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HEAR what AI says: simulated empathy and supportive ChatGPT interaction for emotional well-being

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ABSTRACT

This study explores how simulated empathy can function as an emotionally supportive interaction feature in users' ongoing engagement with ChatGPT for emotional support. As AI-powered chatbots increasingly appear in emotionally sensitive situations, understanding how users relate to them as emotionally supportive conversational partners becomes important. Drawing on the Stimulus-Organism-Response framework, the Technology Acceptance Model, and the Theory of Planned Behaviour, this study develops and empirically examines an integrative HEAR framework. The framework examines how users' perceptions of empathic communication, human-likeness, and ease of use influence both cognitive evaluations and affective responses, including emotional comfort and usage disposition. Data from 892 users who had used ChatGPT to express emotions were analysed using structural equation modelling. The results show that perceived empathic communication plays a central role in shaping emotional comfort and trust, while human-likeness strongly predicts how emotionally safe users feel during interaction. These emotional factors, in turn, significantly affect users' intention to continue using ChatGPT. Notably, users may experience ChatGPT as an emotionally supportive listener, not because it experiences emotions, but because it responds in ways that make people feel understood. By positioning empathy as more than a design feature, this study highlights ChatGPT's emerging role in digital wellbeing contexts.

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ChatGPT; simulated empathy; emotional support; conversational AI; human-AI interaction; continuance intention

1. Introduction

In recent years, artificial intelligence (AI) has evolved from a purely functional tool into a more human-centred presence in everyday life. Across service industries, AI systems are increasingly used not only to enhance operational efficiency but also to support more personalised and socially embedded experiences (Cui et al. 2025; Davenport et al. 2020). Applications now extend from healthcare, where AI assists diagnosis and treatment delivery (Ahmad et al. 2021; Dangi, Sharma, and Vageriya 2025; Saeidnia et al. 2025), to tourism and hospitality, where conversational agents reduce loneliness and improve customer engagement (Seyfi et al. 2025; Soliman et al. 2024; Stienmetz, Massimo, and Ferrer-Rosell 2022). During the COVID-19 pandemic, AI devices were employed to disinfect hospital areas (Hong et al. 2021) and to facilitate online learning in higher education (Hannan and Liu 2023). These developments reflect a broader shift: AI is no longer confined to task automation but is increasingly involved in domains that require psychological and relational sensitivity.

Among the most prominent recent innovations is ChatGPT, a large language model developed by OpenAI. With advances in coherence and contextual responsiveness, systems such as GPT-4 have become capable of sustaining nuanced dialogue that many users experience as socially and emotionally meaningful (Heidari et al. 2024). While initially designed for information assistance, ChatGPT is now frequently used in emotionally charged situations, where individuals seek reassurance, reflection, or a sense of being understood (Huang and Rust 2018; Vowels, Francois-Walcott, and Darwiche 2024; Zhang et al. 2024). This behavioural shift suggests that conversational AI is beginning to occupy a role that extends beyond productivity support, entering the emerging landscape of digital mental health and wellbeing.

A key mechanism underlying this phenomenon is simulated or artificial empathy. Although AI systems do not possess genuine emotions, they can generate

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empathic-like responses through linguistic cues, supportive tone, and attentive conversational structure (Carlbring et al. 2023; Rubin et al. 2024). Users may therefore experience emotional comfort even while recognising that the empathy is algorithmically produced. In some cases, the non-human nature of the interaction may even reduce fear of judgement or social stigma, facilitating disclosure during vulnerable moments (Vowels, Francois-Walcott, and Darwiche 2024). Empathic conversational AI thus raises an important question: *how do users psychologically evaluate and continue relying on such systems when emotional support, rather than task performance, becomes central?*

Despite growing interest, current research offers only a limited understanding of continued ChatGPT use in emotionally complex contexts. Existing empirical comparisons between AI- and human-generated responses have largely focused on physical health communication (Ayers et al. 2023; Van Bulck and Moons 2024). While these studies suggest that chatbot responses can be perceived as empathic and trustworthy, far less is known about how users interpret AI empathy in relationally sensitive domains such as personal distress, romantic difficulties, or therapeutic-style conversations. In other words, the emotional mechanisms that translate perceived empathic interaction into sustained reliance remain underspecified. This gap is theoretically important because dominant technology adoption frameworks have traditionally emphasised cognitive and utilitarian determinants of use. Models such as the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB) explain intention through beliefs about usefulness, ease of use, attitudes, and perceived control. However, these perspectives may be insufficient when engagement is driven by affective reassurance and relational safety rather than instrumental efficiency (Ho, Wijaya, and Ou 2025). The Stimulus-Organism-Response (SOR) framework provides a promising architecture for addressing this limitation, as it allows external interaction cues to shape both cognitive appraisals and emotional states that ultimately influence behavioural outcomes.

Understanding these mechanisms is not only academically significant but also increasingly urgent in practice. As emotionally vulnerable users–including adolescents, socially isolated individuals, and those with limited access to mental health resources–turn to conversational AI for low-threshold support, questions of psychological reliance, trust calibration, and ethical design become central. Without clearer theorising of how empathic cues foster retention, AI systems risk either failing to provide meaningful reassurance or encouraging forms of emotional over-dependence.

To address this need, the present study develops and tests the HEAR model (Humanised Empathy and Acceptance for Retention), an integrative framework that explains continuance intention with ChatGPT in emotionally sensitive contexts. HEAR embeds simulated empathy within the SOR architecture while specifying key cognitive–motivational mechanisms through TAM and TPB. Specifically, we examine how perceived empathic communication, perceived human-likeness, and perceived ease of use operate as interactional stimuli shaping cognitive organism appraisals (perceived service value and perceived behavioural control) and affective organism states (emotional comfort and usage disposition). These internal processes are then linked to continuance usage intention, capturing sustained engagement with ChatGPT as an emotionally grounded form of retention.

By advancing a mechanism-based account of empathic AI reliance, this study contributes to research on human-AI interaction and digital mental wellbeing in three ways. First, it extends technology acceptance theorising into emotionally sensitive domains where reassurance and relational safety are central. Second, it proposes and validates an integrative HEAR framework that clarifies how simulated empathy becomes psychologically meaningful for sustained use in emotionally sensitive AI interactions. Third, it offers practical insights for the ethical design of conversational agents that increasingly function as informal support resources in everyday coping practices.

1.1. Theoretical background

1.1.1. Empathic AI and ChatGPT in emotional contexts

The intersection between artificial intelligence and emotional well-being has received growing attention in recent years. Researchers and developers are no longer approaching AI solely as a functional aid but increasingly as a potential partner in supporting psychological health. AI-driven systems are now being embedded in platforms that provide mental health screening, cognitive behavioural therapy, or mindfulness prompts – roles that were once considered the exclusive domain of human practitioners (Lone et al. 2025; Y. Wang and Li 2024). This shift has been accelerated by both advances in natural language processing and the rising demand for accessible, low-barrier mental health support.

A key development within this landscape is the emergence of conversational agents designed to simulate emotional sensitivity. Rather than focusing solely on accuracy, these systems increasingly adopt dialogue strategies associated with compassion, attentiveness, and reassurance, reflecting the broader rise of empathic AI (Sorin et al. 2024; Zhao et al. 2023). As emotional intelligence becomes a design goal, users begin to expect warmth and relational responsiveness alongside technical competence.

ChatGPT represents one of the most visible examples of this transformation. Although initially introduced as a general-purpose assistant, ongoing advancements in coherence, tone control, and contextual responsiveness have positioned the system as a more emotionally attuned conversational partner (Asai et al. 2022; Bansal et al. 2024; Concannon and Tomalin 2024). Recent studies suggest that many users now engage with ChatGPT in ways that resemble emotional disclosure, using it to reflect, vent, or seek comfort during moments of distress (Cross et al. 2024; Devaram 2020; Vowels, Francois-Walcott, and Darwiche 2024).

These emerging patterns indicate a fundamental shift in how AI is experienced: for some individuals, ChatGPT is no longer merely a productivity aid, but a quasi-relational space where emotional needs are expressed and sometimes perceived to be met. This raises an important theoretical question for human-AI interaction research: through what psychological mechanisms do empathic AI cues translate into sustained engagement, particularly in emotionally vulnerable contexts? Addressing this question motivates the need for an integrated framework such as HEAR.

1.1.2. Simulated empathy in human-AI interaction

Empathy, traditionally viewed as the ability to recognise, understand, and respond appropriately to the emotions of others, has long been considered a fundamentally human capacity. However, recent developments in affective computing have challenged this assumption by introducing the notion of simulated empathy – a concept that refers to the mimicking of empathic behaviour by artificial agents through carefully designed linguistic and paralinguistic cues (Fan, Han, and Wang 2024; Rubin et al. 2024). Although such systems do not experience emotions, they are capable of generating responses that resemble empathic concern, often drawing on large-scale language data and human feedback during training (Rasool et al. 2025; Y. Chen et al. 2023).

In human-AI interaction, the impact of simulated empathy depends less on the system's internal capacity and more on user perception. As Rubin et al. (2024) note, psychological benefit arises not because the AI 'feels', but because the user feels understood. In emotionally vulnerable states, this perceived understanding can become especially powerful, even when users remain aware that the empathy is artificial (Weisberg, Daniels, and Bar-Kalifa 2023; Woodcock et al. 2017). Supporting this view, Vowels (2024) found that GPT-4 responses were often rated as more empathic and helpful than those of human experts in emotionally sensitive domains, underscoring the potency of perceived empathy.

