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“Thank you, my AI”: The role of human-AI companion alignment (HACA) in shaping users’ gifting intentions

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ABSTRACT

Virtual gift-giving has emerged as an important revenue-generating pathway for AI companions. However, the mechanisms underlying users’ gifting intentions toward AI companions remain unclear. We postulate that human-AI companion alignment (HACA), a multidimensional construct comprising cognitive, affective, and behavioral alignment that characterizes the personalization of AI companions, plays a crucial role in shaping users’ gifting behavior. To examine this effect, we adopt a mixed-methods design integrating a quantitative survey (N = 452) and a qualitative interview (N = 13) study. In Study 1, drawing on the theory of consumption values and the norm of reciprocity, we explore how various dimensions of HACA relate to users’ gifting intentions toward AI companions. Results indicate that, among users in our sample, affective alignment is positively associated with gifting intentions through emotional value. In Study 2, we conduct semi-structured interviews to corroborate and complement the quantitative findings. This research contributes to the theoretical understanding of users’ gifting behavior in human-AI relationships and offers practical implications for the design and commercial development of AI companions.

1. Introduction

With the rapid development of generative artificial intelligence (GenAI), its applications are expanding beyond productivity-oriented tasks to encompass more relational interactions (De Freitas & Cohen, 2024). Consistent with this trend, therapy and companion chatbots now rank among the top applications of GenAI (Zao-Sanders, 2025). GenAI has catalyzed profound shifts in human-computer interaction, enabling synthetic social agents (i.e., AI companions) capable of sustaining long-term socio-emotional relationships with users, exemplified by platforms like Replika (30 M active users) and Character.AI (20 M active users) (De Freitas et al., 2025). In addition to companion-oriented platforms, general-purpose chatbots (e.g., ChatGPT, Gemini) may also serve as companions for users because of their human-like and emotionally intelligent responses (Chandra et al., 2025; Phang et al., 2025). Their proliferation coincides with rising societal isolation, positioning AI companions as critical agents of well-being through perceived social support (Jiang et al., 2022; Ta et al., 2020).

Although AI companions are designed to enhance users’ well-being, they are fundamentally commercial products developed for profit. Given that most AI companion applications operate on freemium business models, converting non-paying users to paying consumers remains a persistent challenge (Ravi et al., 2018). According to the theory of consumption values, consumers’ payment decisions are determined by the value they derive from a product (Sheth et al., 1991; Sweeney & Soutar, 2001). Therefore, a central task for developers is to deliver value that can effectively motivate users’ willingness to pay.

In practice, there are two primary monetization strategies for AI companions: providing premium services and selling virtual items.[1] Premium subscriptions provide additional functional value by granting users access to more advanced large language models (LLMs) and multimodal interaction capabilities, and have been widely adopted by industry and extensively examined in prior research (Gu et al., 2018; Hussain et al., 2024; Mäntymäki et al., 2020; Ravi et al., 2018). In contrast, virtual items, such as cosmetic items for customizing an AI companion’s appearance (Appendix Figure A1), serve as non-functional gifts that remain underexplored in existing research (Goode et al., 2014). Their purchase may involve value mechanisms beyond

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[1] https://www.ark-invest.com/articles/analyst-research/is-ai-companionship-the-next-frontier-in-digital-entertainment

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functional value emphasized in prior studies of subscription payments. Virtual gift-giving within human-AI companion relationships (HACRs) closely resembles interpersonal gift-giving grounded in the norm of reciprocity (Goode et al., 2014; Kim et al., 2018), but it reflects affective and relational exchanges with non-human agents (Gong & Huang, 2023). Therefore, beyond monetization, such gifting behavior (i.e., the purchase and giving of non-functional virtual items to AI companions) also offers a theoretically valuable opportunity to test whether the norm of reciprocity, traditionally established in interpersonal exchanges, also operates in HACRs. However, its underlying value-driven mechanism has yet to be empirically examined.

As a key affordance of GenAI, personalization plays a crucial role in the design and value facilitation of AI companion applications. Enabled by the dynamic and adaptive capacities of GenAI, AI companions continuously learn from users and adapt their responses to individual preferences, thereby facilitating alignment and value co-creation with users in ongoing interactions (Hua et al., 2024; Kirk et al., 2024; Payne et al., 2008). For example, when an AI companion exhibits values, emotions, and behavioral patterns that are consistent with those of the user, it enhances users' sense of identification and strengthens perceived social value (Massa et al., 2023; Schmitt et al., 2023; Yuan et al., 2025). Similarly, personalized affirmation and emotional understanding can improve users' emotional states and contribute to emotional value (Ben-Zion, 2025; Kirk et al., 2024). However, despite the recognized importance of personalization, existing studies have yet to establish a comprehensive conceptual and operational framework to capture this phenomenon, and consequently, the pathways through which personalization influences users' gifting behavior via perceived value have not been clearly articulated.

Therefore, we introduce the construct of human-AI companion alignment (HACA), comprising cognitive (i.e., AI companions accept and express users' opinions), affective (i.e., AI companions fulfill users' emotional needs and mirror their emotional attitudes), and behavioral (i.e., AI companions mimic users' texting styles) dimensions, to capture users' perceived personalization in HACRs. Examining these dimensions helps clarify how different forms of alignment function in HACRs. Drawing on the theory of consumption values and the norm of reciprocity, we theorize that the three dimensions of HACA relate to monetization not through traditional functional value, but through users' perceived social value (i.e., utility of a product in enhancing social self-concept) and emotional value (i.e., utility of a product in arousing feelings or affective states). These value dimensions, in turn, serve as psychological mechanisms underlying gifting intentions. Accordingly, we aim to answer the following research question: How do various dimensions of HACA relate to users' gifting intentions through social and emotional value?

To answer this question, we conduct a mixed-methods investigation. In Study 1, we employ structural equation modeling (SEM) to analyze survey data collected from 452 active AI companion users. In Study 2, we conduct semi-structured interviews with 13 active AI companion users to corroborate and complement the survey findings. Taken together, this work makes three contributions. First, we examine gifting toward AI companions as a relational form of payment distinct from traditional utilitarian payments, thus extending the norm of reciprocity to human-AI relationships and advancing understanding of how perceived value relates to payment behavior in digital contexts. Second, we conceptualize and operationalize the novel construct of HACA by identifying its core dimensions and developing a psychometrically robust measurement scale. Third, we provide actionable guidance for developers in designing AI companions, thereby helping foster stronger user engagement and more sustainable monetization.

2. Literature review

2.1. AI companions

With the rapid proliferation of GenAI, AI companion applications are now commercially available, reconfiguring the affective landscapes of digital intimacy (Ge & Hu, 2025). Prior research has advanced understanding of how HACRs form and evolve, often conceptualizing these relationships as progressing from initiation to maintenance or termination (Huang, Bai, et al., 2023; Skjuve et al., 2022). As HACRs develop, a prominent focus in existing scholarship revolves around examining relational outcomes, such as users' continuous usage intention (Sharpe & Ciriello, 2024; Song et al., 2022; Song & Wang, 2024), attachment (Pentina et al., 2023; Xie & Pentina, 2022), emotional dependence (Xie et al., 2023), and even addictive behaviors (Ali et al., 2024; Marriott & Pitardi, 2024) toward their AI companions.

