Journal of Medicine, Humanity and Media 2026
Vol. 4, No. 3. https://doi.org/10.62787/jmhm.v4i3.395

Autonomy Support and Perceived Agency in AI Chatbots: Motivational and Social Pathways in Health Communication

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Abstract

As AI health chatbots become increasingly prevalent, the psychological processes underlying users' behavioral alignment remain insufficiently understood. Drawing on Self-Determination Theory and the Computers Are Social Actors paradigm, this study examines a decomposed specification of the TIME-HAII action route, comprising motivational and social pathways in health communication. Data were collected and analyzed using a multi-method design integrating self-report measures and behavioral indicators. The findings provide robust support for the motivational pathway through indirect associations, while evidence for the social pathway was more limited. Within the motivational pathway, perceived chatbot autonomy support was positively associated with perceived autonomy and self-efficacy, which sequentially mediated its association with interactional behavioral alignment. Within the social pathway, perceived chatbot agency was associated with interactional behavioral alignment through perceived presence. Overall, The findings advance theoretical understanding of human-AI interaction in health communication contexts and offer evidence-based design implications for AI-driven health systems.

Keywords: AI chatbots; human-AI interaction(HAII); motivation; social; health communication

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Introduction

Artificial intelligence (AI) technologies are increasingly taking over health communication roles once reserved for professionals, transforming how people access and use health information (Bickmore & Picard, 2005; Liu et al., 2025). Within this broader transformation, health chatbots have emerged as a particularly consequential technological development, offering scalable, on-demand, and personalized health advice to populations that would otherwise face significant barriers to accessing professional care (Laranjo et al., 2018). These developments hold particular salience in contexts marked by structural inequalities in health resource distribution, most notably in China (Jiang et al., 2021).

Early health information technologies often followed a paternalistic model, delivering standardized content to users with limited attention to individual preferences, literacy, or motivation (Eysenbach, 2000). This model reflected broader asymmetries of knowledge and authority in health communication, while offering limited space for user autonomy (Nassehi et al., 2024). In contrast, a growing body of research has shown that autonomy is central to sustained health behavior change and well-being (Deci & Ryan, 2000; Mackert et al., 2016; Ryan, 1995). These insights have encouraged the development of autonomy-supportive health technologies that rely on personalization, adaptive dialogue, and user control to position users as active participants rather than passive recipients (Laranjo et al., 2018; Singh et al., 2023).

Nevertheless, empirical evidence regarding chatbot effectiveness remains inconsistent. While some studies report gains in health knowledge, self-management, and health behavior change, others identify negligible or adverse effects, especially among digitally vulnerable populations (Rafikova & Voronin, 2025). These mixed findings point to the need for more systematic investigation of the psychological mechanisms underlying human–AI interaction (HAII). Within the TIME-HAII model (Sundar, 2020), AI influence is commonly explained through cue and action routes (Hancock et al., 2020). Existing research has focused primarily on the cue route, examining how interface signals and algorithmic cues shape user perceptions, expectations, and trust (Lee et al., 2023; Waddell, 2019). The action route, which concerns users' active engagement with AI systems, remains less developed. Its internal psychological processes are still under-theorized and under-tested, leaving the action route a conceptual "black box" in HAII research (Raees et al., 2024; Shneiderman, 2020).

The present study seeks to address these deficiencies through a theoretically grounded empirical investigation of autonomy-supportive communication in AI health chatbots. Drawing on Self-Determination Theory (Ryan & Deci, 2002) and the Computers Are Social Actors paradigm (Nass & Moon, 2000), this study examines two complementary mechanisms of the TIME-HAII action route through which AI-mediated interaction may be associated with interactional behavioral alignment. One is a motivational pathway, through which autonomy-supportive human-AI interaction interfaces enhance individuals' perceived sense of autonomy and self-efficacy, thereby serving as a catalyst for interactional behavior (Ng et al., 2012; Pham & Duong, 2025). The other is a social pathway, through which socially embedded conversational agent cues cultivate perceptions of social presence and interpersonal support, consequently facilitating and sustaining continued interactional behavior (Al-Oraini, 2025). By examining these pathways in tandem, the study aims to understand the psychological mechanisms underlying the action route and to inform the design of AI health systems that meaningfully support user autonomy.

Theoretical Framework

AI health communication has moved from expert-driven systems toward conversational platforms that offer natural language exchange, adaptive dialogue, and personalized responsiveness (Hunt et al., 1998; Laranjo et al., 2018). Although these systems may expand informational access, scholars caution that opaque algorithmic architectures and commercial imperatives can still constrain user autonomy (Eysenbach, 2000; Garg et al., 2005; Kumar et al., 2013). In AI-powered health chatbots, this tension is especially consequential: greater conversational sophistication may improve engagement, but it may also intensify users' reliance on machine-generated advice through mechanisms such as the "machine heuristic" (Sundar, 2020). Given the variable effectiveness of conversational agents across physical activity, dietary behavior, and mental health domains (Laranjo et al., 2018; Li et al., 2023), this study examines the psychological mechanisms through which chatbot affordances are associated with health-related interactional behavior.

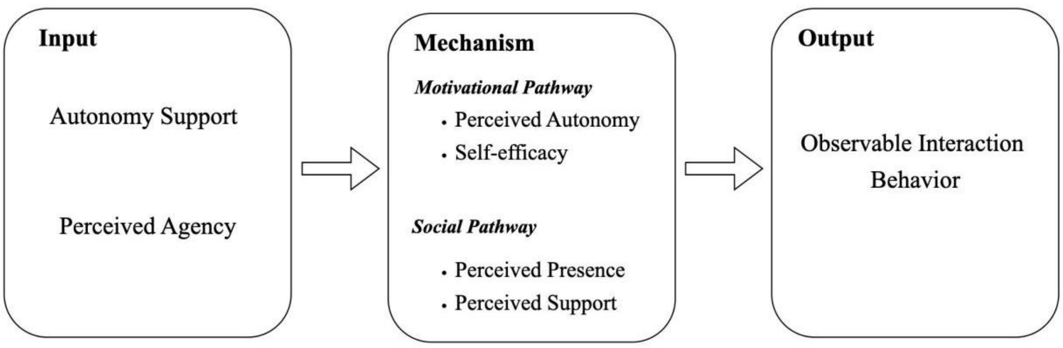
The study is grounded in the input–mechanism–output framework advanced by Chib and Lin (2018), which links technological features of digital health tools to behavioral outcomes through psychological mechanisms. As depicted in Figure 1, the framework is adapted to connect chatbot affordances with observable interaction behavior through motivational and social pathways.

