

Associational Pathways Linking Personalized Need Fulfillment to Continuance Intention among Young AI Companion Users

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CENTRAL FINDING

Personalized need fulfillment is linked to continuance intention through interaction engagement and subsequent satisfaction.

Abstract—This study examined how personalized need fulfillment is associated with continuance intention among young users of AI companions, with particular attention to the sequential roles of interaction engagement and satisfaction. Personalized need fulfillment was conceptualized as a five dimensional higher order construct based on a preceding grounded theory study. Survey data from seven hundred and forty nine users were analyzed using partial least squares structural equation modeling with five thousand bootstrap resamples. The results showed that personalized need fulfillment was positively associated with interaction engagement, interaction engagement was positively associated with satisfaction, and satisfaction was positively associated with continuance intention. The direct association between personalized need fulfillment and satisfaction was statistically significant but weak, while the direct associations between personalized need fulfillment and continuance intention and between interaction engagement and continuance intention were not statistically significant. A significant sequential indirect relationship was identified through interaction engagement and satisfaction. The central pathway remained stable across competitive model analysis, control variable analysis, and split sample validation, although the predictive performance for continuance intention remained limited. These findings suggest that personalized need fulfillment is associated with continuance intention primarily through greater interaction engagement and subsequent satisfaction. The study provides empirical evidence for understanding sustained use of AI companions and offers practical implications for interaction design that supports user engagement and satisfaction.

Keywords—AI companion, personalized need fulfillment, interaction engagement, satisfaction, continuance intention.

I. Introduction

AI companions increasingly support emotionally responsive, role-based, and memory-enabled interaction rather than one-off question answering. Users judge these systems not only by response accuracy but also by whether they understand emotions, maintain a coherent role, remember prior interactions, and respect privacy and emotional boundaries [1], [2]. Yet initial adoption does not guarantee continued use. Among users aged 18–35, a central question is whether sustained use is related to how well AI companions meet personalized relational needs.

Prior research has documented social support and relationship development in companion chatbots [1]–[3]. Separate studies have examined relationship trajectories and potentially manipulative interaction patterns [4], [5]. What remains less clear is how four conceptually different elements fit together: personalized need fulfillment, interaction engagement, satisfaction, and continuance intention. We therefore examine a pathway in which personalized need fulfillment (PNF) is associated with interaction engagement (IE), IE with satisfaction (SAT), and SAT with continuance intention (CI). Three supplementary direct associations were also tested: PNF with SAT, PNF with CI, and IE with CI. These tests assess whether the direct associations add explanatory value beyond the serial pathway.

To address this gap, we extend the earlier qualitative work [6] by translating the five-dimensional need structure into a reflective-formative higher-order measure and testing how it relates to engagement, satisfaction, and continuance intention. IE is treated as an interaction state that is conceptually distinct from both the personalized experience represented by PNF and the overall evaluation represented by SAT. The proposed pathway is examined through direct and indirect effects, competitive and control models, split-sample validation, and out-of-sample prediction.

II. Theoretical Background and Hypotheses

A. Personalized Need Fulfillment

PNF is defined here as users’ overall evaluation of how well an AI companion fulfills five relationship-oriented needs in actual use [6]. Emotional responsiveness (ER) captures timely, appropriate, and stable responses that convey understanding and acceptance; role exclusivity (RE) captures a role identity and relational position that fit user expectations; and relational continuity (RC) captures memory of prior interactions and continuity across sessions. Interaction and contextual adaptation (IA) concerns adjustment to users’ language habits, emotional states, and conversational

situations, whereas safety boundaries (SB) concern privacy, psychological distance, emotional involvement, and user control. The five dimensions therefore address different aspects of the experience: response quality, relational identity, temporal continuity, contextual flexibility, and boundary control.

The measurement logic follows from this distinction. Each first-order dimension is reflected by its indicators, but the five dimensions are not interchangeable; together, they form the broader construct of PNF. A reflective-formative higher-order specification was therefore used [7]–[9]. Self-determination theory provides a supporting perspective by suggesting that environments that support autonomy, competence, and relatedness are conducive to high-quality engagement [10]. We do not map the five PNF dimensions one-to-one onto these basic needs. Instead, they are treated as interactional conditions that may support them: safety boundaries may strengthen agency, emotional responsiveness and relational continuity may reinforce the sense of being understood and remembered, and role exclusivity and contextual adaptation may reduce the effort created by role drift or repeated correction.