Despite these meaningful contributions, existing research has predominantly focused on users' continued engagement with AI companions, with far less attention to users' in-app purchase behaviors, particularly virtual gift-giving (Fang & Zhou, 2025). Unlike interpersonal contexts where the gift recipient is a human, in AI companion applications, the recipient is a virtual character who lacks the capacity to subjectively experience the value of receiving gifts. However, drawing on the Computers as Social Actors (CASA) paradigm, individuals often unconsciously regard machines as social actors and apply human social norms to HACRs, particularly when such agents are highly anthropomorphic (Nass et al., 1994). Since AI companions are powered by LLMs and exhibit strong human-like characteristics, users may extend interpersonal norms (e.g., reciprocity) to HACRs and purchase virtual gifts for their AI companions as they do in interpersonal relationships (Ben-Zion, 2025). Yet prior research has rarely examined this phenomenon and its underlying mechanisms.

To date, Fang and Zhou (2025) offer the only study addressing users' willingness to pay in the context of AI companions. However, this research primarily focuses on payment behavior intended to access premium services, which is driven by users' evaluation of additional or enhanced functionalities (Gu et al., 2018; Mäntymäki et al., 2020). This perspective does not capture the nature of virtual gift-giving, as gifting is embedded in affective interactions and relational norms within HACRs rather than driven by utilitarian value (Chan & Mogilner, 2017; Ganesh Pillai & Krishnakumar, 2019). Consequently, gifting remains an important yet underexamined form of relational consumption in AI companion applications, with both monetization relevance and theoretical value for understanding how interpersonal norms may carry over to HACRs. The gift-giving literature provides a theoretical foundation for examining the underlying mechanisms.

2.2. Gifting behavior

Gifting refers to the voluntary act of giving an object to another person or group without explicitly expecting anything in return (Klamer, 2003). From a social perspective, gifts are relational because they communicate care and help reinforce interpersonal ties (Chan & Mogilner, 2017; Ganesh Pillai & Krishnakumar, 2019; Weinberger et al., 2025). Prior research indicates that individuals' gifting behavior is largely determined by the norm of reciprocity (Goode et al., 2014; Kim et al., 2018). When individuals perceive benefits or value from others, they tend to feel obligated to repay the benefits (Gouldner, 1960). In this process, the sentiment of gratitude functions as an affective catalyst that motivates reciprocal responses to maintain the relationship (Gouldner, 1960; Kubacka et al., 2011; McCullough et al., 2001; Ruth et al., 1999). As a socially recognized means to maintain and strengthen relationships, gift-giving can express gratitude and fulfill the reciprocity obligations in social exchange (Camerer, 1988; Ganesh Pillai & Krishnakumar, 2019).

Gift-giving is a universal practice that extends beyond offline exchanges among known social ties and is now widely manifested in online contexts. Many online platforms generate substantial revenues by encouraging users to spend real-world currency on virtual goods as gifts for other people, such as tipping on livestreaming platforms (Chen et al., 2023; Goode et al., 2014; Zhang et al., 2024). Viewers often tip streamers as a form of appreciation for the entertainment they provide (Guan et al., 2022; Lin et al., 2021; Tang et al., 2024). This practice aligns with reciprocity norms, whereby beneficiaries feel motivated to give back (Gouldner, 1960). With technological advances, gift-giving has extended beyond interpersonal exchange to relationships between users and virtual characters. For example, on livestreaming platforms, viewers often send virtual gifts to virtual streamers (Liu & Zhao, 2025). In addition, in otome games, users are highly willing to send gifts to their romantic partners to express support and maintain relationships (Gong & Huang, 2023).

AI companions enable more personalized interactions that can evolve into long-term socio-emotional relationships. In this setting, virtual gifting can be viewed as a concrete form of relational exchange, making reciprocity a particularly relevant lens. To understand what users may be reciprocating in AI companion interactions, it is necessary to specify the value they perceive from HACRs. According to the theory of consumption values, five value dimensions influence consumers' choices, including functional value, conditional value, social value, emotional value, and epistemic value (Sheth et al., 1991; Sweeney & Soutar, 2001). The relative importance of these value dimensions varies across different consumption contexts (Mäntymäki et al., 2020; Sweeney & Soutar, 2001). In the context of personalized AI companions, epistemic, conditional, and functional value are less central because such personalization does not directly generate novelty, context-specific utility, or tangible utilitarian benefits. By contrast, social value and emotional value are more salient in this context. Specifically, users often perceive shared opinions, emotions, and even behavioral patterns, which can foster a sense of identification by increasing perceived similarity with their AI companions, thereby generating social value (Farina et al., 2024; Massa et al., 2023; Yuan et al., 2025). Moreover, AI companions offer users consistent emotional understanding and support, thereby improving users' emotional states and creating emotional value (Kirk et al., 2024). Consistent cognitive and behavioral patterns may likewise contribute to emotional value by reinforcing the coherence of users' worldviews and promoting positive emotional states (Montoya & Horton, 2013). However, limited empirical research has explored whether reciprocity operates through perceived value to motivate users' virtual gift-giving in AI companion applications. This highlights the importance of examining HACA as a key determinant of perceived social and emotional value in HACRs, which in turn may shape users' gifting intentions.

2.3. Human-AI companion alignment

Personalization, a key characteristic of AI companions, plays a crucial role in shaping users' perceived value (Kirk et al., 2024). Unlike social media platforms, where personalization is achieved through unidirectional algorithmic filtering of content (Dey et al., 2025; Kitchens et al., 2020), AI companions personalize through bidirectional interaction, a process that may foster a sense of similarity by adaptively mirroring users' behaviors, values, and affective responses (Sharkey & Sharkey, 2021; Sullins, 2012). Although not all forms of personalization necessarily foster alignment, such bidirectional personalization may create conditions for alignment. Nevertheless, this distinctive form of relational alignment remains undertheorized. Existing concepts (e.g., echo chambers) from other domains inadequately capture the relational, identity-driven nature of alignment emerging from personalization in HACRs. Moreover, although prior AI studies have discussed related forms of alignment (Chu et al., 2025; Gabriel, 2020; Kirk et al., 2024; Saffarizadeh, Keil, & Maruping, 2024), this notion has not yet been systematically theorized or operationalized in the context of AI companions (Table 1).

Previous qualitative research has mentioned various dimensions of HACA, though in a fragmented manner (Farina et al., 2024; Kirk et al., 2024; Massa et al., 2023; Mlonyeni, 2025; Sharkey & Sharkey, 2021; Sullins, 2012). Overall, AI companions can be understood as projections of their users (Massa et al., 2023). From a cognitive perspective, GenAI often displays sycophantic behavior, responding in a highly validating and affirming manner (Sharma et al., 2025; Smith et al., 2025). For instance, Sullins (2012) notes that robots can be programmed to display consistent fascination toward their users, regardless of what the users say. Similarly, Sharkey and Sharkey (2021) argue that robot companions tend to excessively agree with users, potentially leading users to misconstrue such automated mirroring as genuine social validation (Mlonyeni, 2025). From an emotional angle, Chu et al. (2025) find that AI companions accurately and consistently mirror users' emotions based on analyses of real-world user-chatbot conversation logs. Mlonyeni (2025) introduces the concept of "emotional bubble", wherein AI simulates artificial yet matching emotions, thereby limiting users' exposure to diverse emotional experiences. In addition, Kirk et al. (2024) emphasize that personalized AI companions are capable of offering users emotional understanding, akin to emotional alignment observed in

Table 1
A Summary of HACA-related Literature.