At the input level, the framework incorporates two perceived affordances of AI health chatbots: autonomy support and perceived agency. Autonomy support refers to the extent to which the chatbot facilitates user volition and avoids controlling communication, whereas perceived agency refers to the perceived capacity of the chatbot to independently organize, regulate, and direct its responses in ways that appear intentional and goal-directed (Deci & Ryan, 1985; Ng et al., 2012; Wegner, 2004).

At the mechanism level, the motivational pathway draws on Self-Determination Theory through perceived autonomy and self-efficacy, whereas the social pathway draws on the Computers Are Social Actors through perceived presence and perceived support (Nass & Moon, 2000; Ryan & Deci, 2002).

At the output level, observable interaction behavior represents the behavioral manifestation of the action route, indicating whether users' active configuration choices are retained in the chatbot's terminal state.

Figure 1 Conceptual Framework



The Motivational Pathway: Self-Determination Theory (SDT)

SDT provides the motivational foundation for the present study (Deci & Ryan, 1985, 2000). The theory identifies autonomy, competence, and relatedness as basic psychological needs, with autonomy referring to the experience of acting with volition rather than under external pressure. In health contexts, autonomy-supportive environments are associated with more self-determined motivation, greater perceived competence, and improved behavioral outcomes (Chen et al., 2015; Ng et al., 2012). This makes SDT particularly useful for theorizing how AI health chatbots may support users' internal motivational resources.

A key SDT claim is that autonomy support facilitates internalization by providing meaningful choice, non-pressuring rationale, and acknowledgment of the individual's perspective (Williams et al., 1996, 2004, 2006). In health communication, this process suggests that users are more likely to engage with recommended behaviors when they experience the interaction as aligned with their own goals and values rather than as externally imposed.

The present study theorizes that structurally parallel processes operate within AI-mediated health contexts. Chatbot-provided autonomy support is expected to generate perceived autonomy, which activates autonomous motivational regulation, deepens engagement, and ultimately strengthens health self-efficacy. Self-efficacy, defined by Bandura (1977) as an individual's domain-specific belief in their capacity to execute behavior successfully, is theorized to be enhanced through chatbot-facilitated mastery experiences, modeled behaviors, and progress feedback. The convergence of SDT's internalization mechanism with Bandura's self-efficacy construct provides a coherent theoretical basis for the proposed model.

Recent digital health evidence supports this extension, with research linking psychological need satisfaction and autonomous motivation to positive health outcomes (Ng et al., 2012), and identifying self-efficacy as a key internal motivational process shaped by personal and environmental factors that drives choice, effort, persistence, and achievement (Schunk & DiBenedetto, 2021). Collectively, these findings are consistent with the following hypotheses:

H1: Autonomy support is positively associated with perceived autonomy.
H2: Autonomy support is positively associated with self-efficacy.
H3: Autonomy support is positively associated with observable interaction behavior.
H4: Autonomy support is indirectly associated with observable interaction behavior through a sequential pathway from perceived autonomy to self-efficacy.

The Social Pathway: The CASA Paradigm and Artificial Sociality

The Computers Are Social Actors (CASA) paradigm provides the theoretical foundation for understanding the relational dimension of human-chatbot interaction. Originally proposed by Nass et al. (1994) and consolidated in Reeves and Nass's (1996) media equation thesis, the CASA paradigm has been substantially refined over time. More recently, Go and Sundar (2019) and Glikson and Woolley (2020) have extended the CASA paradigm to AI-driven conversational agents, incorporating affordances such as natural language processing and affective computing.

Building on CASA, the present study conceptualizes chatbot agency as an interactional affordance, referring to the perceived capacity of a chatbot to regulate, organize, and direct its responses in ways that appear intentional and goal-directed. At the user level, this affordance is captured by perceived agency, defined as the extent to which users perceive the chatbot as capable of self-regulated, intentional, and organized action. Perceived agency does not imply consciousness or actual autonomy; rather, it reflects users' interpretation of chatbot behavior as generated and organized by an agent. This conceptualization distinguishes perceived agency from broader anthropomorphism and from generalized attributions of mental capacity (Wegner et al., 2004; Gray et al., 2007; Gray & Wegner, 2012).

In this study, perceived agency refers to the subjective sense that the chatbot is a meaningful social entity (Lombard & Ditton, 1997). Because agentic behavior provides a denser array of social cues, it intensifies the user's experience of genuine social interaction (Go & Sundar, 2019). Perceived presence, in turn, facilitates perceived support, defined following House (1987) as the user's perception that the chatbot provides informational, emotional, and appraisal resources functionally equivalent to those of human relationships. Studies confirm that emotionally responsive and informationally competent chatbots generate social support perceptions comparable to human providers (Lee & Hahn, 2024). These social perceptions may manifest in observable interaction behavior, reflecting the consistency between users' active chatbot configuration choices and their final chatbot configurations. Hence, we posit:

H5: Perceived agency is positively associated with perceived presence.
H6: Perceived agency is positively associated with perceived support.
H7: Perceived agency is positively associated with observable interaction behavior.
H8: Perceived agency is indirectly associated with observable interaction behavior through a sequential pathway from perceived presence to perceived support.