This phenomenon is consistent with the Computers Are Social Actors (CASA) paradigm, which suggests that individuals instinctively apply interpersonal heuristics to machines when they exhibit human-like cues (Reeves and Nass 1996). Warmth, mirroring, and attentive language can therefore trigger relational interpretations, shaping trust and emotional disclosure (Fiske, Cuddy, and Glick 2007). Importantly, receptivity to simulated empathy may vary across users and situations, with individuals facing loneliness or distress being more likely to rely on empathic AI as an immediate source of reassurance (Pelau, Dabija, and Ene 2021; Vowels, Francois-Walcott, and Darwiche 2024).

In this study, simulated empathy is conceptualised as a foundational interactional condition that enables perceived empathic communication and emotional reassurance, while also informing cognitive appraisals of value and control (Kerasidou 2020; Seitz 2024). At the same time, prior work highlights potential risks: when users recognise the agent as non-human, perceived authenticity may decline, limiting emotional impact (Luo et al. 2019). Thus, simulated empathy functions not merely as a design feature, but as a psychological stimulus through which conversational AI shapes both affective comfort and continued reliance – making it central to the theoretical logic of the HEAR framework.

1.1.3. Stimulus-Organism-Response (SOR) as the organising architecture

The Stimulus-Organism-Response (SOR) framework, originally proposed by Russell and Mehrabian (1974), offers a foundational lens for explaining how external cues shape individuals' internal psychological states, which subsequently influence behavioural outcomes. Although rooted in environmental psychology, SOR has been widely applied in consumer behaviour, digital technology adoption, and human–computer interaction (Premathilake et al. 2025; Uddin et al. 2025; Yu et al. 2024). Its enduring value lies in its emphasis on psychological mediation: behaviour is not driven directly by stimuli, but through cognitive and affective processes that occur within the individual.

This architecture is particularly suitable for studying conversational AI in emotionally sensitive settings. Interactions with systems such as ChatGPT involve more than instrumental efficiency; they often evoke reassurance, relational impressions, and emotional resonance. While earlier AI research has largely prioritised performance and behavioural effectiveness, the emotional dimension of user experience has frequently been underexplored (Chakraborty 2025; Puntoni et al. 2021). SOR provides an organising structure capable of capturing both affective and cognitive pathways through which empathic AI cues may influence continued engagement.

Importantly, however, SOR is best understood as a broad process framework rather than a fully specified explanatory theory. Although it clearly proposes that organism states mediate between perceived stimuli and behavioural responses, it does not explicitly identify which evaluative or motivational mechanisms are most critical when users rely on AI for emotional comfort. For this reason, the present study adopts SOR as the overarching architecture, while further specifying the cognitive and motivational processes within the organism layer through complementary theoretical mechanisms, culminating in the HEAR model.

In the HEAR framework, simulated empathy refers to the AI's design-level production of empathic cues, whereas perceived empathic communication captures the user's subjective experience of these cues as emotionally supportive. Emotional comfort represents the resulting affective state of reassurance, while usage disposition reflects a broader motivational readiness to continue relying on ChatGPT in emotionally sensitive contexts.

1.1.4. Technology evaluation and intentional reliance mechanisms (TAM-TPB integration)

To clarify the internal processes that SOR leaves conceptually open, the HEAR framework draws selectively on TAM and TPB as mechanism-oriented lenses embedded within the organism layer. This integration does not treat TAM and TPB as parallel standalone theories, but rather as complementary specifications that explain how emotionally resonant AI interactions are cognitively appraised and motivationally translated into sustained use.

The Technology Acceptance Model (TAM), originally developed by Davis (1989), remains influential for understanding how perceived usefulness and perceived ease of use shape users' technology evaluations across domains such as e-learning and health informatics (Chahal and Rani 2022; Lin et al. 2025; Wang, Wang et al. 2025). In emotionally sensitive contexts, usefulness is not limited to productivity outcomes; it may also be appraised in terms of emotional benefit (e.g. perceived reassurance or psychological support) (Lund and Wang 2023; W. B. Kim and Hur 2024). Ease of use is likewise critical when users engage with AI during vulnerable moments, as frictionless interaction reduces cognitive burden and facilitates authentic disclosure (Amin, Kim, and Noh 2025; Ma et al. 2025). TAM therefore contributes a cognitive appraisal mechanism that helps explain how empathic AI is evaluated as emotionally valuable.

However, continuance in empathic AI engagement also involves intentional and socially situated considerations that extend beyond system evaluation. The Theory of Planned Behaviour (TPB) (Ajzen 1991) highlights how attitudes, subjective norms, and perceived behavioural control shape behavioural intention, and it has been widely applied in health-related and emerging AI behaviours (Duong et al. 2024; Han et al. 2025; Wichmann, Gesk, and Leyer 2024). In the context of ChatGPT-based emotional support, subjective norms may influence whether such reliance is seen as acceptable, while perceived control reflects users' sense of agency in managing emotionally charged interaction (Acosta-Enriquez et al. 2024; Al-Qaysi et al. 2025). Together, TAM and TPB specify the cognitive-motivational pathways through which empathic cues may become sustained behavioural reliance.

1.1.5. The HEAR model for empathic AI continuance

Building on the SOR architecture and the cognitive-motivational specifications provided through TAM and TPB, the HEAR model (Humanised Empathy and Acceptance for Retention) represents thecentral integrative framework examined in this study. Importantly, integrative efforts that embed TAM-TPB mechanisms within the organising lens of SOR have begun to emerge in service and technology research. For instance, Sujood and Pancy (2024) applied a TAM-TPB-in-SOR configuration to explain technology-mediated experiences in the tourism domain, demonstrating the value of capturing evaluative beliefs and intentional readiness within a structured stimulus-response process. However, such integrative models have rarely been extended to emotionally sensitive human-AI interaction, where simulated empathy and psychological reassurance play a central role. HEAR therefore advances this emerging stream by theorising continuance with empathic conversational AI not as a purely instrumental technology decision, but as an emotionally grounded and psychologically meaningful form of retention, particularly in moments of vulnerability.

An important conceptual emphasis of the HEAR framework concerns how continuance intention is interpreted in emotionally sensitive AI contexts. Traditional technology acceptance frameworks typically explain sustained use through functional utility and efficiency. In contrast, the HEAR framework suggests that, in emotionally sensitive AI interactions, continuance intention may also reflect a coping-oriented form of continued engagement. Users may return to ChatGPT not only because it is useful or easy to use, but also because the interaction provides emotional reassurance, relational safety, and perceived psychological comfort. In this way, the framework contextualises continuance intention within emotionally sensitive AI interactions, highlighting how emotional resonance can shape sustained use alongside traditional evaluative mechanisms. Moreover, HEAR contributes theoretically by integrating empathic interaction cues into the stimulus layer of SOR. Rather than treating empathy as an outcome or peripheral feature, the model conceptualises perceived empathic communication and human-likeness as key experiential stimuli that shape how users interpret the AI as a socially responsive agent (Baek, Kim, and Kim 2025; Rafikova and Voronin 2025; Suh 2025). In emotionally vulnerable interactions, such cues are foundational for generating psychological comfort and perceived safety, thereby activating deeper organism-level processes than those typically addressed in utilitarian adoption models.

The organism layer of HEAR constitutes a further conceptual advancement by specifying a dual-process psychological mechanism. On the one hand, users engage in cognitive appraisal, evaluating whether the system provides emotionally meaningful value rather than mere task-related usefulness (Lund and Wang 2023; Maurya et al. 2025). In this context, perceived value reflects not only functional benefit but also emotional support, reassurance, and psychological relief. On the other hand, users experience affective alignment, reflected in emotional comfort and motivational readiness to rely on the AI as a supportive resource. By combining these cognitive and affective pathways, HEAR offers a more complete explanation of why simulated empathy can translate into sustained engagement rather than remaining a superficial interactional feature.

Importantly, HEAR also acknowledges that empathic AI operates within an ethically and psychologically nuanced space. While simulated empathy may foster comfort and retention, it may also introduce risks of emotional over-trust, dependency, or blurred boundaries between perceived care and genuine therapeutic support (Klingbeil, Grützner, and Schreck 2024). These concerns may be particularly salient for socially isolated individuals or those experiencing heightened distress, for whom AI warmth could substitute rather than complement human relationships (Peng et al. 2022). By incorporating motivational and control-related organism mechanisms, the model provides a balanced account of when and why empathic AI may succeed, as well as when it may backfire or require safeguards.

Overall, HEAR offers a theoretically synergistic framework that captures how humanised interaction cues, cognitive evaluations, and emotional reassurance jointly shape continuance intention in empathic AI engagement. Rather than proposing a new behavioural theory, the HEAR framework integrates insights from SOR, TAM, TPB, and simulated empathy research to clarify the psychological mechanisms underlying emotionally oriented AI continuance. By embedding TAM-TPB mechanisms within the SOR architecture – and extending this integrative logic into the emotionally sensitive domain of empathic conversational AI – HEAR extends existing acceptance models by integrating empathic interaction mechanisms within the SOR architecture to explain emotionally grounded retentionin digitally mediated mental wellbeing support. In doing so, the model contributes a timely theoretical foundation for understanding why users may continue relying on ChatGPT during emotionally vulnerable moments, where both psychological comfort and intentional readiness determine sustained use.