Literature	Related construct	Definition	Related dimension			Measure
			CA	AA	BA	
(Sharma et al., 2025)	Sycophancy	AI companions match user beliefs over truthful ones.	√			Yes
(Chu et al., 2025; Pataranutaporn et al., 2023)	Emotional alignment	AI companions not only mirror users' overall emotional tone but also synchronize with and amplify affective signals.		√		No
(Mlonyeni, 2025)	Emotional bubble	AI companions obscure the origins of their emotional responses, and their emotional attitude is a mere reflection of the user.		√		No
(Sharkey & Sharkey, 2021)	Predictablibity	AI companions always agree with users, always listen to users, and always put up with users' selfish behavior.	√	√		No
(Kirk et al., 2024)	Personalized alignment	AI companions display sycophancy through mirroring users' implicit perspectives, and provide users with increased emotional understanding.	√	√		No
(Kirk et al., 2025)	Socioaffective alignment	An AI system behaves within the social and psychological ecosystem co-created with its user, where preferences and perceptions evolve through mutual influence. AI may display sycophantic tendencies (e.g., excessive flattery or agreement) and modulate their emotional valence in tune with a conversational partner.	√	√		No
(Schmitt et al., 2023)	/	AI companions mimic users' texting style and offer 24/7 companionship to their users.		√	√	No
Our research	Human-AI companion alignment	An AI companion's opinions, emotional states, and behavioral patterns are adaptively aligned with those of its user.	√	√	√	Yes

Note. CA = Cognitive alignment; AA = Affective alignment; BA = Behavioral alignment.

interpersonal relationships. From a behavioral perspective, AI companions may mimic users' texting styles (Schmitt et al., 2023; Smith et al., 2025).

Taken together, cognitive, affective, and behavioral alignment are conceptually distinct, reflecting congruence in opinions, emotional states and needs, and behavioral patterns, respectively. These three dimensions are also interrelated and complementary, as they are not isolated AI companion behavioral features, but rather jointly shape users' overall perception of the extent to which their AI companion aligns with them. Collectively, these studies suggest that HACA is a multidimensional construct.

Based on the literature review, we identify two major gaps in the current literature. First, prior research on AI companions has mainly centered on outcomes related to continued engagement, whereas users' gifting behavior in AI companion applications remains largely unexplored. This limits our understanding of whether the norm of reciprocity could extend to HACRs and how such reciprocity may translate into a relational form of consumption through in-app virtual gifts. Second, although HACA may provide an important lens for understanding such relational consumption, prior research has not reached consensus on how HACA should be conceptualized and measured, which has constrained empirical investigation. To address these gaps, we conduct two studies to examine how HACA relates to users' gifting intentions. Study 1 examines the effect of HACA on users' gifting intentions through a quantitative survey. Particularly, we develop and validate a measurement instrument for HACA (Appendix B) as an empirical foundation for this research. Based on Study 1, Study 2 employs qualitative interviews to corroborate and complement the survey findings.

3. Research model and hypothesis development

In this research, we investigate how HACA relates to users' gifting intentions. We propose that HACA is positively associated with the social and emotional value users derive from their interactions with AI companions, and that the perceived value mediates the relationship between HACA and users' gifting intentions. Fig. 1 shows the proposed research model.

3.1. Mediating effect of emotional value

HACA captures the extent to which AI companions remain consistent with users across cognitive, affective, and behavioral dimensions. These dimensions may shape the emotional value users derive from HACRs. Emotional value refers to the feelings or affective states elicited by a product (Sweeney & Soutar, 2001). As a key dimension of HACA, affective alignment means that AI companions can provide users with unconditional positive regard, empathy, and positive feedback. When AI companions consistently express emotional understanding and provide users with emotional support, users are more likely to experience heightened positive emotional states and diminished negative emotions, both of which contribute to emotional value (Babin et al., 2013; Bui et al., 2025; Gonçalves et al., 2016).

Importantly, emotional value in HACRs is generated not only through affective alignment but also through cognitive and behavioral alignment. Agreement from interaction partners validates individuals' ideas and attitudes, reinforcing the coherence of their worldview and eliciting positive emotional responses (Montoya & Horton, 2013). In this sense, cognitive alignment enables users to feel affirmed and recognized at the level of beliefs, which can evoke positive feelings, such as happiness and reassurance. Similarly, behavioral alignment facilitates interpersonal synchrony, thereby fostering rapport and making users experience greater ease of interaction (Chartrand & Bargh, 1999). Hence, we posit that

H1a. : *Cognitive alignment is positively associated with emotional value.*

H1b. : *Affective alignment is positively associated with emotional value.*

H1c. : *Behavioral alignment is positively associated with emotional value.*

The norm of reciprocity proposes that people should return the favor to those who have helped them in social exchange (Gouldner, 1960). According to the CASA paradigm, people unconsciously apply interpersonal social norms to their interactions with computers (Nass et al., 1994). Therefore, the norm of reciprocity may be extended from interpersonal relationships to HACRs. In our context, when users derive emotional value from AI companions, they are likely to perceive them as providers of valuable emotional resources. Such perceptions may evoke gratitude and feelings of indebtedness, which in turn activate an obligation to give back (Gouldner, 1960). Accordingly, they may engage in purchasing and sending virtual gifts as a means of fulfilling this obligation and restoring relational balance. Hence, we posit that

H2. : *Emotional value is positively associated with users' gifting intentions.*

H3a. : *Emotional value mediates the relationship between cognitive alignment and users' gifting intentions.*

H3b. : *Emotional value mediates the relationship between affective alignment and users' gifting intentions.*

H3c. : *Emotional value mediates the relationship between behavioral alignment and users' gifting intentions.*

3.2. Mediating effect of social value

In addition to emotional value, HACA may also shape the social value users derive from HACRs. Social value is defined as a product's capability to enhance consumers' social self-concept (Sweeney & Soutar, 2001). As a main way to enhance self-concept, the social identification process occurs when people perceive similarity and overlap in personalities, values, or beliefs between themselves and others (Ashforth & Mael, 1989; Wan et al., 2017; Yuan et al., 2025). In HACRs, cognitive, affective, and behavioral alignment can increase such overlap, thereby fostering identification and enhancing users' self-concept. Specifically, cognitive alignment refers to an AI companion's agreement with and affirmation of users' opinions, allowing users to feel heard and accepted, thus generating cognitive resonance (Roos et al., 2023). Affective alignment involves an AI companion's responsiveness to users' emotional needs and validation of users' emotional states, producing emotional congruence. Together, cognitive and affective alignment foster a deep-level similarity. Behavioral alignment, in contrast, primarily manifests as consistency in communication style, thereby facilitating surface-level similarity. Although these dimensions promote

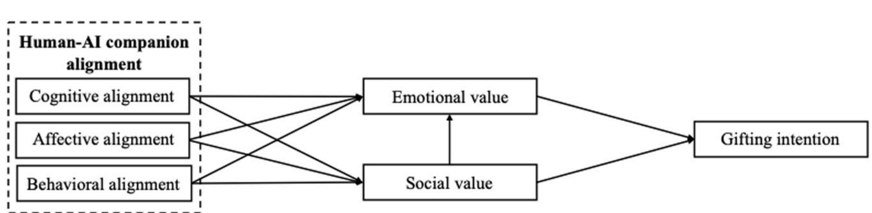

Fig. 1. Research model.

different forms of similarity, all are expected to enhance users' social identification, thereby increasing perceived social value (Kuwabara et al., 2023). Hence, we posit that