Methodology

Participants and Procedure

Participants were recruited from the active user base of EasyHealth AI (www.easyhealth-ai.com), a Chinese AI-powered health communication application that incorporates health incentive prompts within its initialization interface. Research invitations were disseminated to registered users of EasyHealth AI via in-application push notifications, with recruitment commencing on August 1, 2025. Of the 1,100 individuals who provided informed consent to participate, 613 completed the pre-survey, which included a demographic questionnaire assessing background characteristics. Following completion of the demographic questionnaire, 600 participants proceeded to interact with the AI chatbot, constituting the first behavioral observation point.

Of the 600 participants who proceeded to the chatbot interaction stage, 409 completed the post-survey and had corresponding behavioral trace data available for analysis, yielding a final analytic sample of 409 participants (68.2% retention). The post-survey assessed participants' perceptions of their ongoing chatbot interactions, including attitudes, beliefs, and experiential evaluations. The remaining 191 participants were excluded because the required behavioral trace data were unavailable.

Participants were observed for three months following enrollment. Behavioral trace data were collected throughout the observation period, although most participants completed the required chatbot interactions and post-survey within the first month. The broader study protocol comprised three components: (1) behavioral observation following entry into the chatbot interaction stage, (2) a post-interaction survey assessing participants' perceptions, and (3) behavioral trace collection during the three-month observation period. The present study uses only a subset of these data. Final sample inclusion was based on completion of the required procedures and availability of complete, analyzable data. A participant flow diagram is shown in Figure 2.

Among the 409 participants, 57.2% were male. Participants' ages ranged from under 18 to over 60 years, with the largest proportion (49.1%) falling within the 18–25 age group. More than half of the sample (55.7%) reported holding a bachelor's degree or higher. Additionally, 52.1% of participants had a professional background in the health-related sector. A substantial majority (75.1%) resided in urban areas. Regarding annual personal income, 41.1% of participants reported earning less than 30,000 CNY, 45.2% earned between 30,000 and 100,000 CNY, and 13.7% earned more than 100,000 CNY (see Table 1).

Figure 2 Study Procedure

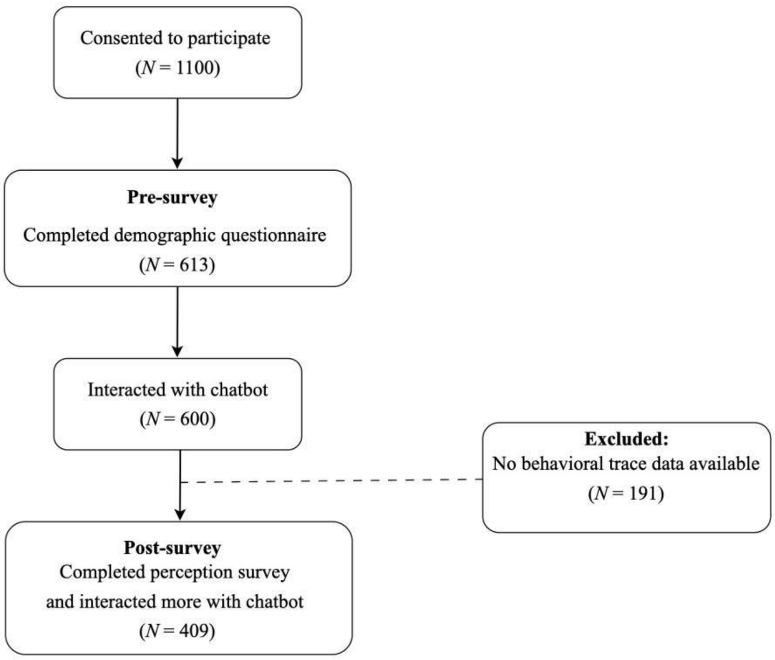


Table 1 Sociodemographic characteristics of participants (N = 409)

	Category	**Percentage**
Gender		
	male	57.2%
	female	42.8%
Age (years old)		
	below 18	2.2%
	18-25	49.1%
	26-35	36.9%
	36-45	9.3%
	46-59	1.5%
	Above 60	1.0%
Education		
	High school or below	17.6%
	Some college/technical school	26.7%
	College graduate or higher	55.7%
Professional Background		
	others	47.9%
	Health-related professionals	52.1%
Residential Location		
	Urban	75.1%
	Rural	24.9%
Income		
	less than 30,000 CNY	41.1%
	30,000–100,000 CNY	45.2%
	More than 10,000 CNY	13.7%

Measures

The present study employed a multi-method measurement design, integrating self-report survey instruments with behavioral indicators. All self-report constructs were operationalized using five-point Likert-type scales (1 = strongly disagree, 5 = strongly agree), with items adapted from previously validated instruments as detailed below and in Table 2. Construct reliability and validity were subsequently evaluated (Table 2; Hair et al., 2019), and discriminant validity was assessed using the heterotrait–monotrait (HTMT) ratio of correlations (Table 3).

Perceived Agency: Following Wegner et al.'s (2004) conceptualization of agency as the perceived capacity to act autonomously and causally, perceived agency was operationalized at the user level as the extent to which users perceive a chatbot as capable of self-regulated, intentional, and organized action. The construct reflects users' interpretations of chatbot behavior as generated and organized by an agent and does not imply consciousness or actual autonomy. The construct was measured reflectively using five indicators adapted from established measures of perceived mental capacity and agency (Gray et al., 2007; Gray & Wegner, 2012). The indicators assessed the chatbot's perceived ability to regulate its reactions, make and implement judgments, express internally organized thoughts or emotions, think, and respond in a planned manner. Collectively, these indicators capture users' perceptions of the chatbot's capacity to independently organize and regulate its behavior during interaction, rather than anthropomorphism or general mind perception. The scale demonstrated acceptable internal consistency ($M = 3.96$, $SD = 0.75$; Cronbach's $\alpha = 0.752$).

Autonomy Support: Grounded in SDT (Deci & Ryan, 2000), autonomy support was operationalized as users' perceived sense of volition and choice within the chatbot interaction environment, measured via three items. The scale demonstrated acceptable internal consistency ($M = 4.17$, $SD = 0.71$; Cronbach's $\alpha = 0.702$), with higher scores reflecting a stronger sense of having options and freedom in interacting with the chatbot.