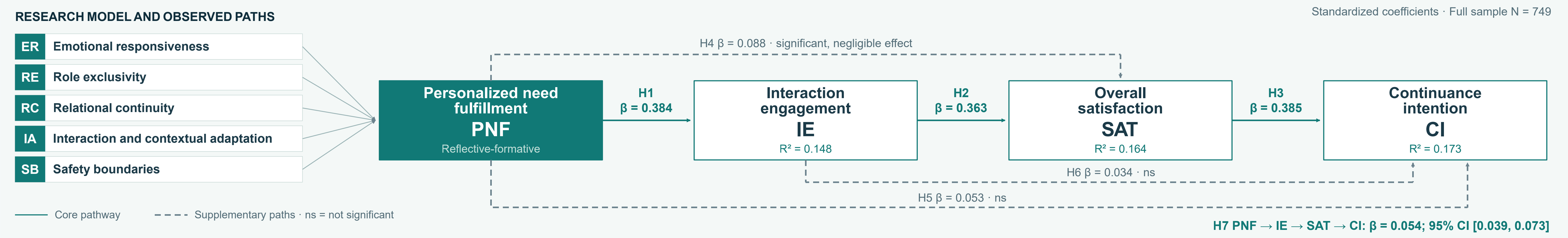
B. Interaction Engagement, Satisfaction, and Continuance Intention

IE refers to the attention, active expression, and involvement users bring to an interaction and is distinct from both usage frequency and future use intention [11], [12]. In this study, it is reflected in whether users focus on the conversation, extend topics, express thoughts and emotions in depth, and respond to system feedback. Deeper expression is closely related to self-disclosure [13]. SAT denotes an overall post-use evaluation, whereas CI refers to the intention to keep choosing and using the AI companion. The information systems continuance model identifies satisfaction as a key antecedent of continuance intention [14]. Accordingly, PNF, IE, SAT, and CI occupy different conceptual positions: personalized experience, interaction state, overall evaluation, and future-oriented intention.

C. Research Model and Hypotheses

These distinctions imply a serial association. If personalized needs are more fully met, users should be more willing to attend to, elaborate on, and participate in the interaction (H1). Greater IE should provide a richer experiential basis for SAT (H2), while higher SAT should be positively associated with CI (H3). Because PNF and IE may also relate to later constructs without passing through every intermediate link, we additionally tested the direct associations of PNF with SAT (H4), PNF with CI (H5), and IE with CI (H6). H7 concerns the serial indirect association from PNF through IE and SAT to CI. Figure 1 summarizes the core pathway and the supplementary direct paths.

Fig 1 Proposed reflective-formative research model. Solid lines indicate the core pathway; dashed lines indicate supplementary direct paths.



B. Measures and Analysis

All items were rated on five-point Likert scales. The 20 PNF items comprised four items for each of ER, RE, RC, IA, and SB and were developed from the preceding grounded theory study of 27 young AI companion users [6]. The qualitative categories were converted into fulfillment statements grounded in actual use, with each item assigned to a single dimension to preserve its conceptual boundary. IE was measured with five items adapted from user engagement scales [11], [12]. SAT and CI were each measured with four items adapted to the AI companion context from Bhattacharjee [14]. A global PNF item was included for redundancy analysis.

The higher-order model was estimated with the disjoint two-stage PLS-SEM approach and 5,000 case-level bootstrap resamples. Reflective constructs were assessed using indicator loadings, Cronbach’s α , rho_A, composite reliability (CR), average variance extracted (AVE), and the heterotrait-monotrait ratio (HTMT) [9], [15]. Formative PNF was assessed using outer weights, outer loadings, variance inflation factors (VIFs), and redundancy validity [7]–[9]. For the structural model, we report standardized coefficients, 95% confidence intervals, R², and f²; indirect effects were evaluated with bootstrap confidence intervals [16]. Common-method bias was examined with Harman’s single-factor test and full-collinearity VIFs [17], [18]. Competitive models, control-variable models, split-sample validation, and PLSpredict were used to assess robustness and prediction [19].

Primary estimation was conducted in Python 3.13.5, and the model was independently reproduced in SmartPLS 4.1.1.8. The main control model included gender, status, and age; an extended model additionally included primary product, use frequency, payment history, and use duration. To examine internal stability, the sample was stratified by primary product and divided into exploratory subsample A (n=375) and validation subsample B (n=374). Subsample A was used for parallel analysis and exploratory factor analysis of the 20 PNF items, while subsample B was used to re-estimate the measurement and structural models. PLSpredict used 10-fold cross-validation repeated 10 times and compared PLS-SEM prediction errors with a linear-model benchmark.

IV. Results

A. Reflective and Formative Measurement Models

All reflective constructs met the usual reliability and convergent-validity criteria: Cronbach’s α , rho_A, and CR were above 0.70, and AVE was above 0.50 (Table 2). HTMT values ranged from 0.079 to 0.499, all below 0.85, indicating adequate discriminant validity. ER4 (0.667) and IA4 (0.696) fell slightly below the 0.70 loading guideline, but both items were retained because their constructs met the CR and AVE criteria and the items contributed conceptually relevant content.