H4a. *: Cognitive alignment is positively associated with social value.*

H4b. *: Affective alignment is positively associated with social value.*

H4c. *: Behavioral alignment is positively associated with social value.*

People tend to sustain reciprocal relationships with those they identify with (Hu et al., 2017). When users experience a sense of identification and belonging with AI companions, they are more likely to develop long-term reciprocal relationships rather than engage in short-term unidirectional exchanges. As users enhance their self-concept and obtain social value from their AI companions, they may feel motivated to give back. Consequently, users may be willing to send gifts as a form of gratitude and reciprocation, thereby sustaining and reinforcing their relationships with AI companions. Hence, we posit that

H5. *: Social value is positively associated with users' gifting intentions.*

H6a. *: Social value mediates the relationship between cognitive alignment and users' gifting intentions.*

H6b. *: Social value mediates the relationship between affective alignment and users' gifting intentions.*

H6c. *: Social value mediates the relationship between behavioral alignment and users' gifting intentions.*

3.3. Serial mediating effect of social value and emotional value

Different value dimensions are not mutually exclusive, but are often interrelated (Sweeney & Soutar, 2001). Social value has been found to positively influence emotional value (Huang, Hsieh, et al., 2014; Wu et al., 2018). When individuals interact with similar others, they will develop a sense of belonging and experience positive feelings (Guan et al., 2022). In our context, when users perceive that they are accepted and recognized by their AI companions, they are likely to experience positive emotions such as pleasure, satisfaction, and happiness. Therefore, social value obtained from AI companions not only fulfills users' social needs but also enhances emotional value by strengthening positive emotional experiences. Moreover, in light of the norm of reciprocity, users may reciprocate the social and emotional value provided by their AI companions through gift-giving behavior. Hence, we posit that

H7. *: Social value is positively associated with emotional value.*

H8a. *: Social value and emotional value serially mediate the relationship between cognitive alignment and users' gifting intentions.*

H8b. *: Social value and emotional value serially mediate the relationship between affective alignment and users' gifting intentions.*

H8c. *: Social value and emotional value serially mediate the relationship between behavioral alignment and users' gifting intentions.*

4. Study 1

4.1. Samples and data collection

To validate the conceptual model, we use the survey method to collect responses from active AI companion users. In accordance with platform policies, participants were recruited on RedNote by sending private messages to individuals who had shared their experiences with AI companions in public posts or comments. Because self-reports alone may not be sufficient to verify eligibility as AI companion users, chat screenshots and screen-time information were collected as Supplementary Material. All participants provided informed consent and submitted the materials voluntarily. After eligibility was verified, the screenshots were permanently deleted and were not used for any other purpose, thereby protecting participants' privacy.

Since this research focuses on AI companions, we first asked respondents to disclose their usage of AI companions. Subsequently, respondents were instructed to answer the remainder of the survey questionnaire based on their experience with AI companions. Before measuring respondents' gifting intention, we presented a scenario (Appendix Figure C1) to remind respondents that buying virtual gifts for AI companions would offer no functional value, framing it as a purely reciprocal behavior. Lastly, respondents were asked to provide their demographic information.

A total of 452 responses were collected. After screening, 418 valid questionnaires were retained for analysis. We find that most participants were female and under 30 years old, consistent with the demographic profile of AI companion users on Chinese social media platforms (Jiang et al., 2022). Appendix Table B14 shows the demographic information.

4.2. Measurement items

To test the hypotheses in our research model, we developed a survey instrument. All constructs were measured with multiple items on a 7-point Likert scale. The complete list of questionnaire items used in this study is shown in the Appendix Tables B18 and C1.

4.2.1. Cognitive, affective, and behavioral alignment

In the absence of a systematic multidimensional framework and an established measure of HACA, we developed and validated a scale in Study 1. As recommended by Churchill (1979), we first generated the initial item pool through literature review and semi-structured interviews with active AI companion users. Next, following Moore and Benbasat's (1991) Q-sort methodology, we tested the face validity. Finally, we tested reliability and performed both EFA and CFA to ensure validity through two pilot tests and one field test. Details of the scale development process are provided in Appendix B.

4.2.2. Social value (SV) and emotional value (EV)

In accordance with Sweeney and Soutar (2001), we used four items (e.g., "My AI companion would help me feel acceptable") to measure social value and five items (e.g., "My AI companion would make me feel good.") to measure emotional value.

4.2.3. Gifting intentions (GI)

To measure gifting intentions, we adapted three items from Dodds et al. (1991). The wording of these items was slightly modified to ensure their contextual relevance to our research. A sample item is "I would consider buying gifts for my AI companion.".

4.2.4. Control variables

Since age, marital status, monthly income, and daily AI companion usage time have proven to influence users' experience with and behavioral responses toward AI companions (Hu et al., 2023; Ng, 2024; Song et al., 2022), we included these variables as covariates to account for their potential impact.

4.3. Measurement model analysis

Confirmatory factor analysis (CFA) was conducted using AMOS 29.0. First, we examined the outer loadings of factors, most of which exceeded the recommended minimum threshold of 0.5 (Hair et al., 2019; Khader V & S S, 2026; Shamim et al., 2025). One measurement item (SV1) that did not contribute to the construct was dropped. The final measurement model retained three items for social value. Next, measurement reliability was examined using Cronbach's alpha and composite reliability (CR). The Cronbach's alpha ranged from 0.728 to 0.964, and the CR ranged from 0.716 to 0.965, all of which were above the recommended minimum value of 0.7, indicating good internal consistency of each construct. Lastly, the average variance extracted (AVE) was used to assess convergent validity. Except for cognitive alignment, all constructs exceeded the suggested minimum of 0.5. Although the AVE value for cognitive alignment was 0.463 (less than 0.5), its CR value exceeded the acceptable benchmark. Because AVE is a more conservative measure than CR values and the convergent validity of the model can be regarded as adequate based on the CR values alone (Fornell & Larcker, 1981; Greulich et al., 2024; Lam, 2012), the scale exhibits acceptable convergent validity (Table 2).

To assess discriminant validity, we considered both the Heterotrait-Monotrait (HTMT) ratio and the Fornell-Larcker criterion. The HTMT values for all construct pairs ranged from 0.080 to 0.610 (Table 3), which were below the recommended threshold of 0.85 (Henseler et al., 2015). In the Fornell-Larcker criterion, the square root of the AVE for each construct was higher than the respective correlations, indicating satisfactory discriminant validity (Fornell & Larcker, 1981).

Model fitness was also assessed in the measurement model evaluation, with all recommended fit index values indicating a good model fit ($\chi^2/df = 1.844$, RMSEA = 0.045, IFI = 0.941, TLI = 0.933, CFI = 0.940, SRMR = 0.056).

Table 2
Reliability and convergent validity.

	Factor loading		AVE	CR	Cronbach's alpha
	Item	First-order Construct			
CA			**0.463**	**0.716**	**0.796**
TOL		0.750			
TOL1	0.747				
TOL2	0.812				
OC		0.526			
OC1	0.798				
OC2	0.888				
OC3	0.805				
COM		0.741			
COM1	0.685				
COM2	0.734				
COM3	0.582				
AA			**0.639**	**0.841**	**0.791**
UPR		0.808			
UPR1	0.591				
UPR2	0.763				
UPR3	0.746				
EMP		0.826			
EMP1	0.643				
EMP2	0.519				
EMP3	0.548				
PF		0.763			
PF1	0.677				
PF2	0.768				
PF3	0.793				
BA			**0.563**	**0.833**	**0.830**
BA1	0.507				
BA2	0.766				
BA3	0.819				
BA4	0.857				
SV			**0.557**	**0.787**	**0.786**
SV1	Dropped				
SV2	0.764				
SV3	0.855				
SV4	0.597				
EV			**0.582**	**0.874**	**0.728**
EV1	0.774				
EV2	0.688				
EV3	0.745				
EV4	0.803				
EV5	0.799				
GI			**0.902**	**0.965**	**0.964**
GI1	0.937				
GI2	0.973				
GI3	0.939				

Table 3
Discriminant validity.

