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Exploring the Factors of AI Chatbot Dependence: An I-PACE Model and AIDUA Framework Perspective

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Article

Keywords: AI chatbots, AI dependency, I-PACE model, AIDUA, Affective appraisal, Performance expectancy

Posted Date: August 28th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10305715/v1

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Additional Declarations: No competing interests reported.

Abstract

Generative AI chatbots are increasingly used as everyday cognitive and emotional support tools, raising concerns that repeated interaction may develop into maladaptive dependence rather than merely technology acceptance. Despite their convenience, they may foster excessive dependence, a concern whose underlying antecedents have received little scholarly attention. Using the I-PACE model as the overarching framework, this study reconceptualises AIDUA appraisal processes as proximal cognitive–affective mechanisms through which person-related factors may translate into AI chatbot dependence and rejection. Participants with prior experience using AI chatbots were invited to take part in the survey. A total of 540 valid responses were collected via the NAODAO survey platform. Structural equation modelling results showed that hedonic motivation and perceived humanness were associated with more favourable performance-related appraisals and lower perceived effort, whereas social influence showed a more limited association with effort-related appraisal. Performance expectancy and effort expectancy are significantly associated with both cognitive and affective appraisals. Finally, only affective appraisal influences AI chatbot dependence and rejection behaviours. AI familiarity and age, entered as control variables, show significant associations with both AI usage behaviour and attitudinal outcomes. These findings suggest that dependence on AI chatbots is not simply an extension of technology acceptance, but may emerge when favourable affective appraisals transform repeated instrumental use into emotionally reinforced reliance.

1. Introduction

Recent advancements in generative artificial intelligence (GenAI) have swiftly transformed various sectors, including higher education (Chiu, 2024). GenAI's abilities in text creation, language understanding, and intelligent interaction open new opportunities for developing educational content, supporting learning, and providing personalised feedback (Chan & Hu, 2023; Chiu, 2024). Among these, AI chatbots such as ChatGPT, Kimi, and DeepSeek are particularly notable. With improvements in natural language processing and machine learning, interactions with AI chatbots have become more natural and engaging. Notably, a Microsoft survey revealed that its chatbot Xiaoice averaged 23 exchanges per session, exceeding typical human-to-human interaction rates (Gaubert, 2021).

Although the potential of GenAI to enhance teaching efficiency and learning experiences is widely acknowledged, it also introduces notable challenges (Adeshola & Adepoju, 2024). Growing attention has been directed toward user dependence on GenAI technologies. Personalised responses from AI chatbots may encourage prolonged engagement and foster strong attachment to highly anthropomorphised systems, potentially leading to compulsive use and dependence (Ramadan, 2021). However, few studies have addressed overreliance on AI chatbots (Hu et al., 2023; Zhang et al., 2024). It can be anticipated that, as AI technologies continue to advance, dependence on chatbots is likely to become increasingly prevalent. Thus, examining the current state of AI chatbot dependence and its underlying determinants is essential.

Previous research has often employed the I-PACE model (Interaction of Person-Affect-Cognition-Execution; Brand et al., 2016) to investigate problematic behaviours associated with internet applications. However, dependence on AI chatbots may differ from other forms of technology dependence. On one hand, AI chatbots can act as direct communicators, interacting with learners (Guzman & Lewis, 2020), whereas mobile phones and social media primarily serve as mediating tools. On the other hand, their interactive nature and anthropomorphic response style are more likely to evoke cognitive and affective reactions, potentially leading to more complex psychological processes. Therefore, these distinctions underscore the need to extend technology dependence research to AI chatbots and explore the interplay of underlying factors.

Drawing on the I-PACE model, this study integrates the AI device use acceptance (AIDUA) framework (Gursoy et al., 2019) and incorporates additional factors. Person-related factors, including social influence, hedonic motivation, and perceived humanness, are conceptualised as primary evaluation factors in the initial stage of AI chatbot dependence, reflecting individuals' assessment of AI's relevance and congruence with the self. Cognitive and affective components function as parallel secondary evaluation factors. In the outcome stage, individuals develop intentions to accept or reject AI based on these evaluations, which subsequently guide their behaviours.

2. Theoretical background and hypothesis development

2.1. The I-PACE model

The I-PACE model (Interaction of Person–Affect–Cognition–Execution) describes how problematic internet use emerges and is maintained by the dynamic interplay of person-related predispositions, affective reactions, cognitive processing, and executive functions (Brand et al., 2016). Person-related factors encompass biological and psychological dispositions, psychopathology, personality and social-cognitive characteristics, and use motivations. Affective processes involve emotional responses to external or internal cues (e.g., pleasure, tension reduction), whereas cognitive processes include attentional biases, cognitive distortions, and evaluative beliefs about online engagement. These processes can influence executive control (e.g., self-regulation, impulse control, decision-making), thereby shaping maladaptive usage behaviours across technology contexts. Although widely applied to problematic internet and social media use, the model has rarely been extended to AI chatbot use; this study addresses that gap.

