subgroups based on shared patterns across multiple dimensions.

In Study 1, which focused on Alexa, only two profiles were found. This aligns with results in human-computer interaction, showing that the interaction modality shapes user experiences with AI tools (Zheng, 2022). Since ChatGPT allows users to interact using text, images, and voice, it is more likely to uncover several user patterns. These profiles are not ranked, and they do not suggest

that any group is better or worse than another. Each profile shows a group of users who use or experience the AI system in similar ways.

Although profile 1, 3, 4, and 6 are depicted as distinct, the post-hoc analysis (Table 14 and Table 15) shows that user satisfaction and interactional justice are not significantly different among these profiles. Users in these groups seem insensitive to AI inclusion and the fairness of the system's treatment. Instead, users in these profiles seem to be practical and more focused on the tangible benefits provided by the system to achieve their tasks. This indicates that the user satisfaction likely stems from the system's utility and its capabilities to meet users' functional needs. Therefore, we have named this pattern "utility-oriented users."

Profile 2 constitutes 16.63% of the ChatGPT sample. This profile shows higher values across all variables. Given that this group demonstrates a strong sense of belonging and authenticity, reports high satisfaction with their ChatGPT experience, and perceives fair treatment by the ChatGPT system, we have named this profile "engaged users."

Profile 5 constitutes 32.75% of the sample, equivalent to 189 participants. This profile shows generally moderately high scorers for belonging (4.95), authenticity (5.29), user satisfaction (6.01) and interactional justice (5.09). Users in this profile recognize the value of the AI system and are also aware of its limitations in fostering inclusion. Accordingly, we label this profile as "balanced user". These user profiles indicate that ChatGPT users experience AI inclusion in different ways. These results show that AI tools should be designed to enhance not only task performance but also users' sense of belonging and authenticity.

5.3.4 Validation of Latent Profile Associations with Outcomes

We conducted ANOVA analysis to determine whether the differences in user satisfaction and interactional justice across profiles are statistically significant. Table 14 indicates significant differences in both user satisfaction and interactional justice across profiles. For user satisfaction, the analysis yielded an F-value of 48.31 and for interactional justice the F-value is 105,75.

Outcomes	**F**	**df**	**p**
User Satisfaction	48.31	5,571	< 0.001
Interactional Justice	105.75	5,571	< 0.001

Table 14. ANOVA Results for Outcomes Across Profiles in ChatGPT Dataset

We conducted a post-hoc test to explore how user satisfaction varies across six different profiles (Table 15). As shown in the table, user satisfaction is significantly different across most of the profiles, suggesting distinct experiences of user satisfaction. However, some profile pairs (profile 1-3, profile 1-4, profile 1-6, profile 3-6) are not significantly different, indicating a similar level of user satisfaction experiences within these profiles.

Outcomes	Group Comparison	Mean Difference	p-adj	Lower CI	Upper CI	Reject
User Satisfaction	Profile 1 vs 2	2.1065	0.00	1.7447	2.4683	True
User Satisfaction	Profile 1 vs 3	0.2136	0.4376	-0.1174	0.5447	False
User Satisfaction	Profile 1 vs 4	-0.4535	0.1198	-0.968	0.061	False
User Satisfaction	Profile 1 vs 5	1.121	0.00	0.7929	1.4492	True
User Satisfaction	Profile 1 vs 6	0.146	0.9396	-0.3044	0.5963	False
User Satisfaction	Profile 2 vs 3	-1.8929	0.00	-2.163	-1.6227	True
User Satisfaction	Profile 2 vs 4	-2.56	0.00	-3.0375	-2.0825	True
User Satisfaction	Profile 2 vs 5	-0.9854	0.00	-1.252	-0.7189	True
User Satisfaction	Profile 2 vs 6	-1.9605	0.00	-2.3681	-1.5529	True
User Satisfaction	Profile 3 vs 4	-0.6671	0.0005	-1.1219	-0.2124	True
User Satisfaction	Profile 3 vs 5	0.9074	0.00	0.6843	1.1305	True
User Satisfaction	Profile 3 vs 6	-0.0677	0.9959	-0.4483	0.313	False
User Satisfaction	Profile 4 vs 5	1.5746	0.00	1.1219	2.0272	True
User Satisfaction	Profile 4 vs 6	0.5995	0.0225	0.0518	1.1472	True
User Satisfaction	Profile 5 vs 6	-0.9751	0.00	-1.3532	-0.597	True

Table 15. Pairwise Comparison of User Satisfaction Across Profiles in ChatGPT Dataset

The post-hoc test results show significant differences in interactional justice across profile comparisons (Table 16). Interactional justice varies across most of the profiles, indicating distinct experiences of interactional justice. For example, Profiles 2 and 4, as well as Profiles 2 and 6, demonstrate notably large differences in interactional justice, with mean differences of -4.33 ($p = 0.00$) and -4.00 ($p = 0.00$), respectively. These results indicate higher interactional justice in Profiles 4 [CI: -4.88 to -3.79] and 6 [CI: -4.46 to -3.53]. In contrast, there are two profile pairs (profile1-3, profile 4-6) that are not significant, indicating a similar level of interactional justice.