Table 2 Summary of the Measurement Model

Construct	Items	Loading range	α	rho_A	CR	AVE
ER	4	0.667–0.832	0.770	0.795	0.853	0.594
RE	4	0.726–0.821	0.800	0.810	0.870	0.626
RC	4	0.760–0.838	0.819	0.822	0.881	0.651
IA	4	0.696–0.846	0.786	0.814	0.862	0.611
SB	4	0.727–0.846	0.782	0.794	0.861	0.608
IE	5	0.705–0.830	0.824	0.839	0.878	0.591
SAT	4	0.764–0.839	0.813	0.820	0.878	0.644
CI	4	0.741–0.826	0.810	0.822	0.876	0.638

For the second-order formative PNF construct, VIFs ranged from 1.092 to 1.278, showing no problematic multicollinearity. ER, RE, RC, and SB had significant outer weights. IA did not (0.160, p=0.106), but its outer loading remained significant (0.526, p<0.001); it was retained be

cause contextual adaptation is conceptually distinct and the significant loading indicated a meaningful absolute contribution (Table 3). The redundancy path from PNF to the global PNF item was 0.726 (R²=0.527). SB had the lowest mean among the five dimensions (M=3.20, SD=0.92). Harman’s first factor accounted for 19.9% of the variance, and full-collinearity VIFs ranged from 1.186 to 1.376.

Table 3 Formative Measurement of Personalized Need Fulfillment

Dimension	Outer weight	p	Outer loading	VIF
ER	0.311	0.001	0.672	1.278
RE	0.403	<0.001	0.723	1.217
RC	0.382	<0.001	0.714	1.236
IA	0.160	0.106	0.526	1.207
SB	0.274	0.004	0.519	1.092

B. Structural Paths and Indirect Effects

The three core paths were supported: PNF was positively associated with IE, IE with SAT, and SAT with CI. The direct association between PNF and SAT was also statistically significant, but its incremental effect was negligible (f²=0.008), while the direct associations between PNF and CI and between IE and CI were not significant. The model explained 14.8% of the variance in IE, 16.4% in SAT, and 17.3% in CI, with an SRMR of 0.0466. The serial indirect effect was significant ($\beta=0.054$, 95% CI [0.039, 0.073]). The total indirect effect of PNF on CI was 0.101 (95% CI [0.067, 0.142]), and the total effect was 0.153 (95% CI [0.089, 0.231]). Taken together, these results indicate that the association between PNF and CI was carried mainly through IE and SAT. Table 4 summarizes the direct and indirect effects.

Table 4 Direct Paths, Serial Indirect Effect, and Total Effects

Hyp.	Path/effect	β	95% CI	f ²	Interpretation
H1	PNF→IE	0.384	[0.328, 0.453]	0.173	Supported
H2	IE→SAT	0.363	[0.290, 0.427]	0.134	Supported
H3	SAT→CI	0.385	[0.318, 0.453]	0.150	Supported
H4	PNF→SAT	0.088	[0.017, 0.170]	0.008	Supported; negligible effect
H5	PNF→CI	0.053	[-0.015, 0.129]	0.003	Not supported
H6	IE→CI	0.034	[-0.040, 0.100]	0.001	Not supported
H7	PNF→IE→SAT→CI	0.054	[0.039, 0.073]	N/A	Supported
	Total indirect: PNF→CI	0.101	[0.067, 0.142]	N/A	Significant
	Total effect: PNF→CI	0.153	[0.089, 0.231]	N/A	Significant

C. Robustness and Prediction

The robustness checks largely reproduced the main pattern. Adding control variables changed no structural coefficient by more than 0.007 and did not alter the significance pattern of the six direct paths. In the competitive model, removing IE lowered R² for SAT from 0.164 to 0.052, whereas R² for CI changed only from 0.173 to 0.172; IE therefore contributed mainly to explaining SAT rather than CI. Parallel analysis of exploratory subsample A retained five factors, and all 20 PNF items loaded most strongly on their theoretically assigned factor, with primary loadings of 0.446–0.813 and absolute cross-loadings below 0.30. Validation subsample B again reproduced the three core associations: PNF with IE ($\beta=0.471$), IE with SAT ($\beta=0.375$), and SAT with CI ($\beta=0.392$). The serial indirect effect was also reproduced ($\beta=0.069$), although the weak direct association between PNF and SAT was not. In this validation sample, ER, RE, and RC retained significant formative weights, whereas IA and SB did not, suggesting that the structural sequence was more stable than the relative contribution of individual formative dimensions.