Focusing on the components most proximal to short-term engagement, the current research examines person-related factors and parallel cognitive-affective appraisals in the context of AI chatbot use, rather than downstream executive dysfunction that is more indicative of entrenched problematic patterns (Romer, A., & Pizzagalli, D., 2021). Empirical work links affective states such as social anxiety, loneliness, and depressive symptoms to AI chatbot dependence (Hu et al., 2023; Huang et al., 2024). Relatedly, personality traits including neuroticism and impulsivity have been shown to predict need frustration and negative academic emotions, which in turn strengthen positive beliefs about ChatGPT and deepen

dependence (Zhong et al., 2024). However, prior I-PACE-based research has rarely specified how chatbot-specific interactional features may shape problematic AI use. Given their responsive and human-like conversational format, AI chatbots may make users' engagement particularly sensitive to social influence, hedonic motivation, and perceived humanness (Kelly et al., 2023). To address this limitation, we integrate the AIDUA framework by modelling person-related factors as antecedents of AI chatbot use and positioning cognitive and affective appraisals as dual core mechanisms through which dependence may develop.

2.2. An AI acceptance framework: AIDUA

AIDUA explains how users evaluate AI technologies before deciding whether to engage with or avoid them (Gursoy et al., 2019; Lu et al., 2019). In the present study, the AIDUA framework is used not primarily as a model of adoption intention, but as a process-oriented account of sequential appraisal. Specifically, users first evaluate AI chatbots through social, motivational, and perceived-humanness cues, and these initial evaluations are then translated into judgments about expected utility and required effort. Such appraisal processes may shape not only acceptance or rejection, but also maladaptive reliance when favourable evaluations are repeatedly reinforced through use.

Building on this validated framework, the present study introduces two key extensions. Consistent with chatbot-specific extensions of AIDUA, we focus on perceived humanness rather than visual anthropomorphism, because text-based chatbots primarily convey human-likeness through conversational coherence, responsiveness, and linguistic style. Given that AI chatbots primarily operate through text-based interaction and lack visual, auditory, or identity cues (Xie et al., 2023), perceived humanness-capturing linguistic, syntactic, and conversational strategies that resemble human communication offer a more suitable construct (Rapp et al., 2021). Second, drawing on the I-PACE model, we incorporate cognitive appraisals into the AIDUA framework. Cognitive appraisals reflect utilitarian evaluations of functionality, whereas affective appraisals encompass evaluative judgments grounded in emotions and visceral reactions (Yeo & Ong, 2024). Prior research suggests that cognitive appraisals exert a stronger influence on learning productivity than affective responses (Wang & Yin, 2025). Integrating these perspectives, the present study proposes a conceptual model for examining technological dependence on AI chatbots, combining insights from the I-PACE and AIDUA frameworks (see Fig. 1).

2.3. Hypothesis development

2.3.1. Person-related factors

Research on AI-enabled service technologies suggests that users' evaluations of intelligent systems are jointly shaped by instrumental beliefs, social influence, hedonic motivation, and perceived human-like agency (Bhuiyan et al., 2024; Das & Datta, 2024; Yu, 2019).

Social influence refers to the degree to which an individual believes that important others believe he/she should adopt a new technology. At the initial stage of AI tool use, users tend to rely on social cues from peers, instructors, or online sources due to limited direct experience. Information from significant others reduces perceived technological uncertainty (Hsieh & Lee, 2021; Xu et al., 2023; Yan et al., 2024). Perceived social consensus regarding a technology's efficiency or ease of use fosters positive judgments via conformity and social identity mechanisms, thereby increasing usage expectancy (Sung et al., 2015).

Hedonic motivation denotes intrinsic affective rewards-pleasure, curiosity, interest-experienced in technology use, independent of external mandates or purely instrumental benefits (Tamilmani et al., 2019). User experiences of novelty and enjoyment with GenAI support positive functional appraisals and an enabling view of AI rather than a perceived burden, which elevates performance expectancy (Habib et al., 2024). By eliciting immersion and positive affect, hedonic motivation narrows attention to the task, diminishes perceived system complexity, and reduces effort expectancy (Tamilmani et al., 2019). Accumulated evidence indicates that hedonic motivation is among the strongest predictors of users' expectations and intentions to use technology (Allam et al., 2019).

Perceived humanness is grounded in the media equation theory, which posits that humans unconsciously apply interpersonal communication norms to human-computer interactions (Nass & Moon, 2000). Consequently, AI systems that exhibit more human-like characteristics are more likely to foster users' emotional identification. Such features also reduce uncertainty and cognitive load regarding system complexity through a simplified cognitive mapping mechanism (Epley et al., 2007). When individuals perceive AI as a "human-like" agent, they tend to overestimate its comprehension, response accuracy, and potential, thereby elevating subjective expectations of usability and ease of use. Thus, we hypothesise as follows:

H1: Social influence is significantly associated with performance expectancy and effort expectancy.

H2: Hedonic motivation is significantly associated with performance expectancy and effort expectancy.

H3: Perceived humanness is significantly associated with performance expectancy and effort expectancy.