Perceived Presence: We operationalized perceived presence drawing on Lombard and Ditton's (1997) social presence framework, which conceptualizes perceived presence as the experiential quality of mediated interaction, specifically the subjective sense of "being there with" another agent rather than merely engaging with system outputs. Three items captured distinct but interrelated facets of this construct: sociability, communicative engagement, and interactional responsiveness. Internal consistency for this scale was acceptable ($M = 4.09$, $SD = 0.87$; Cronbach's $\alpha = 0.809$).

Perceived Autonomy: This construct was defined as users' subjective experience of self-determination during chatbot interactions, reflecting the extent to which health-related interaction behaviors were perceived as self-endorsed and congruent with their internalized values and goals, rather than externally imposed (Ryan & Deci, 2006). Three items were adapted from the Health Care Climate Questionnaire (HCCQ; Williams et al., 1996) and reworded to reflect AI-mediated health communication contexts, capturing perceived self-initiation, values congruence, and volitional willingness ($M = 4.20$, $SD = 0.71$; Cronbach's $\alpha = 0.715$)

Perceived Support: Grounded in House's (1987) conceptualization, perceived support was operationalized as users' appraisals that the AI chatbot provides communicative resources functionally analogous to those exchanged in supportive human relationships. Seven items were adapted from the Online Social Support Scale (Nick et al., 2018) and reworded to reflect AI-mediated health communication contexts, tapping emotional support and social companionship dimensions (M = 4.07, SD = 0.66; Cronbach's α = 0.817).

Self-Efficacy: This construct was operationalized as users' confidence in their capability to successfully execute a designated configuration behavior relevant to the chatbot interaction context, based on Bandura's (2006) social cognitive theory. Three items were adapted from validated configuration behavior self-efficacy scales, targeting three distinct dimensions: capability belief, persistence under difficulty, and obstacle management. Internal consistency was acceptable (M = 4.13, SD = 0.73; Cronbach's α = 0.716), supporting the reliability of the scale.

Behavioral Alignment Score (BAS): Observable interaction behavior was operationalized as the Behavioral Alignment Score (BAS), a proximal behavioral manifestation of the action route reflecting whether users' active configuration choices were retained in the chatbot's terminal state.

Easyhealth-AI offered five configurable features: (1) customizable chatbot response settings, (2) integrated user health profiles, (3) transparent algorithmic reasoning displays, (4) chat record management, and (5) personalized chatbot tone settings. Each feature had two configuration states and could be actively modified no more than once per interaction. For each feature, an active modification was treated as an observable expression of the user's configuration preference. An alignment indicator was coded 1 if the state selected through the active modification was retained in the terminal configuration and 0 otherwise. Participants who did not actively modify any feature were excluded during data cleaning because BAS requires an observable configuration action. The five feature-level indicators were summed to yield a BAS ranging from 0 to 5, with higher scores indicating that more active configuration choices were retained in the terminal chatbot configuration. BAS was treated as a behavioral composite index rather than a reflective psychometric scale because the indicators represent distinct configuration opportunities rather than interchangeable manifestations of a latent construct. Indicators were equally weighted because each represented a single configuration opportunity and there was no theoretical basis for differential weighting.

Data Analysis

Preliminary analyses were conducted to determine which variables to include as covariates. Zero-order correlation analyses revealed that participant education level, professional background, and income were significantly associated with at least one focal study variable and were therefore included as covariates (see Table 4); these variables were therefore included as covariates in the subsequent analyses.

Structural equation modeling (SEM) was used for hypothesis testing, using the sem package in Stata 17. The indirect effects were assessed using 5,000 bootstrapped samples and bias-corrected 95% confidence intervals (Hayes & Scharkow, 2013), with mediation considered significant when the confidence intervals excluded zero. To ensure the robustness of the models, multicollinearity diagnostics were conducted prior to model estimation. Variance inflation factors (VIFs), obtained from auxiliary regression analyses, were all below the commonly accepted threshold of 5 (all VIFs < 2.5).

Table 2 *Measurement Items and Scale Reliability*

Variables (sources)	Items	Loading	Cronbach's α	CR	AVE
Perceived Agency (Wegner, 2004)	The chatbot can control its own reactions.	0.687	0.752	0.771	0.460
	The chatbot can distinguish right from wrong and take the correct actions.	0.732			
	The chatbot can express thoughts or emotions to me.	0.615			
	The chatbot is capable of thinking.	0.687			
	The chatbot responds to me in a planned manner.	0.664			
Autonomy Support (Deci & Ryan, 2000)	I feel that the chatbot provides me with choices and options.	0.717	0.702	0.718	0.529
	The chatbot believes that I am capable of making choices.	0.737			
	The chatbot understands my perspective before offering suggestions.	0.728			
Perceived Presence (Lombard & Ditton, 1997)	Interacting with the chatbot feels like communicating with a real person.	0.741	0.809	0.791	0.635
	The chatbot seems to pay close attention to what I say.	0.787			
	The chatbot's responses make me feel like I am engaged in a real conversation.	0.858			
Perceived Autonomy (Ryan & Deci, 2006; Williams et al., 1996)	I believe I have the choice to decide whether to engage with the chatbot.	0.819	0.715	0.722	0.542
	I feel that the choices I make during interactions with the chatbot are truly my own.	0.648			

	I engage with the chatbot because I choose to do so voluntarily.	0.731			
Perceived Support (House, 1987; Nick et al., 2018)	The chatbot seems to care about me.	0.696	0.817	0.820	0.452
	The chatbot makes me feel good about myself.	0.603			
	The chatbot encourages me during interactions.	0.722			
	I can receive emotional help and support from the chatbot.	0.679			
	I can share both positive and negative health experiences with the chatbot.	0.603			
	During interactions, the chatbot seems to understand my situation.	0.733			
	During interactions, the chatbot expresses liking for what I say or do.	0.655			
Self-efficacy (Bandura, 2006)	I am confident in my ability to improve my health through interactions with the chatbot.	0.669	0.716	0.729	0.542
	Even when faced with challenges, I believe I can successfully address health-related problems with the assistance of the chatbot.	0.755			
	I am confident in my ability to manage health-related obstacles following my interactions with the chatbot.	0.780			