Outcomes	Group Comparison	Mean Difference	p-adj	Lower CI	Upper CI	Reject
Interactional Justice	Profile 1 vs 2	1.4641	0.00	1.0523	1.876	True
Interactional Justice	Profile 1 vs 3	0.2059	0.6239	-0.171	0.5828	False
Interactional Justice	Profile 1 vs 4	-2.8741	0.00	-3.4598	-2.2883	True
Interactional Justice	Profile 1 vs 5	1.0194	0.00	0.6458	1.393	True
Interactional Justice	Profile 1 vs 6	-2.539	0.00	-3.0517	-2.0263	True
Interactional Justice	Profile 2 vs 3	-1.2582	0.00	-1.5657	-0.9507	True
Interactional Justice	Profile 2 vs 4	-4.3382	0.00	-4.8819	-3.7945	True
Interactional Justice	Profile 2 vs 5	-0.4447	0.0005	-0.7482	-0.1413	True
Interactional Justice	Profile 2 vs 6	-4.0031	0.00	-4.4672	-3.539	True
Interactional Justice	Profile 3 vs 4	-3.08	0.00	-3.5977	-2.5623	True
Interactional Justice	Profile 3 vs 5	0.8135	0.00	0.5595	1.0675	True

Interactional Justice	Profile 3 vs 6	-2.7449	0.00	-3.1782	-2.3116	True
Interactional Justice	Profile 4 vs 5	3.8935	0.00	3.3782	4.4088	True
Interactional Justice	Profile 4 vs 6	0.3351	0.6406	-0.2884	0.9586	False
Interactional Justice	Profile 5 vs 6	-3.5584	0.00	-3.9889	-3.1279	True

Table 16. Pairwise Comparison of Interactional Justice Across Profiles in ChatGPT Dataset

6. Discussions

Belonging is found to be positively associated with user satisfaction and interactional justice. Users who feel a connection with the AI system, such as when ChatGPT offers personalized responses or Amazon Alexa remembers important dates, are likely to report higher levels of satisfaction and perceive the system as more just in its interactions with them. This finding is aligned with past studies that show that generative AI systems elicit higher user satisfaction when interactions are perceived as personally attuned and supportive (Kim et al., 2025). This suggests that AI systems should be developed to signal attentiveness in interaction, as such relational cues meaningfully impact users' satisfaction and justice perceptions.

Additionally, the study highlights a significant relationship between authenticity and both user satisfaction and interactional justice. Thus, individuals who feel that the AI system allows them to be authentic, such as when the AI system understands their speech patterns, allows them to express their real thoughts and personal feelings, are likely to report higher values of satisfaction and perceive the system as more just in its interactions with them. This finding aligns with prior research suggesting that when AI systems adaptively respond to user input, perceptions of fairness and satisfaction are enhanced (Haqqu et al., 2025). From a practical point, this suggests that AI systems that allow users to correct and shape interactions are more likely to foster positive user experiences, particularly perceptions of fairness and satisfaction.

Our person-centered analysis revealed distinct AI usage profiles that integrate perceptions of AI inclusion, satisfaction and justice. While some profiles show high AI inclusion and positive outcomes, others reveal more reserved or utility-driven engagement. Studies have shown that user engagement with AI systems is heterogeneous, varying across user segments based on expectations and affective responses. They demonstrate that different types of AI systems evoke different evaluative criteria, such as perceived empathy, perceived uniqueness and neglect, producing distinct acceptance pathways across users (Jiang et al., 2024b). This diversity suggests that user responses to AI systems are shaped by individual interpretations of AI's role in interactions as well as by the emotional or cognitive benefits that users prioritize. As the measurement invariance was not tested, these profiles are interpreted within each dataset rather than as formal cross-sample comparisons between the two Alexa and ChatGPT datasets. Our study shows that only two user profiles emerged for Amazon Alexa, while three distinct profiles were identified for ChatGPT. These patterns may reflect differences in how AI users experience inclusion in each AI system. Amazon Alexa is mainly a voice-based tool, offering two types of functions which are information search and task function (Malodia et al., 2024). Interactions with Alexa are usually command-