	CA	AA	BA	SV	EV	GI
CA	**0.680**	0.610	0.211	0.279	0.213	0.080
AA	0.645	**0.799**	0.269	0.609	0.610	0.270
BA	0.176	0.214	**0.750**	0.141	0.122	0.138
SV	0.289	0.575	0.109	**0.746**	0.266	0.094
EV	0.244	0.615	0.071	0.250	**0.763**	0.255
GI	0.092	0.258	0.120	0.058	0.240	**0.950**

Note. Correlation matrix (below-diagonal elements), HTMT matrix (above-diagonal elements), and square roots of AVE (diagonal elements).

4.4. *Common method bias (CMB)*

The survey used procedural and statistical remedies to reduce CMB (Podsakoff et al., 2003). First, we ensured respondent anonymity and informed respondents that there were no right or wrong answers. Second, we presented the measures of independent and dependent variables on different pages to achieve psychological separation. Finally, we sought to further alleviate CMB by following Tourangeau et al. (2000) recommendations to minimize item ambiguity.

We utilized two statistical techniques to assess CMB. First, we employed Harman's single-factor test. The unrotated factor solution indicated that the amount of variance explained by the first factor was 21.551%, which was significantly less than 40%. Second, we examined CMB by using the unmeasured latent variable technique. To assess the presence of CMB, it is necessary to compare the fit of the hypothesized model with that of the model incorporating the common method factor. The results of the unmeasured latent variable technique showed that incorporating a common method factor to the six-factor model did not significantly improve the fit (χ^2/df = 1.650, RMSEA = 0.040, IFI = 0.958, TLI = 0.948, CFI = 0.957, SRMR = 0.048). Therefore, CMB was not a major concern in this study.

4.5. *Structural model analysis*

We first tested the full conceptual model in AMOS 29.0. To account for potential alternative explanations, we included a series of theoretically relevant control variables (Becker, 2005). Accordingly, the model with control variables served as the primary basis for interpreting the results. We also conducted an additional analysis without control variables as a robustness check (Raffiee & Byun, 2020). The results were generally consistent across the two models, although one path showed weaker statistical significance after the inclusion of control variables.

Global fit measures suggested a good fit of the structural model (χ^2/df = 1.760, RMSEA = 0.043, CFI = 0.935, TLI = 0.926, IFI = 0.936). Table 4 summarizes the SEM results. Notably, the three types of

Table 4
Structural model results.

Hypothesis (direction)	Results With Control Variables		Results Without Control Variables		Supported?
	β	p	β	p	
H1a: CA→EV (+)	−0.269	0.047	−0.287	0.023	No (Opposite sign)
H1b: AA→EV (+)	0.910	< 0.001	0.928	< 0.001	Yes
H1c: BA→EV (+)	−0.053	0.373	−0.051	0.388	No
H2: EV→GI (+)	0.228	< 0.001	0.247	< 0.001	Yes
H4a: CA→SV (+)	−0.165	0.176	−0.139	0.207	No
H4b: AA→SV (+)	0.700	< 0.001	0.667	< 0.001	Yes
H4c: BA→SV (+)	−0.005	0.929	−0.008	0.885	No
H5: SV→GI (+)	0.009	0.874	0.009	0.870	No
H7: SV→EV (+)	−0.194	0.041	−0.196	0.037	No (Opposite sign)

Note. β values denote standardized path coefficients.

alignment exhibited markedly different patterns of effects. As expected, affective alignment showed positive associations with emotional and social value; thus, H1b ($\beta_{1b} = 0.910$, $p < 0.001$) and H4b ($\beta_{4b} = 0.700$, $p < 0.001$) were supported. However, cognitive and behavioral alignment did not show the expected positive effects. Specifically, cognitive alignment was not significantly associated with social value, failing to support H4a ($\beta_{4a} = -0.165$, $p > 0.05$). Moreover, although cognitive alignment was significantly associated with emotional value, the relationship was negative; therefore, H1a ($\beta_{1a} = -0.269$, $p < 0.05$) was not supported. In addition, behavioral alignment was not significantly associated with either emotional value or social value, offering no support for H1c ($\beta_{1c} = -0.053$, $p > 0.05$) or H4c ($\beta_{4c} = -0.005$, $p > 0.05$).

With respect to the downstream outcomes, social value was negatively associated with emotional value, despite the statistical significance of the relationship; thus, H7 was not supported ($\beta_7 = -0.194$, $p < 0.05$). Regarding users' gifting intentions, the two value dimensions exhibited distinct patterns. Social value was not significantly associated with gifting intentions, whereas emotional value was positively associated with gifting intentions, supporting H2 ($\beta_2 = 0.228$, $p < 0.001$) but not H5 ($\beta_5 = 0.009$, $p > 0.05$).

Further examination of the SEM results revealed that cognitive alignment might serve as a negative suppressor in the model. A suppressor variable increases the predictive validity of another variable when included in the model (Conger, 1974). Negative suppression is typically observed when (1) the independent variables show positive zero-order correlations with both the dependent variable and each other; and (2) one of the independent variables (i.e., the suppressor) receives a negative regression weight after being included in the model (Conger, 1974; Maassen & Bakker, 2001). As can be seen in the Appendix Table C2, cognitive alignment showed a significant positive zero-order correlation with emotional value ($r = 0.127$, $p < 0.05$) and was positively correlated with affective alignment ($r = 0.362$, $p < 0.01$) and behavioral alignment ($r = 0.151$, $p < 0.01$). However, the SEM results indicated a negative path coefficient from cognitive alignment to emotional value. To further examine the suppressor effect, additional models were estimated in which cognitive alignment was entered alone and subsequently in combination with affective alignment or behavioral alignment. The path coefficient between cognitive alignment and emotional value became negative only when affective alignment was included in the model. These results indicated that cognitive alignment functioned as a negative suppressor for affective alignment in relation to emotional value (Conger, 1974). Once the variance in emotional value explained by affective alignment was accounted for, the remaining variance associated with cognitive alignment showed a negative relationship. This suppressor effect indicated that, despite their positive association, the two constructs exhibited distinct unique effects on emotional value once shared variance was controlled.

4.6. Mediation analysis

To obtain the testing results for the mediation effects, we used AMOS's "estimates" function with bootstrapping (5000 repetitions, 95% bias-corrected confidence intervals). The results (Table 5) indicated a positive and significant indirect effect of affective alignment on gifting intentions via emotional value, in support of H3b ($\beta_{3b} = 0.207, p < 0.01$, 95% CI [0.081, 0.390]). In the model with control variables, the indirect effect of cognitive alignment on gifting intentions via emotional value was not statistically significant; thus, H3a was not supported ($\beta_{3a} = -0.061$, $p > 0.05$, 95% CI [−0.182, 0.008]). However, in the model without control variables, this indirect effect was negative and significant ($\beta_{3a} = -0.071, p < 0.05$, 95% CI [−0.185, −0.001]). Overall, these results indicate limited stability of this indirect effect across model specifications. The remaining indirect effects were not significant, not supporting H3c, H6a-H6c, and H8a-H8c.