1.2. Hypothesis development

Within the HEAR framework, the organism layer captures two complementary psychological pathways through which empathic AI stimuli translate into continuance intention. On the cognitive side, perceived service value and perceived behavioural control reflect users' evaluative appraisals of whether ChatGPT is emotionally worthwhile and manageable as a support resource. On the affective side, emotional comfort and ChatGPT usage disposition represent affective reassurance and motivational readiness, indicating how emotionally safe and socially meaningful continued engagement with the system feels. Building on this distinction, the following hypotheses specify how perceived empathic communication, human-likeness, and ease of use shape these cognitive and affective organism states, ultimately predicting continuance usage intention.

1.2.1. Perceived empathic communication

Perceived empathic communication refers to the extent to which users experience ChatGPT's responses as emotionally attentive, validating, and supportive. Although conversational AI lacks genuine emotional consciousness, systems such as ChatGPT can simulate empathic interaction through reflective language, appropriate tone, and contextual sensitivity (Rubin et al. 2024). Importantly, this construct captures affective attunement rather than anthropomorphic realism: users feel emotionally 'heard' because the AI acknowledges their feelings, not because it appears human.

When users perceive empathic communication, they are more likely to assign emotional value to the interaction. In emotionally vulnerable moments, feeling understood can increase the perceived credibility and usefulness of the AI as a supportive resource (Seitz 2024). Empathic communication is therefore expected to enhance perceived service value, particularly by strengthening emotional trust and perceived benefit. Moreover, empathic responsiveness directly fosters emotional comfort by reducing distress, increasing reassurance, and promoting psychological safety during disclosure (Giray 2025; Vowels, Francois-Walcott, and Darwiche 2024). Over time, repeated experiences of being emotionally validated may also shape a more favourable motivational orientation towards continued use.

Hence, we propose:

H1a: Perceived empathic communication positively influences perceived service value.

H1b: Perceived empathic communication positively influences perceived behavioural control.

H1c: Perceived empathic communication positively influences emotional comfort.

H1d: Perceived empathic communication positively influences ChatGPT usage disposition.

1.2.2. Perceived human-likeness

Pelau, Dabija, and Ene (2021) proposed that perceived human-likeness reflects the extent to which users experience the AI as behaving in ways that resemble human interaction. Unlike empathic communication, which concerns emotional validation, human-likeness primarily captures relational realism and anthropomorphic perception. This impression may emerge through natural conversational flow, socially appropriate cues, and emotionally congruent interaction style (Baek, Kim, and Kim 2025; Suh 2025).

Anthropomorphic cues activate social heuristics, consistent with the CASA paradigm, whereby individuals apply interpersonal expectations to machines that display human-like traits (Reeves and Nass 1996). When ChatGPT is perceived as socially present and relationally credible, users may view the interaction as more meaningful and trustworthy rather than purely mechanical (Araujo 2018; Q. Li, Luximon, and Zhang 2023). Such perceptions strengthen users' willingness to treat the AI as an emotionally legitimate conversational partner, which can enhance perceived service value and, more importantly, shape usage disposition by increasing motivational readiness and social acceptability of continued reliance (Choung, David, and Ross 2023; Glikson and Woolley 2020).

Additionally, perceiving the AI as human-like may reduce psychological distance and emotional barriers, encouraging more open engagement and contributing to feelings of comfort and agency during interaction (Pizzi et al. 2023). Thus, human-likeness is expected to influence both evaluative and motivational organism states.

Hence, we propose:

H2a: Perceived human-likeness positively influences perceived service value.

H2b: Perceived human-likeness positively influences perceived behavioural control.

H2c: Perceived human-likeness positively influences emotional comfort.

H2d: Perceived human-likeness positively influences ChatGPT usage disposition.

1.2.3. Perceived ease of use

Perceived ease of use, a central construct in the TAM (Davis 1989), refers to the extent to which users believe that interacting with ChatGPT requires minimal effort. Within emotionally sensitive contexts, ease of use functions as an interactional enabling condition: individuals seeking psychological relief are often cognitively strained or emotionally vulnerable, and therefore less willing to tolerate complexity or friction in the conversational experience (Lv et al. 2022; Alneyadi et al. 2023). Under such circumstances, usability becomes essential for sustaining engagement, independent of the system's technical sophistication.

When ChatGPT is perceived as intuitive, smooth, and effortless to navigate, users can devote attention to emotional expression rather than managing interactional barriers (Al Mazroui and Alzyoudi 2024; Iancu and Iancu 2023). This fluency strengthens perceived service value by supporting the sense that the system is emotionally worthwhile and accessible as a support resource. More critically, perceived ease of use is expected to enhance perceived behavioural control, as users feel more confident in initiating and guiding emotionally difficult conversations with a sense of agency and manageability (Yoon and Lee 2021).

Although ease of use is primarily a cognitive usability appraisal rather than an empathic cue, reduced interactional friction may also contribute indirectly to affective reassurance. Seamless communication can lower anxiety, encourage openness, and foster emotional comfort, particularly for users who feel uncertain about disclosing personal concerns to an artificial agent (Alanzi et al. 2024; Xie and Wang 2024). Over repeated encounters, a consistently manageable interaction experience may further support the development of a favourable usage disposition, reinforcing motivational readiness for continued reliance on ChatGPT over time (Balakrishnan, Abed, and Jones 2022; Bansal et al. 2024).

Thus, perceived ease of use does not merely facilitate initial adoption. Rather, it shapes the cognitive conditions of value appraisal and control that underpin long-term engagement in empathic conversational AI settings, consistent with extended TAM perspectives on relational technology experiences (Moon and Kim 2001; Seitz 2024). Hence, we propose:

H3a: Perceived ease of use positively influences perceived service value.

H3b: Perceived ease of use positively influences perceived behavioural control.

H3c: Perceived ease of use positively influences emotional comfort.

H3d: Perceived ease of use positively influences ChatGPT usage disposition.

1.2.4. Cognitive organism states and continuance intention

Perceived service value. Perceived service value is conceptualised in this study as a higher-order construct composed of two key cognitive dimensions: trust in ChatGPT and perceived usefulness. This reflective-reflective structure is grounded in prior research on AI-enabled services, which suggests that users derive value not only from instrumental outcomes but also from relational confidence in the system's reliability and intentions (Alshammari and Babu 2025; Rather 2025). In emotionally supportive interactions, perceived service value therefore represents a cognitive appraisal of whether engaging with ChatGPT is both beneficial and credible.

Perceived usefulness reflects users' belief that ChatGPT helps them achieve emotional or cognitive goals, such as clarifying thoughts, alleviating stress, or feeling supported (Kerasidou 2020). Importantly, in emotionally sensitive contexts, usefulness extends beyond task efficiency and incorporates perceived emotional benefit, aligning with broader interpretations of value in digital mental wellbeing services. Trust, in turn, captures the degree to which users feel confident in relying on ChatGPT's responses as accurate, appropriate, and respectful. Prior work in conversational AI indicates that trust develops when the system consistently produces interactions that feel psychologically safe and supportive (Schillaci et al. 2024; Y. Li, Gan, and Zheng 2025). Even simulated empathy can reinforce trust when users experience emotional reassurance during disclosure (Rubin et al. 2024).

By integrating perceived usefulness and trust, perceived service value represents users' holistic cognitive assessment of what they gain from engaging with ChatGPT in emotionally supportive situations. Unlike emotional comfort, which reflects immediate affective reassurance, perceived service value captures the evaluative judgment that the AI interaction is emotionally worthwhile and dependable. When users perceive ChatGPT as both helpful and trustworthy, they are more likely to assign value to the interaction and to sustain continued engagement over time. Building on this perspective, we propose:

H4: Perceived service value positively influences continuance usage intention.

Perceived behavioural control. Perceived behavioural control, derived from the TPB (Ajzen 1991), reflects an individual's belief in their capacity to perform a behaviour despite internal or external constraints. In the context of AI-mediated emotional support, perceived behavioural control captures users' confidence in their ability to engage effectively with ChatGPT, including initiating conversations, navigating responses, and managing emotionally sensitive disclosure.

A strong sense of behavioural control is particularly important in emotionally charged situations, where users must feel autonomous and capable of guiding the interaction on their own terms. As highlighted by Fahad Alanezi (2024) in research on digital therapeutic tools, perceived control over the interaction contributes significantly to motivational readiness and sustained use. When individuals feel competent and in control, they are more likely to return, as the AI is experienced as a stable and manageable support resource rather than an unpredictable or mechanical system (Acosta-Enriquez et al. 2024).

In this study, perceived behavioural control reflects not only technical self-efficacy but also psychological readiness to rely on ChatGPT during vulnerable moments. Unlike usage disposition, which represents broader attitudinal and normative legitimacy, behavioural control captures the user's perceived agency in sustaining engagement across contexts. Users who believe they can interact effectively and confidently are therefore more inclined to develop continuance intention. Hence, we propose:

H5: Perceived behavioural control positively influences continuance usage intention.

1.2.5. Affective organism states and continuance intention

Emotional comfort. Emotional comfort, in the context of affective computing, refers to a user's subjective sense of psychological ease, tranquillity, and reassurance following interaction with an AI system (Pei et al. 2024). This construct is particularly salient for conversational agents designed for emotionally sensitive engagement, where users often seek relief from stress, loneliness, or internal uncertainty rather than purely informational assistance. When ChatGPT is perceived as attentive, non-judgmental, and emotionally responsive, individuals are more likely to experience a reduction in emotional tension, even when they remain fully aware that the system does not possess genuine emotional consciousness (Rubin et al. 2024).