driven and task-specific which leads to expected limited user experience, hence, the small number of user profiles. While Kim et al. (2025) do not focus on voice assistants, their research highlights that users remain engaged when AI systems offer coherent, enjoyable, and socially vibrant conversations. Generative AI chatbots tend to embody these qualities far more than command-based voice interfaces. Hence, AI voice systems struggle to create immersive experiences and build emotional connections. In contrast, ChatGPT, is a text-based generative AI system, developed to be highly self-adjusting and can process different arrays of users prompts, from sophisticated inputs and artistic texts to fixing challenges and multi-issue written conversation. These wide capacities of ChatGPT lead to varying user perceptions, experience and cognitive response resulting in more diversified user profiles. Consistent with previous research, generative AI systems result in diverse user mental models and interaction strategies. Users vary in their interpretations of system response and perceptions of conversational affordances (Jiang et al., 2024b). This suggests that organizations should not expect uniform inclusion experiences across AI systems and should tailor their deployment strategies based on systems' capabilities.

7. Conclusion

This study suggests that AI inclusion is shaped not only by AI system functionality and access but also by users' emotional experiences during interactions. The findings suggest a positive relationship between inclusion dimensions and satisfaction and interactional justice, indicating that the users feel more satisfied and perceive AI systems to be fair when they experience a sense of belonging and authenticity. Further, the results of the person-centered analysis suggest that AI inclusion is not uniformly experienced by users. The emergence of two profiles for Amazon Alexa and three for ChatGPT suggests that user's inclusion experiences may vary within different AI interaction contexts. These findings may reflect differences in the interactional capabilities of the AI systems (i.e., Alexa and ChatGPT, but they should not be understood as formal cross-system comparisons). The study makes a significant contribution to IS literature by positioning belonging and authenticity as important experiential dimensions to enhance user satisfaction and interactional justice in Human-AI interaction.

8. Theoretical Contributions

The study provides two main theoretical contributions to the IS literature. First, it contributes to research on inclusion in digital and AI contexts by conceptualizing AI inclusion as a micro-level experiential construct. Prior work on digital inclusion and emerging work on AI inclusion have largely focused on access, participation, infrastructure, and design. While these perspectives are vital, they do not comprehensively explain whether users feel included during interaction with AI systems. We argue that AI systems are different from other digital technologies and possess social capabilities that create interactive, and socially rich interactions. Hence, unlike other digital

technologies, mere equitable access and affordability does not truly reflect AI inclusion, rather AI inclusion should capture the users' psychological experience of inclusion during human-AI interactions. We defined AI inclusion as the extent to which interactions with the AI system foster a sense of belonging and authenticity emphasizing that user perceptions of AI are shaped by emotional factors not just by the system's functionality. The conceptualization of AI inclusion in this study adds to the IS inclusion research by shifting the focus from structural access and use to users' psychological and emotional experiences during human-AI interaction. It highlights emotional experience as a central component of AI inclusion, and not merely a peripheral outcome. Second, this study contributes to human-AI interaction research by showing that AI inclusion is associated with user satisfaction and interactional justice. By linking AI inclusion to interactional justice, this research shows that users' perceptions of respect and fairness in AI interactions depend on their sense of belonging and authenticity. The study expands AI evaluation beyond functional performance to include users' emotional experiences during interactions with AI systems.

9. Practical Contributions

9.1 Implications for AI Design and Development

Drawing on our empirical findings, we outline practical implications for AI design and development. By focusing on the emotional aspect of human-AI interaction, this study suggests how users' affective experiences shape their evaluations of AI systems. Hence, AI designers should consider emotional and relational aspects of human-AI interaction alongside functional and structural design. To foster belonging, AI developers could consider features that enable empathetic, non-judgmental responses and personalized interactions. To foster authenticity, AI systems could allow users to express their identity freely, customize their experience, and feel validated during interaction.

9.2 Implications for Organizations and Policymakers

Our findings offer practical considerations for organizations implementing AI in the workplace, highlighting the need to design inclusive systems by training AI models using diverse datasets that allow employees to feel authentic and develop a sense of belonging. The results also highlight considerations for policymakers and strategists responsible for AI governance and evaluation. We suggest that policymakers may consider including metrics related to users' emotional well-being, perceived fairness, and satisfaction when evaluating AI systems, rather than focusing merely on technical performance indicators.