Table 3 *Heterotrait–Monotrait Ratios (HTMT) for Assessing Discriminant Validity*

	Perceived Agency	Autonomy Support	Perceived Presence	Perceived Autonomy	Perceived Support	Self-efficacy
Perceived Agency	—	0.736	0.676	0.566	0.686	0.723
Autonomy Support		—	0.671	0.661	0.757	0.714
Perceived Presence			—	0.362	0.547	0.547
Perceived Autonomy				—	0.785	0.576
Perceived Support					—	0.579
Self-efficacy						—

Note. Values represent HTMT ratios. All HTMT ratios were below the conservative threshold of .85, supporting discriminant validity.

Table 4 *Zero-order Correlations Among Main Variables*

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Gender	—												
2. Age	-0.005	—											
3. Education	0.254***	-0.026	—										
4. Professional Background	0.187***	0.016	0.072	—									
5. Residential Location	-0.064	0.001	-0.236***	0.021	—								
6. Income	-0.029	0.193***	0.086	-0.031	-0.054	—							
7. Perceived Agency	0.061	0.079	0.044	-0.075	0.039	0.037	—						
8. Autonomy Support	0.024	0.032	-0.01	-0.048	0.017	0.061	0.535***	—					
9. Perceived Presence	-0.043	0.089	-0.063	-0.226***	0.088	0.026	0.532***	0.506***	—				
10. Perceived Autonomy	-0.008	0.051	0.046	0.015	0.021	0.013	0.410***	0.467***	0.280***	—			
11. Perceived Support	0.038	0.096	-0.019	-0.124*	-0.013	0.116*	0.538***	0.574***	0.447***	0.598***	—		
12. Self-efficacy	***0.066***	***0.081***	***0.103****	***-0.058***	***-0.02***	***0.037***	***0.524******	***0.507******	***0.415******	***0.413******	***0.441******	—	
13. Behavioral Alignment Score	***0.005***	***0.011***	***-0.002***	***-0.178******	***0.085***	***0.053***	***0.227*****	***0.141*****	***0.223******	***0.009***	***0.09***	***0.159*****	—

Note. Gender (0 = male, 1 = female); professional background (0 = other, 1 = health-related); residential location (0 = urban, 1 = rural).
**p < .05; **p < .01; ***p < .001*

Table 5 *Indirect Effects and 95% Bootstrapped Confidence Intervals*

Pathways	*Effects*	*BootSE*	*BC 95% CI*
Autonomy Support→ Perceived Autonomy→ BAS	-0.063	0.037	[-0.139, 0.005]
Autonomy Support→ Self-efficacy→ BAS	0.076	0.038	**[0.013, 0.162]**
Autonomy Support→ Perceived Autonomy→ Self-efficacy→ BAS	0.019	0.011	**[0.004, 0.049]**
Perceived Agency→ Perceived Presence→ BAS	0.111	0.044	**[0.034, 0.204]**
Perceived Agency→ Perceived Support→ BAS	-0.045	0.033	[-0.115, 0.014]
Perceived Agency→ Perceived Presence→ Perceived Support→ BAS	-0.012	0.010	[-0.038, 0.002]

Note. Unstandardized estimates, bootstrapped standard errors, and bias-corrected confidence intervals were obtained from path analyses based on 5,000 bootstrap samples.

Results

Preliminary Analyses

Construct reliability and validity were subsequently assessed (Table 2). Composite reliability (CR) values ranged from .718 to .820 across constructs. Average variance extracted (AVE) values ranged from .452 to .635 across constructs: perceived agency (CR = .771, AVE = .460), autonomy support (CR = .718, AVE = .529), perceived presence (CR = .791, AVE = .635), perceived autonomy (CR = .722, AVE = .542), perceived support (CR = .820, AVE = .452), and self-efficacy (CR = .729, AVE = .542). Although the AVE values for perceived agency and perceived support were slightly below the conventional .50 threshold, their CR values indicated acceptable reliability. All pairwise HTMT values were below the conservative .85 threshold, indicating no problematic construct overlap (Table 3). Overall, the results provide adequate evidence of internal consistency and discriminant validity, supporting the empirical distinctiveness of the study constructs.

Behavioral trace data further described participants' human–chatbot interaction patterns. The mean session duration was 3.1 minutes, and the mean cumulative interaction time was 9.9 minutes per participant. On average, participants interacted with the chatbot interface six times over approximately one month. Notably, 18.1% of participants showed relatively high engagement, recording more than ten chatbot interactions. For the outcome variable, BAS showed a moderate level of behavioral alignment ($M = 3.15$, $SD = 1.36$; scale range: 0–5), with considerable variability across participants.

Table 4 presents the zero-order correlations among the main study variables. Perceived agency, autonomy support, perceived presence, perceived autonomy, perceived support, and self-efficacy were moderately to strongly and positively correlated.