2.3.2. Process appraisal

Performance expectancy refers to the extent to which individuals believe that using AI will enhance their work performance, whereas effort expectancy was operationalised in the present study as perceived effort or difficulty associated with AI chatbot use; higher scores therefore indicate greater perceived interactional cost. Control-value theory (Pekrun, 2006) holds that perceived control and value in an academic or task context are key antecedents of emotion. When individuals expect AI chatbots to improve efficiency, they experience greater perceived value; when they view AI as easy to use, they experience stronger perceived control (Liu et al., 2023; Kim & Kim, 2025). Heightened control and value perceptions, in turn, promote more favourable affective appraisals.

In addition, from the perspective of rational choice (Atkins & Kim, 2012), performance expectancy and effort expectancy provide key information for users' cost-benefit evaluation of AI usage under the logic of utility maximisation, reflecting their rational trade-off and assessment of the technology's value. In other words, when users perceive high performance returns and low required effort, they are more likely to form positive cost-benefit expectations, thereby enhancing their overall cognitive appraisal. Thus, we hypothesise as follows:

H4: Performance expectancy is positively associated with cognitive and affective appraisals.

H5: Perceived effort is negatively associated with cognitive and affective appraisals.

2.3.3. Usage behaviour

When users positively evaluate the functional attributes of AI tools-such as accuracy, reliability, and personalization-such favourable cognitive judgments tend to enhance their motivation for deeper information processing (Shin, 2021). According to the heuristic-systematic model (HSM), positive cognitive appraisals strengthen trust in the AI system's capabilities, thereby fostering dependence behaviours (Shin et al., 2020). Affect is also a critical predictor of individuals' risk perception and adoption intention toward emerging technologies such as AI. Prior research indicates that emotions play a central role in users' acceptance of AI technologies (Behn et al., 2024).

In contrast to dependence, unwarranted rejection of AI can also represent improper use, especially when driven by AI anxiety or fear (Li & Huang, 2020; Schiavo et al., 2024). Because users are quicker to abandon trust after algorithmic errors than after human errors, which is a key mechanism of algorithm aversion (Dietvorst et al., 2014), their ongoing evaluations of how an AI system performs during use become central to acceptance versus rejection outcomes. Thus, we hypothesise as follows:

H6: Cognitive appraisal is positively associated with AI chatbot dependence and negatively associated with AI rejection.

H7: Affective appraisal is positively associated with AI chatbot dependence and negatively associated with AI rejection.

3. Methodology

This study used a cross-sectional online survey to examine the cognitive–affective appraisal processes associated with AI chatbot dependence. Eligible participants were required to have prior experience using AI chatbots. The questionnaire assessed demographic characteristics, AI-use characteristics, person-related antecedents, appraisal variables, AI rejection, and AI chatbot dependence. Established scales were adapted to the AI-chatbot context, and the hypothesised model was tested using confirmatory factor analysis and structural equation modelling. Data were collected through the NAODAO platform between January and February 2025.

3.1. Questionnaire design

The survey contained three sections. The first section recorded demographic and AI-use information, including age, gender, education, major, frequently used chatbot functions, and the version of chatbot most often used. The second section measured AIDUA-related antecedents and appraisals, including social influence, hedonic motivation, perceived humanness, performance expectancy, perceived effort, cognitive appraisal, affective appraisal, and AI rejection. The third section assessed AI chatbot dependence.

The second section of the questionnaire concludes with the constructs for the usage behaviour and attitudes towards AI chatbots. The scales of this survey were adapted from well-established literature. For AIDUA-related constructs, items were adapted from prior AI-acceptance research and reworded to fit general AI chatbot use rather than ChatGPT acceptance specifically. AI chatbot dependence was measured with items adapted from Zhang et al. (2024), allowing the model to examine maladaptive reliance beyond acceptance or rejection. Items to measure *perceived humanness* (4 items) were adapted from Hsu & Lin (2023). In addition, items to measure *dependence on AI chatbots* (8 items) were adapted from Zhang et al. (2024). These items were rated on a 7-point Likert-type scale anchored by 1 for "Strongly Disagree" and 7 for "Strongly Agree." Since AI familiarity (Chi et al., 2021), age, gender, education, and major are likely to influence participants' attitudes, they were treated as control variables in this study.

3.2. Data collection

From January to February 2025, we distributed an online survey questionnaire on the NAODAO data platform (https://www.naodao.com/). Since this study targets respondents who have used AI chatbots, we included two filter questions at the beginning of the survey: "Have you used AI chatbots?" and "Please select the version of AI chatbots you use most frequently and its primary purpose," to exclude respondents who do not meet our requirements. Attention check questions (e.g., "please select disagree," "please select strongly agree," etc.) were also added in the middle and at the end of the survey to verify whether respondents were paying considerable attention while completing the questionnaires (Yu et al., 2018). Respondents who completed the survey and passed attention checks received a small amount of monetary award. As a result, 540 valid questionnaires were collected after excluding users who did not meet the requirements and did not pay attention.