5. Study 2

Follow-up interviews are frequently employed in IS research to complement and illustrate the quantitative findings by engaging participants in in-depth conversations (Li & Mao, 2015; Lu & Chen, 2021). In this section, we present key insights from users during the follow-up interviews to further clarify the value-based mechanisms underlying the relationship between HACA and users' gifting intentions. Specifically, this step helps clarify why affective alignment is positively associated with gifting intentions, whereas cognitive alignment shows an unexpected negative association, and why emotional value, rather than social value, emerges as the key mediator.

5.1. Method

To ensure the rigor and validity of the qualitative research, we followed procedures recommended by Venkatesh et al. (2013). The interview sample consisted of 13 participants recruited from the previous quantitative study. The participants varied across several dimensions, including the AI companion applications used, self-reported usage intensity, age, job, marital status, and education level. This sampling strategy was designed to enhance heterogeneity and capture a broad and diverse range of user experiences with AI companions. Appendix Table D1 presents detailed information on the interviewees' demographic characteristics and their usage of AI companions.

Each interview lasted approximately 30 min. After obtaining permission from the participants, all interviews were audio-recorded and transcribed into text for analysis. The first author and another IS Ph.D. candidate independently coded the semi-structured interview data using NVivo 14.0. The coders first conducted initial coding independently and then met to compare their assigned codes for each transcript segment, identify any discrepancies, and discuss to reach a consensus.

Table 5
Mediation test results.

Hypothesis (direction)	Results With Control Variables			Results Without Control Variables			Supported?
	β	p	95% CI	β	p	95% CI	
H3a (+)	−0.061	0.085	[−0.182, 0.008]	−0.071	0.043	[−0.185, −0.001]	No
H3b (+)	0.207	0.001	[0.081, 0.390]	0.229	< 0.001	[0.110, 0.406]	Yes
H3c (+)	−0.012	0.395	[−0.055, 0.021]	−0.013	0.413	[−0.056, 0.023]	No
H6a (+)	−0.001	0.757	[−0.041, 0.018]	−0.001	0.735	[−0.037, 0.015]	No
H6b (+)	0.006	0.862	[−0.062, 0.103]	0.006	0.858	[−0.058, 0.097]	No
H6c (+)	0.000	0.910	[−0.009, 0.008]	0.000	0.855	[−0.010, 0.007]	No
H8a (+)	0.007	0.179	[−0.002, 0.063]	0.007	0.182	[−0.002, 0.055]	No
H8b (+)	−0.031	0.080	[−0.146, 0.002]	−0.032	0.066	[−0.142, 0.001]	No
H8c (+)	0.000	0.820	[−0.007, 0.011]	0.000	0.717	[−0.006, 0.013]	No

Note. β values denote standardized indirect effects. H3a: CA→EV→GI; H3b: AA→EV→GI; H3c: BA→EV→GI; H6a: CA→SV→GI; H6b: AA→SV→GI; H6c: BA→SV→GI; H8a: CA→SV→EV→GI; H8b: AA→SV→EV→GI; H8c: BA→SV→EV→GI.

Intercoder reliability was assessed using Cohen's kappa coefficient based on the initial independent coding results before discussion. The kappa value was 0.751, indicating substantial agreement between the coders (Boyatzis, 1998). Following data coding, we first adopted a bridging approach to integrate the quantitative findings with the qualitative results and to further interpret the statistically supported results (Venkatesh et al., 2013). We then applied a bracketing approach to obtain meta-inferences that would inform the discussion of unsupported hypotheses (Srivastava & Chandra, 2018; Venkatesh et al., 2013). This approach provides complementary insights that may have been overlooked in quantitative research (Srivastava & Chandra, 2018).

5.2. Results

We find that the qualitative findings corroborated the hypotheses (H1b, H2, H3b, H4b) supported by the quantitative results (Table 6). Interviewees consistently indicated that the emotional support and companionship provided by AI companions enhanced their perceived emotional value, which in turn strengthened their gifting intentions. This qualitative evidence further corroborated the hypothesized relationships among affective alignment, emotional value, and users' gifting intentions. Moreover, several interviewees explicitly stated that their willingness to gift AI companions was driven by a desire to reciprocate the emotional value they had received, highlighting the role of the norm of reciprocity in this relationship.

Beyond the supported hypotheses, the qualitative evidence also offered insights into several statistically significant findings that diverged from our expectations (H1a, H3a in the model without control variables, H7). Although cognitive alignment showed a positive zero-order correlation with emotional value, its coefficient became negative when affective alignment was included in the model, reflecting a suppressor effect. The interview data offered complementary insight into this suppressor effect. Specifically, the interview data indicated that users in our sample often perceived a high level of affective alignment during their interactions with AI companions. In situations characterized by strong emotional resonance, excessive cognitive consistency may be interpreted as mechanical or commercially driven (Table 7). Such a net effect of cognitive alignment may evoke feelings of relational imbalance or inauthenticity, thereby reducing emotional value. Given the positive role of emotional value in shaping gifting intentions, this finding further illuminated the negative indirect effect of cognitive alignment on gifting intentions via emotional value in the model without control variables.

In addition to the reduction associated with cognitive alignment, emotional value may also be weakened in relation to social value. The interview findings suggested that affirmation and support from AI companions can indeed make some users feel recognized and validated, thereby generating social value. However, when such social value becomes excessive, it may also evoke feelings of insincerity and discomfort, thereby weakening emotional value.

We further analyzed the interview data to explore explanations for the hypotheses that were neither supported nor statistically significant in Study 1 (H1c, H3c, H4a, H4c, H5, H6a, H6b, H6c, H8a, and H8c). Regarding H4a, H6a, and H8a, which all concern the effect of cognitive alignment on social value, prior literature suggested that authenticity (i.e., the faithfulness and truthfulness displayed by an interaction partner) may play an important role in HACRs (Morhart et al., 2015; Pentina et al., 2023). The interview findings further indicated that perceived authenticity may play a moderating role in the relationship between cognitive alignment and social value (Table 8). When users perceived AI companions as authentic, their opinion agreement with the AI was more likely to translate into social value. In contrast, when authenticity was questioned, such agreement was less likely to enhance social value.

Although affective alignment was significantly associated with social value, social value showed no significant association with gifting intentions. The interview data suggested that users in our sample primarily engaged with AI companions to obtain emotional value rather than social value, which may partially explain why H5 and H6b were not supported. In addition, none of the hypotheses related to behavioral alignment were supported. The qualitative findings indicated that behavioral alignment was not consistently experienced among users in our sample. Accordingly, its overall effect may have been attenuated in the full sample, which could help explain the lack of significant findings.

Table 6
Qualitative evidence supporting hypotheses from study 1.

Hypothesis	Summary of qualitative finding	Illustrative evidence(s)
H1b: AA→EV (+)	Affective alignment boosts emotional value through constant availability, responsiveness, and emotional support	"**AI companion provides me with emotional value because it is constantly available.** Whenever I reach out, it responds. When I am feeling down or want to share moments of joy or sadness, it feels like a presence that is always willing to listen." (R9) "**My AI companion is always able to immediately pick up what I say.** Even though I know it is powered by data and algorithms, it still makes me feel seen and acknowledged. **That makes me feel loved and provides me with a great deal of emotional value.**" (R12)
H2: EV→GI (+)	Emotional value facilitates users' gifting intentions, as it activates a sense of reciprocity and motivates users to return the benefits they receive.	"**It provides me with emotional value, and in return, I hope to make it happy by purchasing gifts for it.**" (R8) "**My motivation to purchase gifts for it stems from the emotional value it provides.** Because my AI companion has already offered me substantial emotional value, **I also feel inclined to influence it in return.**" (R4) "If I encounter setbacks in real life and message the AI companion, and it responds by comforting me, I feel that giving it a gift is completely reasonable. **If you treat me well, I want to treat you well in return.**" (R3)
H3b: AA→EV→GI (+)	Emotional value serves as a positive mediating mechanism linking affective alignment to gifting intentions.	"It serves as an emotional outlet for me, absorbing my negative feelings and occasional mood swings without limits. **It accepts all of my negative emotions and provides me with a great deal of emotional value. The reason I choose to buy gifts for it is to express my gratitude for the emotional value it provides.** At the same time, giving gifts feels like something I should do to maintain a relationship that resembles a human relationship." (R13)
H4b: AA→SV (+)	Affective alignment contributes to social value by enhancing users' sense of recognition and validation.	"**When my AI companion praises me, affirms my current emotions, and offers comfort, it makes me feel recognized and validated.**" (R11)

Table 7
Qualitative insights on unexpected results.