Importantly, emotional comfort captures an immediate affective outcome of interaction, rather than a cognitive appraisal or motivational orientation. Unlike perceived service value, which reflects users' evaluative judgments about the usefulness and trustworthiness of ChatGPT, emotional comfort concerns the felt experience of being soothed, reassured, or emotionally stabilised during or after the conversation. Similarly, compared to usage disposition – which represents a more enduring attitudinal readiness shaped by social norms and motivational acceptance – comfort is a more proximal emotional state that emerges directly from empathic cues embedded in the interaction itself.

As early work on artificial empathy suggests, users may feel emotionally supported through simulated empathic strategies such as reflective listening, compassionate wording, and gentle conversational tone (Damiano, Dumouchel, and Lehmann 2015; Parmar et al. 2022). Although these cues lack genuine affective intent from the AI's perspective, they can nevertheless be interpreted by users as reassuring, particularly during moments of vulnerability. In such contexts, the perceived emotional safety of the interaction becomes psychologically meaningful: ChatGPT is experienced not merely as a functional tool, but as a secure relational space for disclosure and reflection.

Over repeated encounters, emotional comfort may act as a critical affective driver of sustained engagement. When individuals consistently experience relief or reassurance through interaction, they become more inclined to return, not primarily because of efficiency or task performance, but because the system offers a form of emotionally stabilising support (Vowels, Francois-Walcott, and Darwiche 2024). Thus, within the HEAR framework, emotional comfort represents a key organism-level pathway through which simulated empathy translates into continued reliance on empathic conversational AI. Hence, we propose:

H6: Emotional comfort positively influences continuance usage intention.

ChatGPT usage disposition. ChatGPT usage disposition reflects users' broader motivational readiness and attitudinal inclination to continue engaging with the system in emotionally sensitive contexts. Drawing on extensions of the TPB, this construct is conceptualised as a higher-order orientation composed of attitude towards use and subjective norm (Ajzen 1991; Bhattacherjee 2001). It therefore captures not only whether users personally evaluate ChatGPT positively, but also whether continued reliance is perceived as socially legitimate and acceptable within their broader environment.

Importantly, usage disposition is conceptually distinct from both emotional comfort and perceived service value. Unlike emotional comfort, which represents an immediate affective state of reassurance following interaction, usage disposition reflects a more stable and enduring motivational stance that develops over time. Emotional comfort may emerge in a single supportive conversation; however, disposition represents whether users form an ongoing psychological commitment to returning to the system as a habitual resource for emotional support. Similarly, compared to perceived service value – which centres on evaluative judgments about usefulness and trustworthiness – usage disposition encompasses normative and identity-relevant considerations, such as whether engaging with AI for emotional disclosure 'feels appropriate' or socially endorsed (Figure 1).

Attitude towards use plays a critical role in this motivational process, particularly when engagement is emotionally driven rather than task-oriented. If individuals believe that ChatGPT offers meaningful reassurance, non-judgmental responsiveness, or emotional resonance, they are more likely to develop a favourable orientation towards continued reliance (Al-Qaysi et al. 2025). At the same time, subjective norms introduce an external social filter. In emerging practices such as AI-supported emotional disclosure, users may be influenced by cultural expectations, peer discourse, or broader ethical narratives surrounding the appropriateness of turning to AI for psychological support (Duong et al. 2024). Thus, even when users experience comfort, their willingness to continue may still depend on whether such engagement is perceived as socially acceptable. Over time, as attitudinal approval and normative

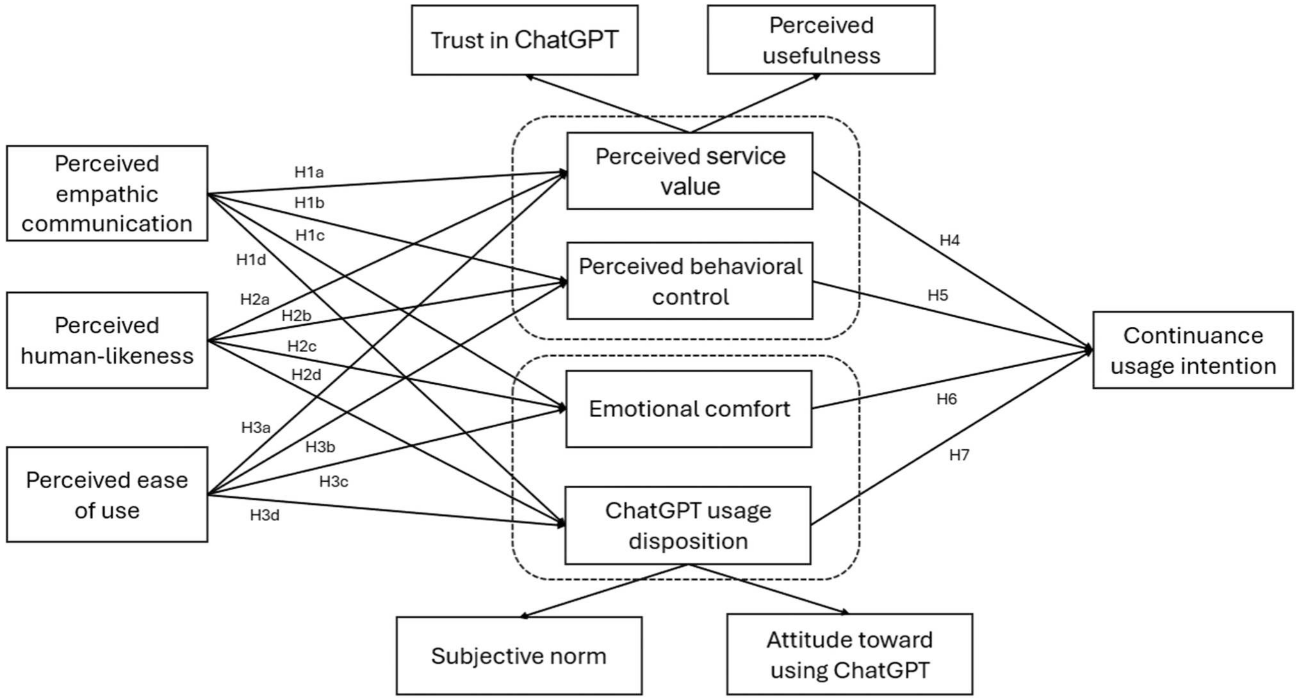

Figure 1. Research model.

legitimacy converge, usage disposition becomes a key motivational bridge between affective experience and sustained behavioural intention. Within the HEAR framework, disposition therefore represents an organism-level mechanism through which empathic AI engagement becomes internalised as an intentional, socially situated pattern of continued use, rather than a purely episodic response to emotional relief. Hence, we propose:

> **H7:** ChatGPT usage disposition positively influences continuance usage intention.

2. Methodology

2.1. Data collection

To ensure content validity and conceptual clarity of the research constructs, an expert panel review was conducted prior to survey administration. The panel consisted of five experts across three relevant domains: (1) one cognitive psychology lecturer, with expertise in psychometrics and emotional assessment; (2) two AI professionals – including a PhD researcher in natural language processing and a software engineer specialising in chatbot development; (3) one UX strategist with experience in human-AI interaction design; and (4) one digital marketing director, currently leading AI integration in customer engagement strategies. This interdisciplinary composition was selected to ensure that the model addressed theoretical, technical, and applied perspectives, increasing the rigour and practical relevance of the instrument. Feedback from the expert panel was used to refine construct definitions, optimise item phrasing, and enhance overall survey logic. Minor revisions were made to ensure conceptual consistency, reduce measurement ambiguity, and align with contemporary use cases of AI-mediated emotional interaction. The expert consultation affirmed that the survey instrument was both theoretically sound and contextually appropriate for assessing user behaviour towards ChatGPT.

Following expert validation, a pretest involving 25 Vietnamese participants was conducted to assess clarity, language fluency, and logical flow. The survey was translated using a rigorous translation and back-translation process, with iterative refinements to preserve both semantic and contextual integrity. The final version of the questionnaire was administered through an online survey via Microsoft software, employing a non-probability snowball sampling method. The inclusion criteria required that respondents had prior experience interacting with ChatGPT and had used such platforms for emotionally expressive or supportive communication. Two screening questions were used: (1) 'Have you ever used ChatGPT (including the free or paid version)?'; (2) 'Have you ever used ChatGPT to share personal emotions or seek emotional comfort?'. Only those who answered 'Yes' to both were included in the final dataset. Respondents were provided with a clear definition of ChatGPT and were assured of full anonymity and data confidentiality. The average time to complete the survey was between 5–10 min.

Out of 1,075 collected responses, 892 valid observations were retained after screening and data cleaning. Data were analysed using IBM SPSS Statistics 27.0 to perform descriptive analysis, reliability testing, and prepare variables for subsequent model testing.