3.3. Data description and analysis

Among all valid responses, 40.4% were males and 59.6% were females. The demographic characteristics of the respondents are presented in Table 1. More than 80% of respondents were younger than 30, and 76.7% held a bachelor's degree. Information searches and text production are the most frequently used AI chatbot functions.

Table 1
Demographics of the respondents (n = 540).

Variables	Items	Frequency	Percent
Gender	Male	218	40.4%
	Female	322	59.6%
Age	18–25	378	70.0%
	26–30	98	18.1%
	31–40	57	10.6%
	41–50	6	1.1%
	51–60	1	0.2%
Education	Senior high school or below	8	1.5%
	Undergraduate degree	414	76.7%
	Master's degree.	100	18.5%
	Doctor's degree	18	3.3%
Major	Humanities	64	11.9%
	Social sciences	149	27.6%
	Natural sciences	327	60.6%
The most frequently used function	Information search	174	32.2%
	Text production	222	41.1%
	Syntax check	18	3.3%
	Debugging code	42	7.8%
	Language translation	41	7.6%
	Interactive dialogue	43	8.0%
The version of AI chatbots	ChatGPT-3.5	191	35.4%
	ChatGPT-4	208	38.5%
	ChatGPT o1	25	4.6%
	ChatGPT Pro	16	3.0%
	Others	100	18.5%

4. Results

4.1. Measurement model

Mplus 8.10 and SPSS 27.0 were utilised to evaluate the model fit of the measurement model. χ^2 = 1709.92 (df = 780), RMSEA = 0.046, SRMR = 0.047, CFI = 0.933, and TLI = 0.926 indicate that the data are well represented by the model. Table 2 displays the test results for reliability and convergent validity. Internal consistency is indicated by Cronbach's alpha values greater than 0.70 for all constructs (Raykov & Marcoulides, 2011). Each construct's composite reliability (CR) value exceeds the benchmark value of 0.7, and the average variance extracted (AVE) for each construct is greater than 0.5 (except for AI rejection), which is the suggested threshold for convergent validity. According to Fornell and Larcker (1981), discriminant validity is ensured, as Table 3 reveals that the square root of the AVE of each concept is greater than its correlations with other constructs. Furthermore, applying the heterotrait monotrait (HTMT) ratio approach (Henseler et al., 2015), all HTMT values of the constructs (as shown in Table 4) were found to be below the conservative cut-off value of 0.85, demonstrating satisfactory discriminant validity.

Table 2
Reliability and validity results.

Constructs/Items	Mean	SD	Loading	Cronbach's α	CR	AVE
Social Influence (SI)				0.884	0.873	0.582
SI1	4.23	1.57	0.642***			
SI2	4.70	1.45	0.733***			
SI3	4.41	1.59	0.664***			
SI4	5.00	1.39	0.887***			
SI5	5.11	1.42	0.857***			
Hedonic Motivation (HM)				0.903	0.905	0.655
HM1	5.71	1.07	0.803***			
HM2	5.73	1.07	0.831***			
HM3	5.44	1.12	0.766***			
HM4	5.79	1.00	0.829***			
HM5	5.76	0.98	0.815***			
Perceived Humanness (PH)				0.877	0.878	0.644
PH1	5.54	1.16	0.795***			
PH2	5.13	1.26	0.847***			
PH3	5.49	1.16	0.781***			
PH4	5.36	1.15	0.785***			
Performance Expectancy (PE)				0.795	0.799	0.501
PE1	6.06	0.84	0.700***			
PE2	6.24	0.84	0.786***			
PE3	6.25	0.83	0.641***			
PE4	5.92	0.89	0.697***			

Note: n = 540; $\chi 2 = 1709.92$; df = 780; RMSEA = 0.046; SRMR = 0.047; CFI = 0.933; TLI = 0.926; ***$p < 0.001$.

Constructs/Items	Mean	SD	Loading	Cronbach's α	CR	AVE
Effort Expectancy (EE)				0.835	0.837	0.562
EE1	2.22	1.01	0.779***			
EE2	2.10	0.89	0.718***			
EE3	2.23	0.97	0.739***			
EE4	2.28	1.04	0.760***			
Cognitive Appraisal (CA)				0.797	0.800	0.511
CA1	6.22	0.88	0.769***			
CA2	6.31	0.76	0.717***			
CA3	6.27	0.72	0.666***			
CA4	6.14	0.79	0.675***			
Affective Appraisal (AA)				0.847	0.849	0.584
AA1	5.91	0.92	0.752***			
AA2	5.83	0.93	0.764***			
AA3	5.91	0.89	0.752***			
AA4	5.92	0.88	0.788***			
AI Rejection (AR)				0.733	0.757	0.441
AR1	2.97	1.35	0.688***			
AR2	3.83	1.55	0.678***			
AR3	3.41	1.61	0.718***			
AR4	1.73	1.02	0.561***			
AI chatbot dependence (AD)				0.919	0.920	0.592
AD1	4.92	1.46	0.676***			
AD2	4.78	1.53	0.841***			

Note: n = 540; $\chi 2 = 1709.92$; df = 780; RMSEA = 0.046; SRMR = 0.047; CFI = 0.933; TLI = 0.926; $^{***}p < 0.001$.