9.3 Societal Implications

As AI becomes increasingly embedded in different domains, its societal influence continues to expand. However, policymakers and governments have largely focused on addressing digital inequalities arising from disparities in technology access, affordability, users' cognitive capabilities (Faik et al., 2024), and challenges in adopting and utilizing AI technologies. While these issues are important, our study suggests that AI inclusion is also experiential and personal. Users may have access to AI systems yet still feel excluded if interactions do not foster belonging, respect, dignity, and authentic self-expression. Therefore, AI systems could be designed to be culturally sensitive, empathetic, non-judgmental, and responsive to diverse user needs. Promoting AI inclusion may support psychological safety, perceived justice, satisfaction, and meaningful engagement with AI systems

9.4 Implications for Teaching and Education

This study has practical relevance for teaching and education as AI-enabled platforms and learning tools are becoming increasingly integrated into educational environments. Given that educational institutions have diverse student populations, fostering students' felt sense of belonging and authenticity during interaction with AI tools may support effective teaching and learning outcomes. Hence, developers and educators could focus on designing AI systems that encourage students to express their ideas and feelings freely without fear of being judged, thereby fostering a sense of inclusion among students.

10. Limitations and Future Research

While the findings of our study provide several contributions to the inclusion research, it has some limitations. First, the study did not consider economic barriers to AI inclusion such as digital infrastructure disproportions, cost of AI access and AI literacy. Future research could examine how these factors interact with users' felt experiences of belonging and authenticity during AI interaction. Future research should expand upon this work in several ways. Second, this study focuses on direct relationships to capture the immediate experiential outcomes of AI inclusion. Future studies could investigate more complex relationships including potential mediators and moderators. Third, future research should adopt a comprehensive approach to AI inclusion that integrates both systemic and emotional perspectives, supporting the development of more inclusive AI systems. Fourth, because measurement invariance was not tested, the Alexa and ChatGPT findings should not be interpreted as formal cross-sample comparisons or pooled results. Future studies should assess measurement invariance before comparing mean levels, path coefficients within AI systems and could use SEM to test measurement and structural models simultaneously.

1. Appendix

AI Inclusion: Amazon Alexa

Belonging

1. Alexa gives me the feeling that I belong (e.g., Alexa remembers my special days, items in my schedule).
2. Alexa gives me the feeling that I am part of it (e.g., Alexa allows me to help her learn how to respond correctly to my requests).
3. Alexa gives me the feeling that I fit in. (eg. Alexa does not discard my suggestions rather built on it)
4. Alexa cares about me (e.g., Alexa warns me when there is a severe thunderstorm, the door is unlocked, or the window is left open).

Authenticity

1. Alexa allows me to be authentic (e.g., Alexa understands the speed of my speech and my sound shapes).
2. Alexa allows me to be who I am (e.g., Alexa enables me to express my real feelings and identity).
3. Alexa allows me to express my authentic self (e.g., Alexa enables me to express my innermost feelings and preferences).
4. Alexa allows me to present myself the way I am (e.g., Alexa enables me to speak the way I do day-to-day).

AI Inclusion: ChatGPT

Belonging

1. ChatGPT gives me the feeling that I belong (e.g., ChatGPT remembers my interests and past conversations).
2. ChatGPT gives me the feeling that I am part of it (e.g., it allows me to help improve its responses based on my feedback).
3. ChatGPT gives me the feeling that I fit in (eg., ChatGPT does not discard my suggestions rather built on it)
4. ChatGPT cares about me (e.g., it provides empathetic responses and offers encouragement when I'm facing challenges).

Authenticity

1. ChatGPT allows me to be authentic (e.g., it supports my use of personalized expressions and helps me articulate my ideas clearly).
2. ChatGPT allows me to be who I am (e.g., it enables me to express my real thoughts and opinions freely).
3. ChatGPT allows me to express my authentic self (e.g., it helps me convey my innermost feelings and personal insights).
4. ChatGPT allows me to present myself the way I am (e.g., it allows me to communicate as I normally

would in daily conversations).

Interactional Justice

2. Whenever a conflict arises between Alexa/ChatGPT and myself, we always seek a complete understanding of each other's position and opinion in the first place.
3. Alexa/ChatGPT and I always communicate openly and directly.
4. In the process of making decisions relating to household and work tasks, Alexa/ChatGPT always respects my input.

User Satisfaction

How do you feel about your overall experience with Alexa?

1. Very Dissatisfied (1)	Very Satisfied (7)
2. Very Displeased (1)	Very Pleased (7)
3. Very Frustrated (1)	Very Contented (7)
4. Absolutely Terrible (1)	Absolutely Delighted (7)

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