Hypothesis Testing

To test the proposed hypotheses, two serial mediation models were estimated separately, corresponding to the motivational pathway (H1-H4) and the social pathway (H5-H8). Prior to these analyses, an integrated model including all predictors and mediators was also initially specified to examine both pathways simultaneously. Although the bootstrap estimation converged, the integrated model yielded an inadmissible solution, indicating substantial estimation instability and limiting the interpretability of the results. Specifically, the model produced nonsignificant total associations for autonomy support ($\beta = -0.249$, $p = .649$, 95% CI

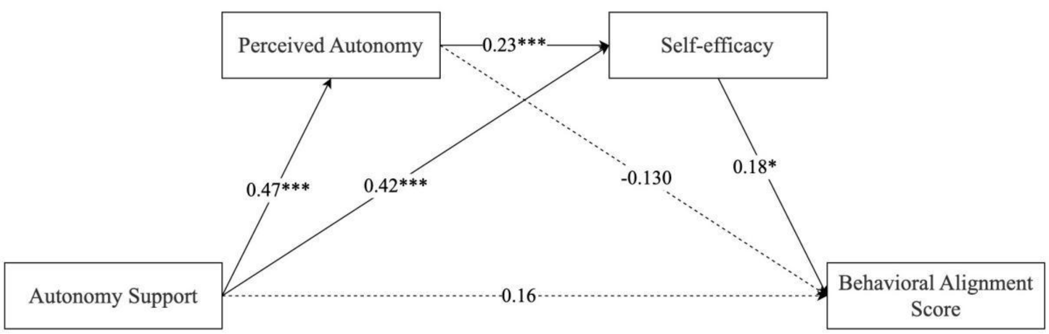
[−1.587, 0.408]) and perceived agency (β = 0.475, p = .382, 95% CI [−0.100, 1.895]). Given the substantial shared variance among constructs and the resulting estimation instability, the integrated model was not retained for substantive interpretation. The motivational and social pathways were therefore examined separately.

Motivational Pathway

The estimated path model for the motivational path is presented in Figure 3. The model showed a good fit to the data: $\chi^2(4) = 3.391$, $p = .495$, RMSEA = .000, CFI = 1.000, TLI = 1.007, SRMR = .017. Autonomy support was positively associated with both perceived autonomy ($\beta = 0.47$, $p < .001$) and self-efficacy ($\beta = 0.42$, $p < .001$). However, the direct association between autonomy support and the Behavioral Alignment Score (BAS) was not statistically significant ($\beta = 0.16$, $p = .060$). Thus, H1 and H2 were supported, but H3 was not supported.

Bootstrapping analyses further clarified these indirect mechanisms (see Table 5). Autonomy support had a significant indirect effect on BAS via self-efficacy (indirect effect = 0.076, BootSE = 0.038, BC 95% CI [0.013, 0.162]), as well as a serial indirect effect through perceived autonomy and self-efficacy (indirect effect = 0.019, BootSE = 0.011, BC 95% CI [0.004, 0.049]). These results indicate a significant indirect association between autonomy support and BAS through self-efficacy, as well as a significant sequential mediation by perceived autonomy and self-efficacy. Thus, H4 was supported.

Figure 3 Standardized path estimates for the Motivational Pathway



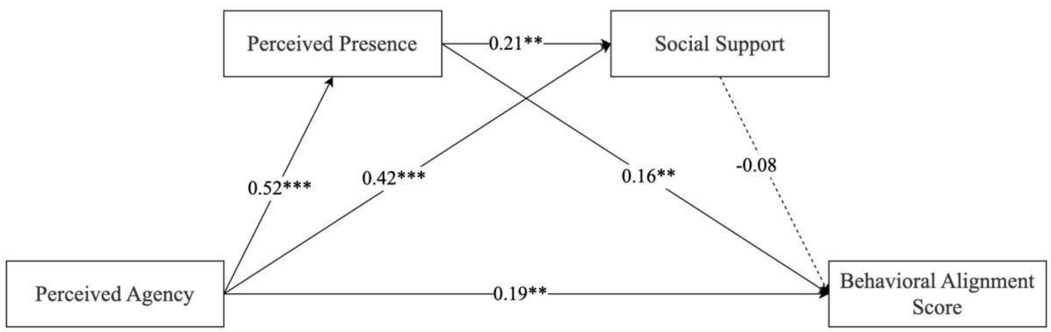
Notes. Standardized coefficients are depicted in the figure. *p < .05, ***p < .001.

Social Pathway

The estimated path model for the social path is presented in Figure 4. The social pathway model showed an acceptable fit, $\chi^2(3) = 9.96$, $p = .019$, RMSEA = .075, CFI = .980, TLI = .921, SRMR = .032. Consistent with H5–H7, perceived agency was positively associated with perceived presence ($\beta = 0.52$, $p < .001$), perceived support ($\beta = 0.42$, $p < .001$), and BAS ($\beta = 0.19$, $p = .002$). These findings indicate that higher levels of perceived agency were associated with higher levels of perceived presence, perceived support, and behavioral alignment.

Bootstrapping results showed a statistically significant indirect association between perceived agency and BAS through perceived presence (indirect effect = 0.111, BootSE = 0.044, BC 95% CI [0.034, 0.204]). The indirect association through perceived support was not statistically significant (indirect effect = −0.045, BootSE = 0.033, BC 95% CI [−0.115, 0.014]), and neither was the sequential indirect association through perceived presence and perceived support (indirect effect = −0.012, BootSE = 0.010, BC 95% CI [−0.038, 0.002]). These results indicate that perceived agency influences BAS primarily through perceived presence, providing partial support for H8.

Figure 4 Standardized path estimates for the Social Pathway



Notes. Standardized coefficients were depicted in the figure. *p < .05, ***p < .001.

Discussion

Drawing on the input–mechanism–output framework (Chib & Lin, 2018), this study examined two theoretically distinct pathways within a decomposed TIME-HAII action route. Drawing on the input–mechanism–output framework (Chib & Lin, 2018), this study examined two theoretically distinct pathways within a decomposed TIME-HAII action route. In the motivational pathway, perceived chatbot autonomy support was positively associated with perceived autonomy and self-efficacy, but its direct association with BAS was not statistically significant. The association between autonomy support and BAS was instead statistically accounted for by motivational mechanisms, with self-efficacy emerging as the principal mediator and perceived autonomy functioning as an upstream factor in the sequential mediation pathway. In the social pathway, perceived chatbot agency was associated with BAS through social perceptions. Perceived presence was the primary mediator, whereas the hypothesized sequential pathway involving perceived support was not statistically significant. Overall, the findings suggest that the motivational pathway was primarily characterized by self-efficacy, while the social pathway was primarily characterized by perceived presence. These findings carry several theoretical implications for understanding the psychological architecture of the action route in human–AI health communication.