Constructs/Items	Mean	SD	Loading	Cronbach's α	CR	AVE
AD3	4.87	1.54	0.801***			
AD4	4.82	1.63	0.704***			
AD5	4.70	1.63	0.783***			
AD6	4.54	1.76	0.784***			
AD7	5.06	1.50	0.768***			
AD8	5.27	1.46	0.785***			
Note: n = 540; χ2 = 1709.92; df = 780; RMSEA = 0.046; SRMR = 0.047; CFI = 0.933; TLI = 0.926; ***p < 0.001.						

Table 3
Construct correlations.

SI	SI	HM	PH	PE	EE	CA	AA	AR	AD
	0.763								
HM	0.492	**0.809**							
PH	0.563	0.606	**0.802**						
PE	0.246	0.318	0.308	**0.708**					
EE	-0.266	-0.407	-0.410	-0.286	**0.750**				
CA	0.170	0.333	0.267	0.358	-0.323	**0.708**			
AA	0.326	0.497	0.466	0.312	-0.382	0.352	**0.764**		
AR	-0.349	-0.349	-0.393	-0.281	0.310	-0.280	-0.377	**0.664**	
AD	0.530	0.468	0.492	0.228	-0.301	0.219	0.361	-0.399	**0.769**
Note: The square roots of AVE values for each construct itself are in bold.									

Table 4
HTMT of all constructs.

HTMT	SI	HM	PH	PE	EE	CA	AA	AR	AD
SI	—								
HM	0.624	—							
PH	0.720	0.754	—						
PE	0.334	0.419	0.408	—					
EE	0.351	0.522	0.528	0.392	—				
CA	0.231	0.439	0.354	0.506	0.443	—			
AA	0.427	0.632	0.595	0.424	0.505	0.478	—		
AR	0.489	0.474	0.501	0.410	0.438	0.408	0.528	—	
AD	0.692	0.593	0.626	0.309	0.396	0.296	0.471	0.557	—

4.2. Structural model

The regression analysis offered preliminary evidence regarding the effects of control variables on AI chatbot dependence and rejection. Apart from age (β_{AR} = -0.12, p = 0.006; β_{AD} = 0.12, p = 0.008) and familiarity (β_{AR} = -0.40, p < 0.001; β_{AD} = 0.50, p < 0.001), no other demographic variables showed significant associations with usage behaviour. Therefore, age and AI familiarity were included as control variables in the structural model.

The structural model was evaluated by estimating the hypothesised paths among person-related antecedents, appraisal variables, and AI-use outcomes while controlling for age and AI familiarity. Social influence is significantly positively correlated with effort expectancy (β = 0.215; p < 0.001), while no significant correlation is found with performance expectancy (β = 0.038; p = 0.520), providing no support for H1. Hedonic motivation is significantly positively correlated with performance expectancy (β = 0.620; p < 0.001) and negatively correlated with effort expectancy (β = -0.397; p < 0.001), providing support for H2. Similarly, perceived humanness is significantly positively correlated with performance expectancy (β = 0.191; p = 0.013) and negatively correlated with effort expectancy (β = -0.174; p = 0.027), which supports H3.

The results demonstrate that performance expectancy is significantly positively correlated with cognitive appraisal (β = 0.891; p < 0.001) and affective appraisal (β = 0.621; p < 0.001), providing support for H4. Effort expectancy was significantly negatively associated with cognitive appraisal (β = -0.311; p < 0.001) and affective appraisal (β = -0.308; p < 0.001), supporting H5. Furthermore, affective appraisal is significantly positively correlated with dependence on AI chatbots (β = 0.299; p = 0.005) and significantly negatively correlated with rejection (β = -0.333; p = 0.002), which supports H7. However, cognitive appraisal does not show a significant correlation with AI chatbot dependence (β = 0.010; p = 0.910) or

rejection (β = -0.069; p = 0.455), providing no support for H6. The standardized path coefficients of the final structural model are presented in Fig. 2.

5. Discussion

5.1. Antecedents of AI chatbots' dependence

The current study's findings partially support the AIDUA model. Consistent with the prior study (Gursoy et al., 2019; Ma & Huo, 2023), the results indicate positive correlations between personal factors and process appraisal variables. Specifically, hedonic motivation and perceived humanness are significantly positively correlated with performance expectancy, but significantly negatively correlated with effort expectancy. However, in contrast to previous studies (Wong et al., 2023; Manzoor et al., 2024), we found that social influence is positively correlated with effort expectancy but not with performance expectancy after controlling for AI familiarity. This suggests that when individuals perceive higher societal expectations, this stronger subjective norm leads them to believe that they need to exert more effort to meet societal expectations (Domina et al., 2011). Some studies have also found that social influence is positively associated with individuals' beliefs that they should make an effort to use AI effectively (Alzyoud et al., 2024).