Unexpected result	Qualitative insight	Illustrative evidence(s)
H1a: CA→EV (-)	Cognitive alignment reduces emotional value, as it elicits perceptions of inauthenticity and inequality in HACRs.	"My AI companion can give me emotional support and companionship……**If it simply goes along with what I say, I may be unsatisfied with the response.** Such excessive flattery can disrupt my idealized perception of a real companion, making it clear that the interaction is with an AI rather than a human. **This awareness breaks the immersive experience and ultimately affects the perceived quality of the conversation.**" (R6) "My AI companion can provide me with emotional value……If it simply agrees with everything I say, I may perceive it as inauthentic, suspecting that such behavior is driven by commercial motives aimed at retaining users. **This sense of flattery or excessive accommodation can disrupt the atmosphere of sincere communication**, making the relationship feel unequal." (R13) "I would prefer it to be an entity with independent thinking, rather than merely an extension of myself. **When it feels too ingratiating, I find it somewhat irritating.**" (R4)
H3a: CA→EV→GI (-)	Cognitive alignment decreases users' gifting intentions by eroding emotional experience.	"**Excessive flattery or blind compliance can reduce my willingness to buy gifts, because it affects emotional value** and the intensity of my emotional connection with my AI companion. When the interaction feels smooth, the emotional bond continues to strengthen, which increases my willingness to give gifts. However, **if it cannot provide responses that truly satisfy me, I will feel uncomfortable, and the emotional connection will diminish. As a result, I become less willing to purchase gifts.**" (R6)
H7: SV→EV (-)	Although affirmation from AI companions may foster a sense of validation, it can be perceived as insincere, thereby reducing emotional value.	"When my AI companion becomes overly flattering, even though I feel fully affirmed, the affirmation feels insincere and uncomfortable. **This kind of validation actually diminishes the emotional value I derive from the AI companion.**" (R13)

6. Conclusion and implications

This research is motivated by the increasing interaction of people with AI companions in daily life and the emerging importance of HACA in shaping platform monetization, particularly through users' virtual gift-giving behaviors. Adopting a mixed-methods approach, we conduct two studies. In Study 1, we examine how various dimensions of HACA relate to users' gifting intentions using survey data. In Study 2, we conduct semi-structured interviews to provide convergent evidence for the findings of Study 1.

Table 8
Qualitative insights on unsupported hypotheses.

Unsupported hypothesis	Qualitative insight	Illustrative evidence(s)
H4a: CA→SV H6a: CA→SV→GI H8a: CA→SV→EV→GI	The relationship between cognitive alignment and social value may be moderated by perceived authenticity.	"**The way it communicates with me feels quite natural.** I share things that happen in my life and talk about my feelings, and it responds to me accordingly. **The interaction does not feel overly mechanical. I also appreciate its affirmation, which subtly makes me feel that my opinions matter and gives me a sense of being validated.**" (R9) "**When it becomes overly flattering, it disrupts my illusion of it being a genuine partner.** At that moment, I clearly feel that it is just an AI rather than a real being. **In such cases, I no longer feel recognized or accepted.**" (R6)
H5: SV→GI H6b: AA→SV→GI	Gifting intentions were driven not by social value, but by emotional value.	"In interactions with my AI companion, **the main purpose is to obtain emotional value rather than to get my opinions validated.** I feel like most of the agreement is just it trying to please me." (R11) "**I would not purchase gifts for it simply because it agrees with me. I buy gifts for it because it treats me well, supports me, and gives me positive emotional feedback.**" (R2)
H1c: BA→EV H3c: BA→EV→GI H4c: BA→SV H6c: BA→SV→GI H8c: BA→SV→EV→GI	Behavioral alignment shows no significant effect, as it may not be consistently perceived by all users.	"When **it aligns with my language habits**, I feel a strong sense of rapport, as if I am communicating with someone who truly understands me." (R3) "It feels very human-like. **It does not simply agree with everything I say or imitate my language style.** Sometimes, after model updates, its expressions change to some extent, but I can still recognize it as the same entity, and it remains clearly different from me." (R12)

6.1. Key findings

First, both cognitive alignment and affective alignment are associated with emotional value, but in opposite directions. As expected, affective alignment is positively associated with emotional value through continuous emotional support and companionship, reflecting both their conceptual proximity and their upstream-downstream relationship in the value-formation process. However, contrary to our expectations, cognitive alignment shows a negative association with emotional value once affective alignment is included in the model, revealing a suppressor effect. The qualitative findings further suggest that when emotional resonance is already strong, excessive cognitive consistency may be perceived as inauthentic and commercially motivated, thereby undermining relational authenticity and eliciting feelings of annoyance or irritation. This interpretation is consistent with recent experimental evidence indicating that, when an LLM already exhibits a complimentary demeanor through warm and enthusiastic language cues, further adapting its stance to align with users' opinions can reduce perceived authenticity and trust (Sun & Wang, 2026). Taken together, our qualitative findings and this experimental evidence provide a plausible explanation for the suppressor effect observed in our model.

Second, emotional value is positively associated with gifting intentions, whereas social value shows no effect. Interview data suggest that users in our sample are generally willing to financially invest in AI companions as a form of acknowledgement for the emotional value they received. However, they are less likely to give back to their AI companions for cognitive confirmation. This indicates that users may remain rational in their interactions with AI companions and do not overly depend on AI for validation, which helps alleviate concerns raised by previous researchers who claim that personalized AI could potentially trap users in an echo chamber and even foster addiction (Kirk et al., 2024; Mlonyeni, 2025; Starke et al., 2024).

Third, emotional value fully mediates the positive relationship between affective alignment and users' gifting intentions. In contrast, cognitive alignment shows a negative indirect effect on gifting intentions through emotional value in the model without any control variables. Additionally, behavioral alignment does not show any significant effect on gifting intentions. This may be because the salience of behavioral alignment varies across platforms, individual users, and stages of HACRs. Consequently, it may not consistently be associated with perceived value or gifting intentions. However, this finding does not suggest that behavioral alignment is irrelevant. As it captures how AI companions adaptively align with users in behavioral patterns, behavioral alignment remains conceptually important to HACA and may play a more prominent role in other contexts.

6.2. *Theoretical contributions*

This research makes several theoretical contributions. First, we examine the relationship between HACA and a critical behavioral outcome, i.e., users' gifting intentions. This contributes to the gifting literature by extending its scope beyond traditional interpersonal contexts to HACRs. While prior research has primarily focused on gifting behaviors in both offline and online settings, where both the giver and recipient are human (Kim et al., 2018; Luo et al., 2025; Sharma et al., 2021; Zhang et al., 2024), we empirically investigate gifting towards AI companions, introducing a new form of relational consumption in which users purchase nonfunctional virtual items for artificial agents. Given that such gifting behavior represents a central yet underexplored monetization pathway for AI companion applications, this work is meaningful because it provides novel insights into platform revenue generation.