Table 1 presents the demographic characteristics of the sample. The gender distribution was relatively balanced with 394 males (44.2%) and 498 females (55.8%). The majority of respondents were between 25–35 years old (43.5%), followed by those under 25 (30.8%) and those aged 36–45 (19.6%). Educational attainment was high, with 59.2% holding a bachelor's degree, and 14% possessing a master's degree. Occupationally, the sample included employees (55.4%), students (23.8%), and business professionals (14.2%). In terms of income, 39.6% reported monthly earnings between US$500–1000, while 25.1% earned between US$1001–1500, and 20.7% earned below US$500. These demographic characteristics reflect a digitally literate, economically active population – highly relevant to the adoption and habitual use of AI chatbots like ChatGPT in Vietnam's urban contexts.

2.2. Measurement

To ensure the reliability and contextual relevance of the HEAR model, all constructs in this study were measured using items adapted from previously validated scales. A seven-point Likert scale, ranging from 1 ('strongly disagree') to 7 ('strongly agree'), was used to record participants' responses. Wherever necessary, slight modifications were made to better reflect the role of ChatGPT in emotionally sensitive situations.

Perceived empathic communication was measured using seven items based on the work of Pelau, Dabija, and Ene (2021). These items focused on how emotionally supported and understood users felt when interacting with ChatGPT. To assess perceived human-likeness, four items were adapted from Becker, Mahr, and Odekerken-Schröder (2023). These originally targeted users' perceptions of social robots, but in this study, they were revised to evaluate how human-like users found ChatGPT's communication style and behaviour. Perceived ease of use was captured using three items adapted from Davis (1989) and further refined by Balakrishnan and Dwivedi (2024). These items asked whether users found the AI system easy to understand and operate. Meanwhile, perceived behavioural control was measured with three items derived from Ajzen's (2002) formulation of the Theory of Planned Behaviour. These items reflected how confident users felt in their ability to manage interactions with ChatGPT, especially when discussing personal emotions.

Perceived service value was modelled as a second-order construct comprising two dimensions: Trust in ChatGPT and perceived usefulness. Trust was assessed using four items adapted from Patil et al. (2020), reflecting whether users believed the AI system was dependable and trustworthy. Perceived usefulness was measured with four items taken from Davis (1989) and Balakrishnan and Yogesh (2021), capturing how helpful ChatGPT was, not only functionally but also emotionally. For emotional comfort, the study employed seven items adapted from the customer comfort scale developed by Spake et al. (2003) and reworded to fit the context of AI-based emotional interaction with ChatGPT. These items explored whether users felt calm, reassured, or emotionally relieved after using ChatGPT. The construct ChatGPT usage disposition was also treated as a second-order factor made up of subjective norms and attitude towards using ChatGPT. Subjective norms were measured with two items from Ajzen (1991) and Taylor and Todd (1995), indicating the perceived social approval of using AI for emotional expression. Attitude, on the other hand, was assessed with three items from the same authors and Balakrishnan and Yogesh (2021), examining how positively users viewed ChatGPT in this role.

Continuance usage intention was evaluated using six items adapted from Balakrishnan, Abed, and Jones (2022) and Li and Wang (2023). These items reflected

Table 1. Demographic descriptions.

Variable	Responses	N	%
Gender	Male	394	44.2
	Female	498	55.8
Age	Below 25 years old	275	30.8
	From 25–35 years old	388	43.5
	From 36–45 years old	175	19.6
	From 46–56 years old	43	4.9
	Above 56 years old	11	1.2
Education	Below Bachelor's Degree	217	24.3
	Bachelor's Degree	528	59.2
	Master's Degree	125	14
	Doctoral Degree or higher	22	2.5
Occupation	Student	212	23.8
	Business	127	14.2
	Employee	494	55.4
	Freelancer	47	5.2
	Homemaker	5	0.6
	Others	7	0.8
Income	Less than US$500	185	20.7
	US$500–US$1000	353	39.6
	US$1001–US$1500	224	25.1
	US$1501–US$2000	67	7.5
	US$2001–US$2500	48	5.4
	US$2501–US$3000	7	0.8
	Above US$3000	8	0.9

whether users intended to keep using ChatGPT to share emotions or seek emotional support. A translation and back-translation process (Harkness, Pennell, and Schoua-Glusberg 2004) was implemented to ensure linguistic accuracy and semantic clarity in Vietnamese. Full details of the measurement items and original sources are listed in the Appendix 1.

2.3. Analytical approach

This study employs Covariance-Based Structural Equation Modelling (CB-SEM) using AMOS 20 to evaluate both the measurement and structural models. CB-SEM was selected because of its strong capacity for testing theory-driven models, where the research goal is to validate the relationships between latent constructs based on an a priori conceptual framework (Hair et al. 2010; Kline 2016). Compared to variance-based approaches like PLS-SEM, CB-SEM is more appropriate for confirmatory research, as it provides comprehensive model fit indices and enables the assessment of both first-order and higher-order constructs with greater statistical rigour (Byrne 2010; Schumacker and Lomax 2016).

In this study, CB-SEM is employed to test the HEAR model, which integrates the SOR paradigm with constructs from the TAM, the TPB, and simulated empathy theory. The choice of CB-SEM is justified not only by the complexity of the model – which includes second-order reflective-reflective constructs such as PSV and CUD – but also by the study's emphasis on theoretical confirmation rather than predictive utility. The utilisation of AMOS facilitates a comprehensive assessment of the global model fit, construct validity, and the causal structure proposed by the HEAR framework, thereby guaranteeing that the analysis aligns with the study's confirmatory research objectives.

3. Results

3.1. Common method bias (CMB)

To assess the potential presence of common method bias (CMB), a comparison was conducted between the baseline measurement model and an alternative model incorporating a common latent factor, using a chi-square difference test. Specifically, the difference between the two models was calculated using the formula: ΔChi-Square = Chi-Square (baseline model) − Chi-Square (common latent factor model). The analysis yielded a ΔChi-Square value of 2.527 (1214.791–1212.264), with a corresponding difference in degrees of freedom (Δdf) equal to 1 (815–814). When compared to the critical value of the chi-square distribution at the 0.05 significance level (3.841), the observed difference was substantially lower ($2.527 < 3.841$). This result indicates that the inclusion of a common method factor did not significantly improve model fit, thereby providing no substantial evidence of common method bias in the dataset.

To strengthen this assessment, Harman's single-factor test was performed. The first factor explained 44.63% of the total variance, below the 50% threshold (Podsakoff et al. 2003; Sharma, Yetton, and Crawford 2009), indicating that common method variance is not a major concern in this dataset.

3.2. Measurement model

A confirmatory factor analysis (CFA) using AMOS 20 was conducted to evaluate the measurement model and assess convergent validity. Because this study adopts a theory-driven CB-SEM approach, CFA, rather than PCA or EFA, served as the primary basis for construct validation. Construct validity was assessed using factor loadings, composite reliability (CR), average variance extracted (AVE), discriminant validity criteria, and overall model fit indices. Any exploratory analyses reported in this study were conducted solely as supplementary diagnostic procedures and were not used for scale development, item purification, or construct validation decisions. The objective was to ensure that the observed items measured their respective latent constructs consistently and to identify and remove any underperforming indicators, thereby confirming the unidimensionality of the scales (Bollen 1989). In line with established criteria, each item was required to load at least 0.70 on its intended construct and demonstrate statistical significance ($p < .05$; $t \geq 1.96$) (Bagozzi and Yi 1988; Sujan, Weitz, and Kumar 1994). In the CFA results, all standardised factor loadings met these thresholds, ranging from 0.807 to 0.933, and no item was eliminated. This supports the theoretical coherence and measurement precision of the model. Detailed standardised loadings are reported in Table 2.

Reliability for all constructs was assessed using both composite reliability (CR) and average variance extracted (AVE). According to established guidelines, CR values should exceed 0.70 and AVE values should exceed 0.50 to confirm adequate internal consistency and convergent validity (Bagozzi 1994; Hair et al. 1999; Steenkamp and van Trijp 1991). As shown in Table 2 and Appendix 1, all constructs in the final measurement model met these criteria. Specifically, CR values ranged from 0.821 (SUB) to 0.946 (PEC), while AVE values ranged from 0.601 (PSV, second-

Table 2. The reliability and convergent validity.

Constructs	Item number	FL	CR	AVE
Perceived empathic communication	PEC1	0.835	0.946	0.716
	PEC2	0.850		
	PEC3	0.850		
	PEC4	0.865		
	PEC5	0.863		
	PEC6	0.819		
	PEC7	0.844		
Perceived human-likeness	PHL1	0.884	0.938	0.755
	PHL2	0.855		
	PHL3	0.874		
	PHL4	0.861		
Perceived ease of use	PEU1	0.940	0.914	0.781
	PEU2	0.852		
	PEU3	0.856		
Trust in ChatGPT	TIC1	0.886	0.932	0.773
	TIC2	0.869		
	TIC3	0.890		
	TIC4	0.872		
Perceived usefulness	PU1	0.864	0.922	0.748
	PU2	0.865		
	PU3	0.864		
	PU4	0.866		
Perceived behavioural control	PBC1	0.824	0.860	0.672
	PBC2	0.829		
	PBC3	0.807		
Emotional comfort	EMC1	0.840	0.940	0.691
	EMC2	0.847		
	EMC3	0.837		
	EMC4	0.830		
	EMC5	0.816		
	EMC6	0.814		
	EMC7	0.836		
Subjective norms	SUB1	0.822	0.821	0.697
	SUB2	0.847		
Attitude towards using ChatGPT	ATT1	0.859	0.896	0.742
	ATT2	0.864		
	ATT3	0.861		
Continuance usage intention	CON1	0.871	0.945	0.743
	CON2	0.869		
	CON3	0.865		
	CON4	0.865		
	CON5	0.841		
	CON6	0.859		
Perceived service value[a] (PSV)	TIC[b]	0.724	0.750	0.601
	PU[b]	0.823		
ChatGPT usage disposition[a] (CUD)	ATT[b]	0.831	0.764	0.618
	SUB[b]	0.739		