III. Method

A. Participants and Procedure

For this study, AI companions were defined as generative conversational systems that combine role configuration, affective response, memory, and continuing dialogue. Xingye AI Companion, Zhumengdao, Character.AI, Replika, Glow, and functionally similar applications were included, whereas general search or question-answering tools, task-oriented service bots, and content-only virtual idols were excluded. Participants were 18–35 years old and had to be current users or have used an AI companion within the previous month, have at least one month of cumulative use, and be able to identify a specific product. The anonymous survey was distributed through AI companion communities and targeted sharing through social networks from June 15 to 25, 2026. Of 897 responses, 148 were removed for failed attention checks (n=90), invariant responding (n=12), completion in less than 180 s (n=31), or duplicate submissions (n=15), leaving 749 valid cases (83.5%). Participation was voluntary, respondents could withdraw at any time, and no personally identifying information was collected. Table 1 summarizes the sample and use characteristics.

Table 1 Sample and Use Characteristics (N=749)

Characteristic	Distribution
Gender	Women, 60.2%; men, 35.5%; prefer not to say/other, 4.2%
Age	18–22, 29.2%; 23–26, 37.2%; 27–30, 24.6%; 31–35, 8.9%
Status	Students, 49.1%; employed, 38.3%; other statuses, 12.5%
Use frequency	Almost daily, 30.0%; 4–6 times/week, 25.5%; 1–3 times/week, 29.1%; several times/month, 11.7%; rarely, 3.6%
Payment history	Ever paid, 32.7%; never paid, 67.3%
Region	Mainland China, 95.9%; other regions, 4.1%
Most-used product	Xingye AI Companion, 28.8%; Character.AI, 21.5%; Zhumengdao, 17.9%; Glow, 13.8%; other, 10.9%; Replika, 7.1%

PLSpredict yielded Q²predict values above zero for all endogenous indicators, but its prediction errors were close to those of the linear-model benchmark. For CI indicators, Q²predict ranged only from 0.0055 to 0.0216, pointing to limited out-of-sample prediction of continuance intention. Across these checks, the serial sequence from PNF through IE and SAT to CI remained the most consistent pattern, while predictive performance for CI and the relative formative weights were less stable.

V. Discussion

A. Theoretical Implications

The results point to a staged association rather than a direct link between personalization and continuance. PNF was not directly associated with CI once IE and SAT were included in the model. Instead, higher PNF was associated with greater IE; IE, in turn, was associated with SAT, and SAT showed the strongest direct association with CI. The nonsignificant direct associations between PNF and CI and between IE and CI suggest that favorable personalization and active participation do not necessarily correspond directly to future use when satisfaction is considered. Personalization is therefore better understood here as an experiential condition associated with engagement and satisfaction rather than as a stand-alone retention mechanism.

The role of IE is also more specific than a simple engagement-retention relationship would imply. In this study, IE refers to the user’s state of participation rather than to perceived social qualities of the agent. The competitive model showed that removing IE sharply reduced the explained variance in SAT but had almost no effect on the explained variance in CI, and the validation sample reproduced the associations between PNF and IE and between IE and SAT. This pattern places IE primarily between PNF and SAT. The exploratory five-factor pattern and the discriminant-validity results were also consistent with the five need dimensions being distinguishable at the first-order level, while their formative combination offers an initial quantitative representation of PNF in AI companion use. The modest R² values for IE, SAT, and CI (14.8%–17.3%), however, show that the model captures only part of the factors related to continuance intention. Future work should examine whether habit, emotional attachment, social presence, loneliness, and switching costs add explanatory value beyond PNF, IE, and SAT.

B. Design Implications

From a design standpoint, the findings suggest prioritizing continuity and user control rather than simply intensifying personalization. Role identity, communication style, relationship positioning, and cross-session memory should remain reasonably consistent, while users should be able to inspect, modify, disable, or reset these settings. Context-sensitive follow-up questions, emotional acknowledgment, and clear feedback may support richer expression without forcing greater intimacy. Because safety boundaries (SB) had the lowest mean among the five PNF dimensions (M=3.20, SD=0.92), products should also provide clear privacy explanations, memory controls, topic-exit options, notification controls, adjustable emotional intensity, and transparent payment prompts. These safeguards may help preserve user agency and reduce the risk of manipulative dependency [5].

VI. Conclusion and Limitations

Across the full sample and the validation analyses, the clearest pattern was the serial sequence from PNF through IE and SAT to CI. PNF was associated with CI mainly through IE and SAT, while the direct associations between PNF and CI and between IE and CI were not supported. The contribution of the model is therefore to clarify a specific associational process rather than to offer a comprehensive account of continuance intention. Its explanatory power was modest (R²=14.8%–17.3%), and the cross-sectional, self-reported, non-probability design does not support causal inference. Recruitment primarily from online communities in mainland China also limits generalizability across regions, occupational groups, and products, and some formative weights varied across split samples. Future studies should use multi-wave longitudinal, experimental, or behavioral-log data; replicate the model across regions and products; refine the five-dimensional measure through expert review, cognitive interviewing, and independent samples; and test additional determinants such as habit, emotional attachment, social presence, loneliness, and switching costs.

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