Theoretical Implications

The present study advances theory by unpacking the action route in human–AI health communication. Rather than treating the action route as a unitary mechanism through which technological affordances translate into behavioral outcomes, our findings suggest that it is better understood as a differentiated psychological architecture composed of asymmetric motivational and social processes. This theoretical move helps open the black box of the action route by specifying not only whether AI affordances matter, but also how different affordances activate distinct psychological mechanisms that subsequently shape health-related interactional behavior. In this sense, the study contributes to communication theory by showing that the action route may not operate as a single coherent pathway, but as a set of parallel processes driven by distinctive affordance–mechanism linkages.

A central implication concerns the motivational mechanism underlying autonomy-supportive AI. The findings suggest that autonomy support promotes behavioral intention not simply by increasing users' perceived freedom or choice, but by strengthening behavior-specific capability beliefs. Self-efficacy therefore serves as a key motivational bridge between autonomy-supportive interaction and intended health behavior. This pattern is theoretically coherent with self-determination theory, which treats autonomy and competence as distinct but mutually reinforcing psychological needs (Deci & Ryan, 2000). Although self-efficacy is not identical to competence need satisfaction, it can be understood in this context as a behavior-specific capability belief closely related to perceived competence. Prior SDT research has shown that autonomy-supportive environments tend to foster competence-related perceptions and self-determined motivation, and that these motivational processes are consequential for health behavior change (Edmunds et al., 2006; Hagger & Chatzisarantis, 2009; Ntoumanis et al., 2021). Extending this line of work to AI-mediated health communication, the present findings suggest that autonomy-supportive AI may shape behavioral intention by helping users feel not only free to act, but also capable of acting.

The study also refines the social mechanism through which AI agency shapes behavioral intention. The findings suggest that AI agency may influence users less through perceived social support than through the more immediate experience of social presence. This distinction is theoretically important because perceived presence and perceived support capture different layers of social response. Perceived presence reflects an experiential sense that a socially responsive other is available within the interaction, whereas perceived support reflects a more evaluative judgment that the other provides useful emotional, informational, or instrumental resources. This conceptual distinction is consistent with classic accounts of presence as the subjective experience of being with another entity in a mediated environment (Lombard & Ditton, 1997), as well as with social support research that conceptualizes support as an appraisal of available or received relational resources (Thoits, 2011). In the context of AI health chatbots, agentic cues may therefore matter because they make the system feel socially present, attentive, and interactionally responsive, even if users do not necessarily evaluate the system as a substantive source of support.

This distinction contributes to communication theory by suggesting that social influence in human–AI interaction may begin with presence before support. Users may not need to perceive an AI agent as genuinely supportive in an interpersonal sense for the agent to shape their behavioral intentions. Instead, a thinner but psychologically consequential sense of co-presence may be sufficient to activate social responses. The social pathway identified here therefore complicates support-based accounts of digital health communication by showing that the experiential immediacy of social presence may be more central than users' reflective appraisal of support provision. This interpretation also aligns with emerging work on AI-mediated relational processes, which suggests that users may respond to agentic systems as socially meaningful actors even when such systems do not provide support in the same way human partners do (Scherr et al., 2025).

Practical Implications

Our findings suggest that merely incorporating autonomy-supportive features, such as offering customizable interface options, is insufficient to promote meaningful user engagement. Instead, chatbot design should prioritize enhancing users' self-efficacy, which emerged as the key mechanism driving behavioral alignment. Practically, this can be achieved by embedding structured feedback systems (e.g., progress tracking and reinforcement), providing step-by-step guidance for health-related tasks, and enabling users to actively participate in decision-making processes rather than passively selecting options. Such strategies align with prior research showing that self-efficacy is strengthened through guided, actionable instruction and participatory engagement in health decision-making (Ng et al., 2012; Williams et al., 2006; Yardley et al., 2016). In this sense, effective design should move beyond "allowing choice" toward "supporting competence," ensuring that users feel capable of executing recommended behaviors.

Moreover, the results highlight that perceived presence plays a more critical role than perceived support in shaping user interaction outcomes. This finding offers a more actionable design direction, as perceived presence can be directly enhanced through interface and interaction features. Specifically, chatbots should prioritize responsiveness (e.g., timely and contingent replies), conversational continuity (e.g., maintaining context across turns), and adaptive personalization (e.g., referencing prior interactions). Additional strategies documented in prior literature include using natural language styles, simulating turn-taking dynamics, and incorporating subtle socio-emotional cues that signal attentiveness (Go & Sundar, 2019; Janson, 2023). Together, these features can strengthen users' sense of "being with" the system, thereby fostering sustained engagement even in the absence of perceived emotional support.

Limitations and Future Directions

Despite its contributions, this study has several limitations that suggest directions for future research. First, participant attrition and potential selection bias may limit the generalizability of the findings. Of the 1,100 individuals who initially consented, 409 were retained in the final analytic sample. Because baseline characteristics were not collected for the full consented sample, we could not assess whether retained participants differed systematically from those excluded. Thus, selective retention and data-availability bias cannot be ruled out. Future studies should collect baseline measures for all recruited participants and systematically document attrition and missing behavioral data. Second, the professional background question in the demographic questionnaire employed a binary response format, categorizing participants as either "health-related professionals" or "others," which substantially constrains the granularity of occupational data collected. This dichotomous classification restricted a more nuanced examination of how specific professional backgrounds may differentially shape participants' responses. Third, the motivational and social pathways were modeled separately, which precludes examination of their potential interactions. Future research should adopt integrated and longitudinal designs to capture the dynamic interplay between these mechanisms over time. Fourth, despite integrating behavioral trace and survey data, the observational design precludes firm conclusions about temporal precedence or causality. Experimental and field-based approaches are therefore needed to more rigorously test the proposed action-route mechanisms. Finally, the study focused on Chinese users interacting with a single AI health platform, which may limit cross-cultural and contextual generalizability. Future research should replicate these findings across diverse cultural contexts, AI systems, and healthcare settings.