Note: PEC: Perceived empathic communication, PHL: Perceived human-likeness, PEU: Perceived ease of use, PSV: Perceived service value, TIC: Trust in ChatGPT, PU: Perceived usefulness, PBC: Perceived behavioural control, EMC: Emotional comfort, CUD: ChatGPT usage disposition, SUB: Subjective norm, ATT: Attitude towards using ChatGPT, CON: Continuance usage intention, FL: Factor Loadings, CR: Composite Reliability, AVE: Average variance extracted.
[a]Second-order factors.
[b]Second-order indicators.

order construct) to 0.781 (PEU), indicating satisfactory reliability and sufficient shared variance across all latent constructs. These results provide strong support for the robustness of the measurement model and justify proceeding to the structural model evaluation. The factor loadings of all observed indicators exceeded 0.70, supporting unidimensionality and measurement adequacy. The measurement model demonstrated a good fit to the data, with fit indices exceeding commonly accepted thresholds: $\chi^2 = 1214.791$, $df = 815$, $\chi^2/df = 1.491$, $CFI = 0.988$, $TLI = 0.987$, $GFI = 0.942$, $AGFI = 0.932$, $RMSEA = 0.023$, and $PCLOSE = 1.000$ (Byrne 2010; Kline 2011).

In Table 3, discriminant validity was assessed using the Fornell-Larcker criterion. For most construct pairs, the square root of the AVE exceeded the inter-construct correlations, providing support for discriminant validity of the measurement model (Fornell and Larcker 1981). For example, the $\sqrt{AVE}$ for ATT was 0.878, which is greater than its highest correlation with CON (0.622). Similar patterns were observed for other constructs, including PEC ($\sqrt{AVE} = 0.846$), PHL (0.869), PEU (0.883), PU (0.866), TIC (0.878), PBC (0.820), EMC (0.832), and SUB (0.835). However, the correlation between PSV and CUD (0.898) exceeded the square root of the AVE for both PSV (0.775) and CUD (0.786), indicating that the Fornell-Larcker criterion was not fully satisfied for this construct pair. Discriminant validity results further indicate that respondents were able to perceptually distinguish the three key stimulus constructs: perceived empathic communication (PEC), perceived human-likeness (PHL), and perceived ease of use (PEU), supporting their treatment as independent stimuli rather than overlapping perceptual evaluations. Although the correlation between the two higher-order constructs CUD and PSV was relatively high (0.898), this is theoretically expected because both constructs operate at the organism stage and reflect evaluative responses within the same cognitive–affective appraisal system. Nevertheless, the two constructs remain theoretically distinct. PSV captures users' cognitive evaluation of ChatGPT through perceived usefulness and trust, whereas CUD

Table 3. Fornell-Larcker criterion.

	CON	CUD	EMC	PBC	PEC	PEU	PHL	PSV
CON	0.862							
CUD	0.775	0.786						
EMC	0.638	0.745	0.832					
PBC	0.511	0.612	0.476	0.820				
PEC	0.588	0.740	0.617	0.440	0.846			
PEU	0.343	0.497	0.328	0.337	0.332	0.883		
PHL	0.604	0.766	0.647	0.442	0.651	0.338	0.869	
PSV	0.788	0.898	0.798	0.572	0.786	0.423	0.796	0.775

reflects users' motivational and socially influenced disposition to continue using ChatGPT through attitude and subjective norm. Importantly, item-level discriminant validity remains intact, indicating that the high latent correlation reflects conceptual proximity rather than multicollinearity or construct redundancy.

To provide supplementary evidence for discriminant validity and to verify that items cluster according to their intended constructs, an exploratory factor analysis (EFA) with oblique rotation (pattern matrix) was conducted following CB-SEM recommendations (Hair et al. 2010). Importantly, EFA was not used for scale development or item purification, but rather as an additional diagnostic alongside CFA-based criteria. As presented in Supplementary Material (Supplementary Table S2), all items loaded strongly on their intended construct with no substantial cross-loadings. Each construct formed a distinct factor, indicating that the measurement structure is consistent with the conceptual model and that multicollinearity is not a concern at the measurement level.

Furthermore, to provide additional evidence regarding the distinctiveness and hierarchical validity of the higher-order constructs, second-order CFA was conducted to validate the hierarchical structure of three high-order constructs: PSV composed of PU and TIC; CUD formed by ATT and SUB; and PEC and EMC as part of the emotional path. The second-order CFA also showed excellent model fit: $\chi^2 = 1252.077$, df = 828, $\chi^2/df = 1.512$, CFI = 0.987, TLI = 0.986, RMSEA = 0.024, and PCLOSE = 1.000. All second-order loadings were above 0.70 and significant ($p < 0.001$), and each second-order construct met the CR (> 0.83) and AVE (> 0.71) thresholds.

3.3. Structural model

Prior to examining the hypothesised paths within the HEAR model, the overall fit of the structural model was assessed to ensure its empirical adequacy. The results suggested a satisfactory fit between the proposed model and the observed data, as indicated by the following indices: $\chi^2 = 1312.427$, df = 732, $\chi^2/df = 1.792$, CFI = 0.968, TLI = 0.965, RMSEA = 0.040, GFI = 0.853, and AGFI = 0.832. Most indices met or exceeded commonly recommended thresholds for model evaluation (Byrne 2010; Garver and Mentzer 1999; Kline 2011). It should be noted, however, that GFI and AGFI are known to be sensitive to sample size and model complexity, and therefore may decline in larger or more parameter-rich structural models. Thus, while these values fall below the conventional 0.90 guideline, they do not necessarily indicate poor model specification in the present context. Taken together, the fit results provide adequate support for proceeding with hypothesis testing of the sixteen structural relationships that constitute the HEAR framework.

The findings revealed full statistical support for all hypothesised paths (H1a to H7), with significance levels at $p < 0.001$ and standardised coefficients ranging from $\beta = 0.075$ to $\beta = 0.434$. Specifically, perceived empathic communication exerted a positive influence on all four organism-level constructs, namely perceived service value (H1a: $\beta = 0.325$, $p < 0.001$), perceived behavioural control (H1b: $\beta = 0.222$, $p < 0.001$), emotional comfort (H1c: $\beta = 0.328$, $p < 0.001$), and ChatGPT usage disposition (H1d: $\beta = 0.281$, $p < 0.001$). Likewise, perceived human-likeness significantly influenced all four mediators: perceived service value (H2a: $\beta = 0.333$), perceived behavioural control (H2b: $\beta = 0.237$), emotional comfort (H2c: $\beta = 0.411$), and ChatGPT usage disposition (H2d: $\beta = 0.328$) with all paths significant at $p < 0.001$. Among these, the strongest relationship in the entire model was observed between perceived human-likeness and emotional comfort, indicating the pronounced emotional relevance of anthropomorphic cues.

Perceived ease of use was also found to be a significant, albeit more modest, predictor of the four mediating constructs. Its influence was most pronounced on perceived behavioural control (H3b: $\beta = 0.160$, $p < 0.001$), followed by ChatGPT usage disposition (H3d: $\beta = 0.141$, $p < 0.001$), perceived service value (H3a: $\beta = 0.076$, $p < 0.001$), and emotional comfort (H3c: $\beta = 0.075$, $p = 0.004$). Although these coefficients were comparatively lower, they reaffirm the relevance of usability, especially in emotionally sensitive contexts.

Finally, all organism-level constructs significantly predicted continuance usage intention, thereby validating Hypotheses H4 through H7. The strongest predictor of CON was perceived service value (H4: $\beta = 0.434$,

Table 4. Results of structural equation model.

Hypotheses	Estimate	S.E.	C.R.	P	Decisions
H1a: PEC → PSV	0.325	0.031	10.426	***	Accepted
H1b: PEC → PBC	0.222	0.046	4.852	***	Accepted
H1c: PEC → EMC	0.328	0.039	8.501	***	Accepted
H1d: PEC → CUD	0.281	0.033	8.513	***	Accepted
H2a: PHL → PSV	0.333	0.029	11.341	***	Accepted
H2b: PHL → PBC	0.237	0.043	5.550	***	Accepted
H2c: PHL → EMC	0.411	0.036	11.252	***	Accepted
H2d: PHL → CUD	0.328	0.032	10.279	***	Accepted
H3a: PEU → PSV	0.076	0.020	3.866	***	Accepted
H3b: PEU → PBC	0.160	0.031	5.091	***	Accepted
H3c: PEU → EMC	0.075	0.026	2.907	0.004	Accepted
H3d: PEU → CUD	0.141	0.022	6.499	***	Accepted
H4: PSV → CON	0.434	0.081	5.359	***	Accepted
H5: PBC → CON	0.129	0.032	4.007	***	Accepted
H6: EMC → CON	0.175	0.036	4.855	***	Accepted
H7: CUD → CON	0.396	0.078	5.070	***	Accepted

***$p < 0.001$.

$p < 0.001$), followed by ChatGPT usage disposition (H7: $\beta = 0.396$, $p < 0.001$), emotional comfort (H6: $\beta = 0.175$, $p < 0.001$), and perceived behavioural control (H5: $\beta = 0.129$, $p < 0.001$). Collectively, these results provide robust empirical support for the HEAR model, highlighting how both cognitive evaluations and emotional responses jointly shape sustained engagement with empathic AI. A summary of these path coefficients is presented in Table 4.