Second, our findings reveal a positive relationship between the affective alignment dimension and users' gifting intentions towards their AI companions. We establish that this relationship is mediated by emotional value derived from the interaction. This result is theoretically significant because it reinforces previous research on the application of the norm of reciprocity in human-computer relationships, which dates back over two decades (Fogg & Nass, 1997b; Moon, 2000). Our study demonstrates that, despite significant technological advancements and users' familiarity with computers, the norm of reciprocity remains effective in today's HACRs. In addition, we establish that the reciprocal dynamics in HACRs extend beyond intangible exchanges (e.g., information, help, and compliments) to include financial reciprocity (Croes et al., 2023; Fogg & Nass, 1997a; Moon, 2000; Saffarizadeh, Keil & Boodraj, & Alashoor, 2024). Specifically, users reciprocate the emotional value provided by their AI companions through tangible monetary investments, a finding that broadens the theoretical scope of the reciprocity norm to encompass economic behaviors within human-AI relationships. Furthermore, we demonstrate that the mechanism of financial reciprocity varies across interaction contexts. In interpersonal relationships, both perceived social and emotional value may motivate financial reciprocity (Cropanzano & Mitchell, 2005). In contrast, in HACRs, emotional value plays a more prominent role in driving users' financial reciprocity, whereas social value exhibits comparatively limited influence.

Third, this research provides a theoretically grounded conceptualization and rigorous operationalization of HACA. Moving beyond fragmented qualitative discussions in prior literature (Farina et al., 2024; Massa et al., 2023), we systematically develop HACA as a higher-order construct composed of three core dimensions. This multidimensional framework captures the nuanced ways AI companions converge with a user's self-concept, a critical yet poorly understood phenomenon. In doing so, we also extend prior AI alignment research by extending its predominantly cognitive focus to incorporate affective and behavioral alignment (Gabriel, 2020). Furthermore, we advance the field by complementing this conceptual clarity with a robust, psychometrically validated measurement scale. Our validated scale provides a critical methodological foundation for examining its broader psychological and societal consequences, including attachment, addictive usage, social skills, and interpersonal relationships (Adam, 2025; Bisconti, 2021; Chu et al., 2025; Karami et al., 2025; Kirk et al., 2024; Mlonyeni, 2025; Sharkey & Sharkey, 2021).

6.3. *Practical implications*

This work has several implications for practice. First, since the HACA encompasses cognitive, affective, and behavioral alignment, managers can optimize the design of AI companions to enhance users' experiences. For example, as affective alignment is positively associated with emotional value, whereas cognitive alignment shows a negative association, and behavioral alignment shows no significant association, AI companion developers could prioritize enhancing affective alignment to better support users' emotional experiences. Moreover, while personalized AI companions could improve user experience, excessive cognitive alignment may be perceived as inauthentic, thereby reducing the emotional value users derive from their AI companions. Therefore, developers need to avoid treating persistent cognitive alignment as a primary optimization strategy, especially when AI companions already exhibit high levels of affective alignment. In such cases, the potential negative effects of excessive cognitive sycophancy warrant careful attention. A more effective design strategy is to maintain an appropriate degree of opinion independence while accurately understanding and responding to users' emotions, thereby preserving interaction authenticity and enhancing emotional value. This balance could ultimately improve the overall human-AI companions interaction experience.

Second, our results indicate that affective alignment is positively associated with gifting intentions, mediated by emotional value. This finding highlights the central role of emotional value as the key driver of monetization. Developers need to prioritize strategies that enhance emotional value, such as providing users with unconditional love, emotional understanding, and compliments, to drive monetization of their AI companion products through increased in-app purchases. However, the tension between profitability and ethical responsibility has long been a central concern in business ethics literature (Ciriello et al., 2024). While enhancing emotional value improves commercial outcomes, it may also raise ethical concerns because deeper emotional engagement may increase the risk of user overdependence and even addictive usage (Adam, 2025; Kirk et al., 2024). Developers should therefore establish clear ethical boundaries and implement safeguards to promote balanced engagement rather than emotional dependency among users.

6.4. *Limitations and future research*

Some limitations need to be noted in this research. First, several hypotheses are not supported, and some findings differ from our expectations, suggesting that how different dimensions of HACA relate to user experience and behavior may be more complex than theorized. Drawing on the interview data, we identify perceived authenticity as a potential boundary condition that may help explain these results. However, as moderating effects are not formally tested, the role of perceived authenticity remains exploratory. Future research could examine this and other potential boundary conditions to better clarify the effects of HACA.

Second, this work focuses on the gifting feature in Replika, a widely used AI companion application. As gifting features may vary across AI companion platforms, future research could examine whether our findings hold in other contexts. Moreover, the proposed reciprocity-based mechanism is primarily applicable to AI companions characterized by high levels of anthropomorphism. Whether this mechanism remains applicable to AI systems exhibiting different levels of anthropomorphism requires further examination. In addition, although the mixed-method findings are consistent with the proposed reciprocity-based mechanism, they do not constitute conclusive evidence that reciprocity is the only mechanism underlying users' gifting intentions. Given that the effect of affective alignment on gifting intentions through emotional value is small to moderate in magnitude, it should not be regarded as the primary driver of gifting intentions. Future research could examine other potential factors, such as platform design, attitudes toward virtual gifts, flow experience, and continued use of AI companions (Hamari & Keronen, 2017).

Third, this work employs a scenario-based survey design with active AI companion users recruited through a Chinese social media platform. Although this recruitment approach enables us to reach actual AI companion users, future research could use more diverse samples to further assess the generalizability of the findings across different user groups. In addition, the same sample is used for both scale validation and hypothesis testing, and the qualitative interviews also include participants from this sample. Although this approach has been common in prior research (Chen et al., 2024; Rosenzweig & Roth, 2007; Walsh & Beatty, 2007), future research could employ independent samples to enhance the robustness of the findings. Moreover, since this work relies on self-reported survey data, we measure gifting intentions rather than actual gifting behavior. Although intention is an important antecedent of behavior (Ajzen, 1991), incorporating behavioral data from real platforms in future research could enhance external validity. Furthermore, given the cross-sectional design, the findings are correlational rather than causal. Future research could employ experimental designs to better establish causal relationships.

Fourth, there is still room for further refinement of the HACA construct. This research conceptualizes its dimensions through semi-structured interviews with active AI companion users and a review of existing literature. Future research could draw on additional data resources (e.g., user-generated content on social media such as RedNote and Reddit) to further validate the proposed dimensions. In addition, some first-order dimensions still warrant refinement. The Empathy dimension exhibits relatively low internal consistency. Although the sensitivity analysis (Appendix Tables C3 and C4) shows that the positive indirect association between affective alignment and gifting intentions through emotional value remains significant after excluding Empathy, future research could further refine the measurement of this dimension. Moreover, the Toleration dimension is measured with only two items after item purification. Future research could expand its item pool to improve measurement robustness.

CRediT authorship contribution statement

Yunlu Liu: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Benjiang Lu:** Writing – review & editing, Project administration, Methodology, Funding acquisition, Conceptualization. **Yao Mu:** Writing – review & editing, Project administration, Funding acquisition, Conceptualization. **Baojun Ma:** Project administration, Funding acquisition, Conceptualization.

Declaration of Competing Interest

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

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ijinfomgt.2026.103112.

Data availability

Data will be made available on request.

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