Moreover, we also found that when AI familiarity was not controlled for, social influence was significantly negatively correlated with effort expectancy. This indicates that AI familiarity may be a stronger influencing factor on AI usage expectancy (Apriyadi & Juwitasary, 2024). When individuals have inadequate experience with new technologies (e.g., AI devices), referents' opinions tend to change their subjective evaluation of perceived benefits and costs, such as overestimating effort expectancy. As familiarity with AI increases, individuals' usage experience plays a dominant role, reducing the learning and usage costs, thereby lowering the effort expectancy.

In addition, perceived humanness has a significant effect on individuals' evaluations of performance and effort expectancy. In the context of AI chatbot dependence, compared to the concept of anthropomorphism in the original model, "humanness" places greater emphasis on the chatbot's ability to accurately comprehend user questions or commands and respond in a human-like and natural manner, making it more closely associated with individuals' usage behaviour. This is consistent with previous research, which suggests that perceived humanness can enhance individual trust in AI chatbots, lead to improved user experiences, and thereby promote a greater tendency to engage with chatbots (Li et al., 2023; Shin, 2022).

Lastly, among the three antecedents, hedonic motivation has the strongest effect on performance and effort expectancy. This resonates with Gursoy et al.'s (2019) argument that hedonic motivation plays a major role in determining individuals' usage behaviour. Enjoyment and fun derived from AI use make users more likely to believe that AI will be effective and less effortful in their tasks (Li et al., 2024; Huang & Zou, 2024). There are two possible explanations for this result. First, based on Cognitive dissonance

theory (Cooper, 2012), individuals with a high level of hedonic motivation toward using AI devices may bias their perception of usage costs, making them more likely to form evaluations that favour the use of AI devices. Second, as an intrinsic motivation, hedonic motivation exerts a stronger driving force on individual behaviour compared to extrinsic motivations such as social influence. In conclusion, among the antecedents of AI chatbot dependence, factors related to intrinsic motivation, such as hedonic motivation and AI familiarity, play a more significant role.

5.2. Affective appraisal as the mediating factor in AI usage behaviour

This study found that performance expectancy is significantly positively correlated with both cognitive appraisal and affective appraisal, whereas effort expectancy is significantly negatively correlated. Moreover, the effect of performance expectancy is stronger than that of effort expectancy. This indicates that individuals' cognitive and affective appraisal during AI usage depends on their assessment of expected benefits and costs. Given the functional limitations of AI chatbots, primarily related to learning and work, performance may serve as a more critical motivating factor than perceived effort. This is supported by the findings of this study, which show that information retrieval and text generation are the most commonly used functions of AI chatbots.

Drawing on the I-PACE model (Brand et al., 2016), this study conceptualised cognitive appraisal and affective appraisal as direct antecedents of AI chatbot dependence. However, only affective appraisal was found to have a significant effect. Unlike the previous AIDUA paradigm, which focused on individuals' usage intentions, this study centres on actual usage behaviour, specifically AI chatbot dependence. In the early stages of AI chatbot use, individuals primarily seek assistance to enhance work efficiency. Therefore, compared to affective appraisal, cognitive appraisal-being a utilitarian attitude-plays a more dominant role in shaping usage intentions (Ma & Huo, 2023). As individuals engage more deeply with AI chatbots, the highly human-like and interactive nature of these systems can lead to the formation of inappropriate emotional attachments, with users beginning to perceive AI not merely as a tool but as a genuine companion. Consequently, the primary influencing factor shifts from cognitive appraisal to affective appraisal. For example, Hu et al. (2023) investigated the relationship between social anxiety, loneliness, and problematic use of conversational AI (PUCAI) and found a significant association between negative emotions and PUCAI.

5.3. Implications

Although previous research has shown that human-AI interaction can bring beneficial outcomes and has great potential, this study acknowledges the negative impacts of AI device use and explores the potential factors and pathways of AI chatbot dependence by integrating the AIDUA and I-PACE models. Specifically, this study identified the pathway of "Personal factors (social influence, hedonic motivation, perceived humanness) → Perceived expectations (performance, effort) → affective appraisal → AI chatbot dependence". In addition, the study compared the importance of various factors and found that antecedents related to intrinsic motivation have the strongest impact on perceived expectations, such as

hedonic motivation and AI familiarity. However, although this study examined cognitive appraisal and affective appraisal as core factors of process appraisal, it only found evidence that affect acts as a direct impact factor of AI usage behaviour. Therefore, theoretically, this study has verified the feasibility of the integrated model in the context of AI chatbot dependence and has advanced the research on AI-dependent behaviour.