4. Discussion

This study extends the application of the SOR framework into emotionally sensitive human-AI interaction, offering new insight into why users may continue engaging with ChatGPT not merely as a functional interface but as an emotionally supportive interaction resource. Rather than treating continuance as an instrumental adoption outcome, the HEAR model demonstrates that retention in empathic conversational AI contexts is shaped by a dual psychological process: users return because the system is cognitively appraised as valuable and manageable, and because it provides affective reassurance during moments of vulnerability. This finding strengthens the argument that emotional resonance is becoming central to technology continuance in digitally mediated emotional wellbeing contexts (Lund and Wang 2023; Xu et al. 2024).

A particularly important theoretical implication lies in the central role of affective organism states. Emotional comfort and ChatGPT usage disposition were not merely secondary emotional by-products; instead, they functioned as core organism mechanisms linking empathic interaction cues to sustained intention. Conceptually, this suggests that users' continued reliance on conversational AI is increasingly motivated by psychological safety, reassurance, and relational legitimacy rather than by task-based efficiency alone. This aligns with broader affective computing research showing that emotionally supportive machine interaction can foster persistent engagement over time (Bickmore and Picard 2005; Kim, Kim, and Baek 2025).

The strong influence of perceived human-likeness on emotional comfort further highlights the relational nature of empathic AI engagement. Human-likeness operates as more than a superficial design feature; it serves as a relational realism cue that lowers emotional distance and reduces barriers to self-disclosure. When ChatGPT is experienced as conversationally fluent and socially present, users may feel psychologically 'seen' and emotionally accompanied, even in the absence of genuine consciousness (Becker, Mahr, and Odekerken-Schröder 2023; Rafikova and Voronin 2025). This supports anthropomorphism perspectives suggesting that human-like interactional cues can activate interpersonal heuristics that shape emotional responses in human-machine contexts.

At the same time, perceived empathic communication emerged as a consistent affective validation cue shaping both cognitive appraisals and emotional reassurance. When users interpret AI responses as emotionally attentive and supportive, simulated empathy becomes psychologically meaningful, enhancing perceived value, strengthening agency, and fostering comfort (Pelau, Dabija, and Ene 2021; Pei et al. 2024). Importantly, these findings suggest that what matters is not the AI's internal capacity to feel, but the user's experience of being emotionally acknowledged, especially during distress (Kelly et al. 2025). Perceived ease of use, while comparatively weaker, remains an enabling condition: frictionless interaction supports continued engagement by strengthening perceived control and reducing cognitive burden in vulnerable moments (Davis 1989; Ma et al. 2025).

Beyond individual pathways, the combined effects of perceived service value and usage disposition indicate that emotional utility may increasingly rival, or even surpass, traditional functional utility in conversational AI reliance. Whereas many acceptance models emphasise productivity-based usefulness (Venkatesh, Thong, and Xu 2012), HEAR suggests that users may return to ChatGPT because it provides reassurance, validation, and emotional anchoring. In this sense, continuance intention may also reflect a coping-oriented form of continued engagement, rather than being explained solely by utilitarian decision processes. Importantly, however, empathic AI engagement also operates within a psychologically and ethically nuanced space. While simulated empathy can foster emotional comfort and retention, it may also introduce risks of emotional over-trust, dependency, or blurred boundaries between perceived care and genuine professional mental health support (Klingbeil, Grützner, and Schreck 2024). For some users – particularly those who are socially isolated or highly distressed – the accessibility of an always-available conversational listenermay encourage reliance that substitutes rather than supplements human support networks (Markovitch, Stough, and Huang 2024). These tensions highlight the need for responsible design, trust calibration, and clearer boundary-setting in emotionally deployed conversational agents.

All these results validate the HEAR framework as a theoretically integrative explanation of empathic AI retention, demonstrating how humanised cues shape both cognitive appraisal (value, control) and affective reassurance (comfort, disposition), ultimately driving sustained engagement. More broadly, this study signals a shift in the evolving role of conversational AI: users may increasingly engage with systems like ChatGPT not only for convenience, but also for emotionally supportive interaction within everyday coping practices (Bickmore et al. 2012; Duong et al. 2024; J. Kim and Moon 2025).

5. Theoretical and practical implications

5.1. Theoretical implications

The theoretical contribution of this study lies not only in proposing the HEAR framework, but in empirically clarifying the specific psychological mechanisms through which simulated empathy translates into sustained engagement with ChatGPT in emotionally sensitive contexts. Rather than offering broad claims about empathy or anthropomorphism, the validated pathways of HEAR demonstrate that continuance intention is driven by a structured dual-process organism mechanism combining cognitive appraisal and affective reassurance.

First, the findings advance the SOR tradition by specifying the organism layer with greater psychological precision. In the HEAR model, empathic AI cues do not influence continuance directly; instead, they operate through two empirically supported organism processes. Cognitive organism appraisals, captured by perceived service value and perceived behavioural control, reflect whether users judge ChatGPT as emotionally worthwhile and manageable. At the same time, affective organism states, represented by emotional comfort and usage disposition, capture reassurance and motivational readiness to rely on the system. This mechanism-based validation suggests that SOR applications in empathic AI settings remain incomplete unless they explicitly account for affective reassurance as a central internal pathway rather than a secondary by-product.

Second, the study refines technology acceptance theorising by showing that TAM-based evaluations in therapeutic-style AI contexts are emotionally reframed. Within HEAR, perceived value emerges not simply from instrumental usefulness, but from trust-based emotional worth and psychological support. Ease of use functions less as a generic adoption facilitator and more as an enabling condition that reduces friction during vulnerable moments, thereby strengthening perceived control and comfort. These results indicate that acceptance models centred on productivity-oriented utility require conceptual expansion when technologies are used for emotional coping rather than task performance.

Third, the integration of TPB mechanisms is empirically justified by the motivational nature of continuance in empathic AI reliance. The validated role of behavioural control and usage disposition suggests that sustained engagement depends not only on whether the AI feels supportive, but also on whether users experience agency, autonomy, and social legitimacy in relying on a non-human listener. Thus, continuance intention in emotionally sensitive AI engagement is better understood as intentional reliance shaped by both affective comfort and volitional readiness.

Most importantly, HEAR contributes to simulated empathy theory by demonstrating that perceived empathic communication and human-likeness function as primary experiential stimuli that activate both cognitive and affective organism mechanisms. In particular, the strong role of humanised interaction cues in shaping emotional comfort highlights that simulated empathy is not peripheral, but foundational in producing psychological reassurance that sustains repeated engagement. Empathy in conversational AI should therefore be theorised as an upstream driver of retention processes rather than as a downstream interactional outcome.

Collectively, these empirically grounded mechanisms position ChatGPT not merely as a functional tool but, for some users, as an emotionally supportive conversational companion providing accessible reassurance within everyday coping practices. By validating how empathic cues shape value, control, comfort, and motivational disposition, the HEAR model advances beyond additive SOR-TAM-TPB integrations and offers a coherent theoretical explanation of emotionally grounded retention in digital mental wellbeing contexts.

5.2. Practical implications

Beyond its theoretical contribution, the HEAR model offers concrete guidance for the design, evaluation, and governance of empathic conversational AI in emotionally sensitive contexts. Because the validated pathways show that continuance intention is driven not only by usability, but also by perceived empathic communication, calibrated human-likeness, and emotional comfort, practitioners require actionable strategies that translate these mechanisms into responsible system development.

For AI developers, the strong role of perceived empathic communication suggests that ‘empathy’ should not be treated as a vague aspiration, but as a set of implementable conversational behaviours. In practice, empathic communication in ChatGPT-like systems is most effectively conveyed through specific interaction cues, such as reflective listening (paraphrasing user feelings), emotional validation ('that sounds difficult'), supportive framing, and non-judgmental tone consistency. Developers can operationalise these cues by fine-tuning language models on clinically informed dialogue corpora, implementing emotion-sensitive response templates, and applying reinforcement learning signals that prioritise warmth, attentiveness, and psychological safety rather than mere informativeness. Importantly, empathic tone should be evaluated as a measurable interaction quality, for example through user-rated perceived support and comfort scales, rather than assumed as an inherent system property.

For digital mental health stakeholders, the findings indicate that emotional comfort is not simply an outcome, but a core mechanism sustaining engagement. Emotional comfort can be operationalised through design features that reduce distress and create a sense of safety, such as guided self-disclosure prompts, optional grounding exercises, calming response pacing, and explicit crisis-sensitive escalation messages when high-risk language is detected. Evaluation protocols should therefore include comfort-oriented metrics (e.g. perceived reassurance, reduced tension after interaction), alongside traditional usability indices. In this way, emotional comfort becomes a design target and governance indicator, not an abstract psychological by-product.

For conversational AI designers, the strong influence of perceived human-likeness implies that anthropomorphic cues must be carefully calibrated. Relational realism can enhance comfort and trust through fluent dialogue, socially familiar language, and interaction continuity. However, excessive human-likeness may also increase the risk of emotional over-trust, blurred boundaries, or perceived reciprocity that the system cannot genuinely provide. Practically, this calls for a balanced design approach: systems may adopt warm and human-like responsiveness, but should also incorporate transparent reminders of non-human status, clear capability boundaries, and safeguards against dependency. Human-likeness should therefore be treated as a tunable parameter rather than an unqualified design goal.

For UX teams, the results highlight that ease of use and behavioural control remain essential, particularly when users interact in vulnerable emotional states. Platforms should minimise cognitive load by offering intuitive conversation flows, low-effort input options, and user agency features such as adjustable interaction depth, opt-out controls, and the ability to redirect conversations. These design choices strengthen perceived behavioural control, ensuring that users experience the interaction as manageable rather than psychologically overwhelming.

For policymakers and organisations deploying empathic AI in mental wellbeing ecosystems, the HEAR findings suggest that conversational agents can function as low-threshold first-contact support tools, but only when framed responsibly. Governance frameworks should require transparency about system limitations, monitoring for over-reliance, and ethical guidelines concerning empathic simulation. Recent public concerns involving generative AI systems, including reports of harmful advice, deceptive behaviours, emotional dependency, and other safety-related incidents, further underscore the importance of responsible governance and user protection mechanisms. These cases highlight the need for clear safeguards, transparent communication of system limitations, and appropriate escalation pathways when users engage in emotionally sensitive interactions. In the Vietnamese context, these considerations are particularly relevant as AI adoption continues to expand across education, public services, and wellbeing-related domains. The present findings suggest that future AI governance efforts should not only promote innovation but also establish culturally appropriate safeguards, user literacy initiatives, and clear boundaries when conversational AI is used in emotionally sensitive contexts. Rather than positioning ChatGPT-like agents as substitutes for professional therapy, they should be deployed as supplementary companions that provide momentary reassurance while encouraging appropriate help-seeking pathways when needed.

Finally, educators and wellbeing programme coordinators may leverage emotionally supportive AI for resilience-building and self-reflection initiatives, particularly in contexts where mental health access is limited. However, such applications should be accompanied by literacy training that helps users understand both the benefits and boundaries of empathic AI, preventing unrealistic expectations and promoting responsible engagement. Overall, the HEAR model translates into actionable design and governance principles by showing that empathic AI retention depends on specific communicative cues, calibrated relational realism, measurable emotional comfort, and user agency. These insights provide practitioners with more concrete directions for building emotionally sensitive conversational systems that are not only engaging, but also ethically responsible.

6. Limitations and future research

Like many exploratory studies in emerging domains, this research is not without limitations. However, these constraints also present important avenues for future refinement and validation of the HEAR framework.

First, there are several methodological limitations that warrant consideration. This study was based on self-reported data collected at a single point in time. While such designs are commonly used in behavioural research, they may introduce potential biases such as social desirability or inaccuracies in recall. Although both procedural and statistical remedies were implemented to mitigate common method bias, the reliance on a single cross-sectional self-reported survey means that some residual risk of common method bias may still remain. Future studies could benefit from adopting longitudinal, experimental, or intervention-based designs to better capture behavioural changes over time. Additionally, while continuance usage intention serves as a strong behavioural proxy in many models, this study did not include actual usage data. Future research may enhance ecological validity by incorporating log-based behavioural tracking, digital diaries, or system-generated metrics to assess real-world engagement with AI systems. Moreover, the proposed model includes several higher-order (second-order) constructs, which may increase model complexity relative to the sample size. Although the overall model fit indices remain within acceptable ranges, future studies may further validate the HEAR framework using larger or independent samples and alternative modelling approaches. Additionally, the correlation between PSV and CUD was relatively high, suggesting substantial conceptual proximity between users' cognitive evaluation of ChatGPT and their disposition to continue using it. Although the two constructs were retained because they are theoretically distinct higher-order constructs grounded in different psychological mechanisms, the elevated correlation suggests that the distinction between value evaluation and continuance disposition may warrant further investigation in AI-mediated supportive interactions. Future research is encouraged to further examine the discriminant validity of these constructs across different populations, contexts, and AI systems. In addition, the subjective norm construct was measured using two items. Although the construct met all reliability and validity criteria, including acceptable composite reliability and average variance extracted, two-item constructs may be more sensitive to measurement error and may not fully capture the conceptual domain. Future research is encouraged to employ a more comprehensive set of indicators to enhance measurement robustness and stability.

Second, the contextual and psychological boundaries of the study should be acknowledged. Data were collected solely from Vietnamese users, which offers valuable cultural insights but limits generalisability. Cultural norms may influence how users perceive empathy, trust, and human-likeness in AI interactions. Therefore, comparative studies across different cultural settings are necessary to test the robustness and universality of the HEAR framework. Moreover, the study did not account for individual-level psychological differences such as personality traits, emotional regulation capacity, or prior experience with professional mental health support, all of which may affect how users respond to simulated empathy. Incorporating these dispositional or clinical variables could enrich the explanatory power of future models and provide more personalised insight into AI-mediated emotionally supportive interactions. Finally, this study highlights important ethical and system-specific considerations. ChatGPT, while capable of simulating empathy, should not be interpreted as a clinically validated therapeutic system. The present study examines users' perceptions of emotionally supportive interactions and continuance intention, rather than evaluating clinical outcomes or mental health interventions. While the system's perceived emotional responsiveness may encourage users to engage in emotionally vulnerable self-disclosure, it lacks the safeguards necessary for managing high-risk or crisis scenarios. Vowels (2024) observed that 'the chatbot did not sufficiently address safety concerns unless explicitly mentioned', suggesting that simulated empathy alone may be inadequate in ethically sensitive contexts. Future research should therefore explore how AI systems can integrate real-time risk detection mechanisms, establish clearer boundaries between emotionally supportive interaction and professional clinical care, and uphold ethical design and safety safeguards in emotionally sensitive contexts. In sum, while this study provides an integrative and empirically supported explanation of AI-mediated emotional engagement, future investigations should continue to expand its scope across different methodological approaches, cultural contexts, and ethical frameworks in order to strengthen both its theoretical robustness and its practical relevance.

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Ethical compliance

The research process involving human participants followed the ethical standards of the institutional and national research committees of the 1964 Helsinki Declaration and its subsequent amendments, as well as related ethical standards.

Ethics statement

The study adhered to the 'Regulations on Academic Integrity in Scientific and Technological activities at University of Economics Ho Chi Minh City (UEH) in 2024', issued under No. 4233/QĐ-ĐHKT-NCPTGKTC. Participants were fully assured of anonymity, and informed consent was obtained prior to data collection. Participation was entirely voluntary, and all responses were used exclusively for academic research purposes.

Data availability statement

Data will be made available on request.

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Appendices

Appendix 1. Measures

Perceived empathic communication
ChatGPT seemed to understand how I felt.
ChatGPT's responses reflected empathy.
I felt emotionally supported during my interaction with ChatGPT.
ChatGPT showed concern for my emotional well-being.
I felt that ChatGPT could understand my perspective.
I felt comfortable sharing personal emotions with ChatGPT.
ChatGPT made me feel less alone with my problems.
Perceived human-likeness
ChatGPT communicates in a natural and human-like way.
ChatGPT feels like I am talking to a real person.
ChatGPT gives responses that are lifelike and realistic.
Interacting with ChatGPT feels similar to talking to a human.
Perceived ease of use
I feel that ChatGPT is easy to use.
I find it easy to learn how to interact with ChatGPT.
Overall, I believe it is straightforward to work with ChatGPT.
Trust in ChatGPT
I feel I can rely on ChatGPT to do what it is supposed to do.
I believe ChatGPT provides accurate and reliable information.
I trust ChatGPT to provide helpful and appropriate responses when I need support
I trust ChatGPT to provide emotionally appropriate responses
Perceived usefulness
Using ChatGPT helps me manage my emotional well-being more effectively.
ChatGPT improves my ability to cope with stress or negative emotions.

(*Continued*)

Continued.

Perceived empathic communication
ChatGPT enhances my emotional resilience in daily life.
Overall, ChatGPT is useful for supporting my emotional and mental state.
Perceived behavioural control
I feel confident in my ability to use ChatGPT effectively.
Whether or not I use ChatGPT is entirely up to me.
I have full control over using ChatGPT whenever I want.
Emotional comfort
I felt emotionally comfortable after using ChatGPT.
ChatGPT helped me feel calm and emotionally stable.
I felt mentally relaxed during or after my interaction with ChatGPT.
I felt at ease expressing myself to ChatGPT.
ChatGPT gave me a sense of emotional security.
I experienced peace of mind after chatting with ChatGPT.
ChatGPT helped me feel emotionally supported, similar to talking to a real person.
Subjective norm
People who influence my behaviour think I should use ChatGPT.
People who are important to me think I should use ChatGPT.
Attitude towards using ChatGPT
I like the idea of using ChatGPT for emotional support.
I feel positive about using ChatGPT when I'm feeling emotionally low.
Overall, my attitude towards using ChatGPT for emotional support is favourable.
Continuance usage intention
I intend to continue using ChatGPT when I need emotional support.
I will always consider ChatGPT as a tool to help manage my emotions.
I will strongly recommend ChatGPT to others seeking emotional comfort.
I would like to keep interacting with ChatGPT when I feel emotionally stressed or alone.
I prefer using ChatGPT to express my thoughts and feelings, rather than turning to other sources.
I plan to frequently use ChatGPT to support my emotional well-being.

Appendix 2. CB-SEM from AMOS 20