Our findings also have noteworthy practical implications. First, for AI product design, continuously enhancing the emotional understanding and communication capabilities of AI to interact in a human-like manner in order to increase user acceptance is currently a mainstream research direction. However, in practical applications, it is necessary to avoid problematic usage behaviours such as dependence caused by the over-humanisation of AI. Some studies have found that interaction with emotionally supportive AI may lead to inappropriate emotional attachments between individuals and AI (Gillath et al., 2021). Therefore, this study suggests that in the development of AI products, protocols should be established to balance the emotional tone and effectiveness of AI. Second, for users of AI devices, how to use AI reasonably to improve the quality of life is a question worth paying attention to. However, it is worth noting that although this study found the existence of AI chatbot dependence, most of it stems from normal usage behaviours such as information search and text generation, which is consistent with previous studies (Zhang & Xu, 2025). But with the advancement of AI technology, the emergence of AI with social interaction attributes and entertainment functions may lead to addiction and other consequences, which is worth the attention of future researchers.

5.4. Limitations

This study has some limitations. First, since a cross-sectional survey was employed and the data were collected solely from users of AI chatbots in China, it is not possible to verify the causal relationships between the measured variables. Regarding the adverse consequences of AI chatbot dependence, we encourage future research to adopt a longitudinal design to investigate potential negative impacts. Second, although this study investigated both AI chatbot dependence and AI rejection as usage behaviours, the measurement validity of AI rejection was not satisfactory, which may be related to the content of the items. Individuals may express dissatisfaction with certain aspects of AI, but still choose to continue using it. Future research should pay attention to the consistency between attitudes and behaviours when designing relevant questionnaires. Finally, this study focused only on AI chatbots, which have relatively limited functions. Given the wide variety of AI products on the market, such as virtual assistants and embedded robots, which are designed to meet different user needs (e.g., utilitarian, entertainment, or social purposes), the unique characteristics of different AI devices and their impact on AI chatbot dependence may require further investigation.

6. Conclusion

Integrating the I-PACE and AIDUA model, this study examines the series of impact factors and their interrelationships that affect dependence on AI chatbots. The results indicate that in the primary evaluation stage, social influence, hedonic motivation, and perceived humanness are significantly

associated with performance expectancy and effort expectancy. In the secondary evaluation stage, performance expectancy is significantly positively correlated with cognitive and affective appraisal, while effort expectancy shows a significant negative correlation. Ultimately, only affective appraisal is the main prerequisite influencing AI chatbot dependence and AI rejection behaviour. Overall, this study makes a new contribution to the field by extending the AIDUA model to the context of AI chatbot dependence and exploring the effectiveness of different impact factors. These findings also have practical significance, providing references for future interventions addressing maladaptive reliance.

Declarations

Data availability

The anonymized raw datas and the supplementary materials containing the variable coding guide, scale specifications, and questionnaire items are available through the following anonymized OSF view-only link: https://osf.io/x9mhc/overview?view_only=342c008b80fe4f0eb7f24ae6d74a39d7

Ethics approval and consent to participate

The study received approval from the institutional review board of the authors' institution. The study was conducted in accordance with the Declaration of Helsinki, and all participants provided informed consent prior to participation.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

Author Contribution

Z.L. and D.W. contributed equally to this work and should be regarded as joint first authors. Z.L. and D.W. contributed to conceptualization, study design, data analysis, and drafting of the manuscript. Y.T. contributed to conceptualization, supervision, funding acquisition, and critical revision of the manuscript. M.L. contributed to data collection, literature review, and manuscript revision. J.H. contributed to literature review, interpretation of the findings, and manuscript revision. All authors reviewed and approved the final manuscript.

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Figures

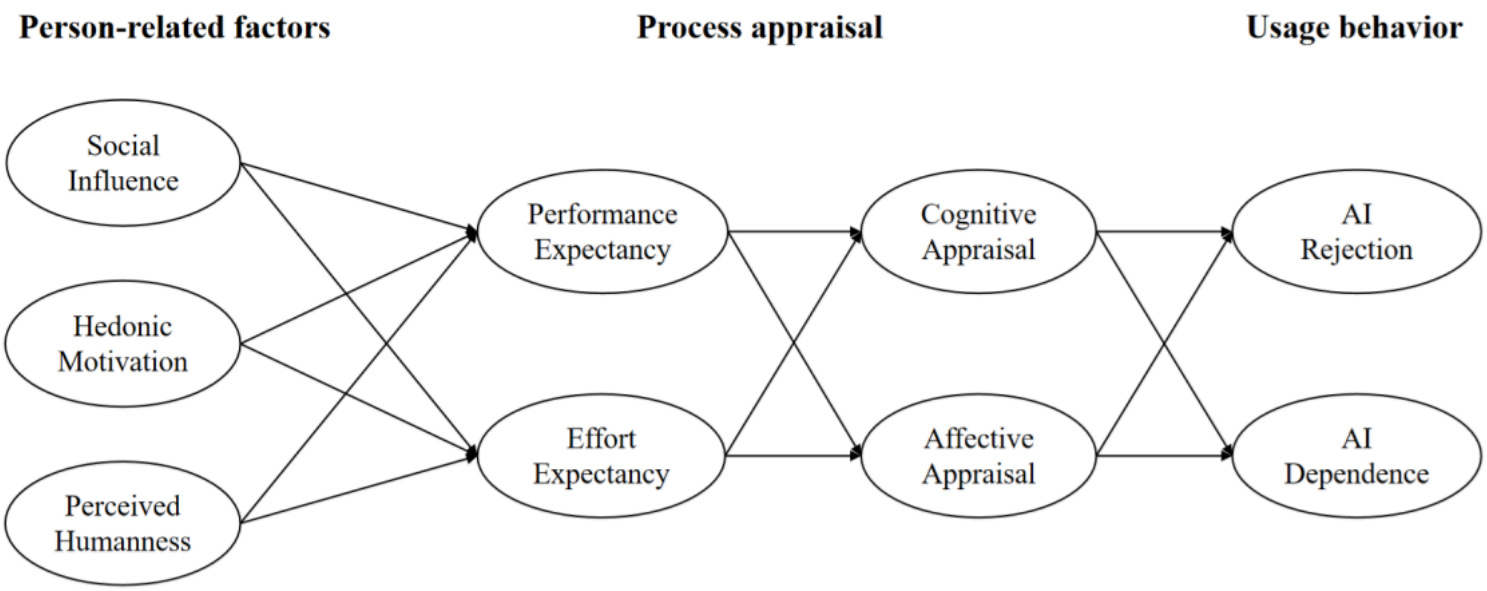

Figure 1

Proposed model

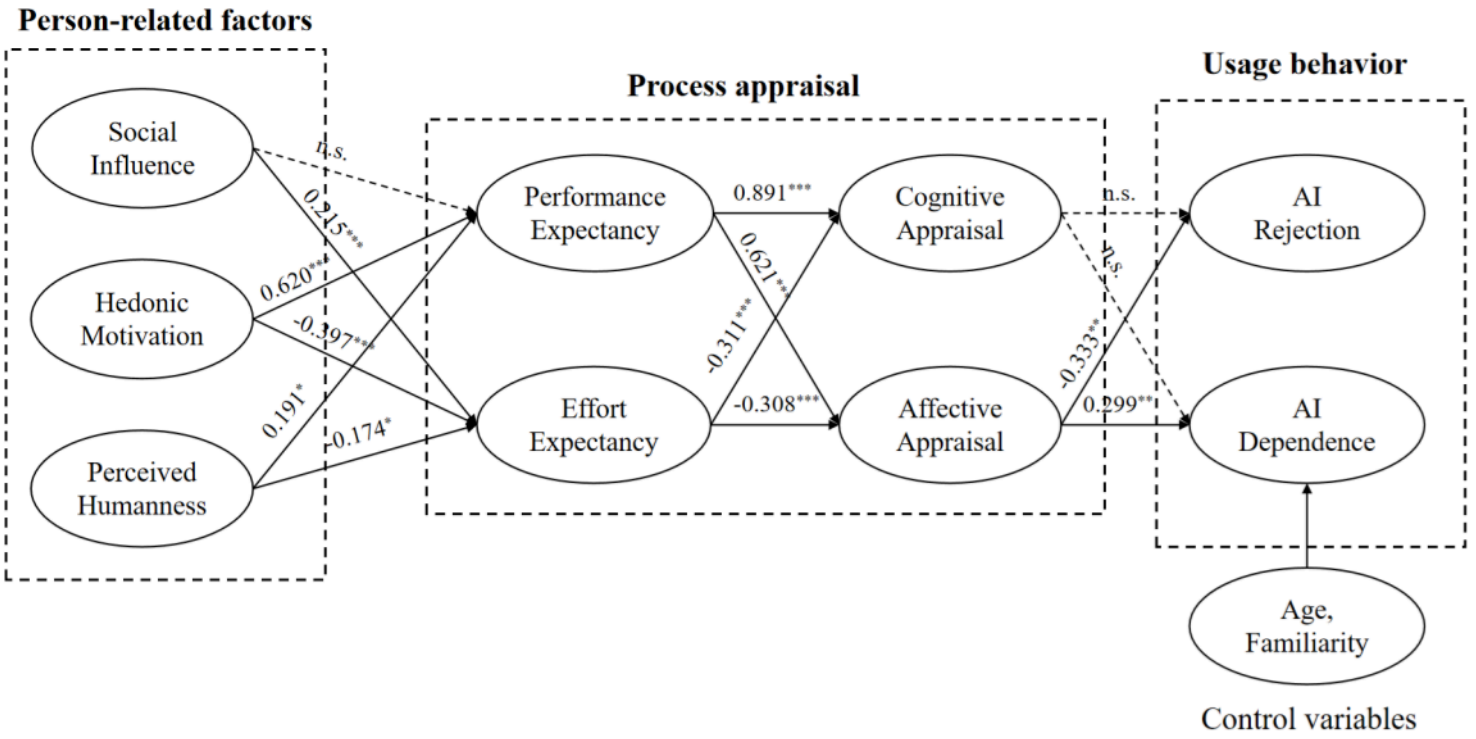

Figure 2

Results of structural model testing. Standardized path coefficients are reported. *p< 0.05; **p < 0.01; ***p< 0.001; *n.s.* = not significant.