In addition, several findings point to important avenues for further inquiry. The non-significant role of perceived social support raises unresolved theoretical questions regarding the conditions under which AI systems can function as meaningful sources of social support. Future research should explore potential boundary conditions, such as user characteristics or interaction contexts, that may moderate this relationship. Finally, although the BAS provides a novel behavioral indicator of human–AI interaction, its relationship with downstream health behaviors and outcomes remains unclear. Further research is needed to establish its predictive validity in relation to concrete health-related outcomes.

Conclusion

This study examined how autonomy-supportive and agentic features of AI health chatbots are associated with users' behavioral alignment. Drawing on the input–mechanism–output framework and a decomposed TIME-HAII action route, the findings suggest two distinct pathways: autonomy support was linked to behavioral alignment primarily through motivational mechanisms, especially self-efficacy, whereas chatbot perceived agency was linked to behavioral alignment primarily through perceived presence. These patterns indicate that the action route may be better understood as a differentiated psychological architecture. The findings suggest that effective AI health chatbots should support both users' capability beliefs and their sense of socially responsive interaction.

Acknowledgements

We gratefully acknowledge the support of the Peking University Health Communication Program for the development of EasyHealth AI, the application used in this study.

Funding

This work was supported by City University of Hong Kong under the Grant "Designing AI-Powered Mental Health Intervention Through Positive Expressive Writing" (No:7020144).

Disclosure Statement

No potential conflict of interest was reported by the authors.

Ethics Statement

Survey respondents provided informed consent. The study protocol was approved by the City University of Hong Kong Ethics Committee (Approval No. HU-STA-00001638). As access to the Easyhealth-AI platform requires use of WeChat, and Tencent requires users under 18 years of age to obtain parental or legal guardian consent, all respondents younger than 18 years had obtained prior written consent from a parent or legal guardian before participating in the questionnaire study.

References

Abran, A., Khelifi, A., Suryn, W., & Seffah, A. (2003). Usability meanings and interpretations in ISO standards. Software Quality Journal, 11(4), 325–338. https://doi.org/10.1023/A:1025869312943

Al-Oraini, B. S. (2025). Chatbot dynamics: Trust, social presence and customer satisfaction in AI-driven services. Journal of Innovative Digital Transformation, 2(2), 109–130. https://doi.org/10.1108/JIDT-08-2024-0022

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. Psychological Review, 84(2), 191–215. https://doi.org/10.1037/0033-295X.84.2.191

Bandura, A. (2006). Guide for constructing self-efficacy scales. In F. Pajares & T. Urdan (Eds.), Self-efficacy beliefs of adolescents (Vol. 5, pp. 307–337). Information Age Publishing.

Bickmore, T. W., & Picard, R. W. (2005). Establishing and maintaining long-term human-computer relationships. ACM Transactions on Computer-Human Interaction, 12(2), 293–327. https://doi.org/10.1145/1067860.1067867

Chen, B., Vansteenkiste, M., Beyers, W., Boone, L., Deci, E. L., Van der Kaap-Deeder, J., Duriez, B., Lens, W., Matos, L., Mouratidis, A., Ryan, R. M., Sheldon, K. M., Soenens, B., Van Petegem, S., & Verstuyf, J. (2015). Basic psychological need satisfaction, need frustration, and need strength across four cultures. Motivation and Emotion, 39(2), 216–236. https://doi.org/10.1007/s11031-014-9450-1

Chib, A., & Lin, S. H. (2018). Theoretical advancements in mHealth: A systematic review of mobile apps. Journal of Health Communication, 23(10–11), 909–955. https://doi.org/10.1080/10810730.2018.1544676

Deci, E. L., & Ryan, R. M. (1985). The general causality orientations scale: Self-determination in personality. Journal of Research in Personality, 19(2), 109–134. https://doi.org/10.1016/0092-6566(85)90023-6

Deci, E. L., & Ryan, R. M. (2000). The “what” and “why” of goal pursuits: Human needs and the self-determination of behavior. Psychological Inquiry, 11(4), 227–268. https://doi.org/10.1207/S15327965PLI1104_01

Edmunds, J., Ntoumanis, N., & Duda, J. L. (2006). A test of self-determination theory in the exercise domain. Journal of Applied Social Psychology, 36(9), 2240–2265. https://doi.org/10.1111/j.0021-9029.2006.00102.x

Eysenbach, G. (2000). Recent advances: Consumer health informatics. BMJ, 320(7251), 1713–1716. https://doi.org/10.1136/bmj.320.7251.1713

Garg, A. X., Adhikari, N. K., McDonald, H., Rosas-Arellano, M. P., Devereaux, P. J., Beyene, J., Grover, S. A., & Haynes, R. B. (2005). Effects of computerized clinical decision support systems on practitioner performance and patient outcomes: A systematic review. JAMA, 293(10), 1223–1238. https://doi.org/10.1001/jama.293.10.1223

Gibson, J. J. (2014). The ecological approach to visual perception: Classic edition. Psychology Press.

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. Academy of Management Annals, 14(2), 627–660. https://doi.org/10.5465/annals.2018.0057

Go, E., & Sundar, S. S. (2019). Humanizing chatbots: The effects of visual, identity and conversational cues on humanness perceptions. Computers in Human Behavior, 97, 304–316. https://doi.org/10.1016/j.chb.2019.01.020

Gray, H. M., Gray, K., & Wegner, D. M. (2007). Dimensions of mind perception. Science, 315(5812), 619. https://doi.org/10.1126/science.1134475

Gray, K., & Wegner, D. M. (2012). Feeling robots and human zombies: Mind perception and the uncanny valley. Cognition, 125(1), 125–130. https://doi.org/10.1016/j.cognition.2012.06.007

Hagger, M. S., & Chatzisarantis, N. L. D. (2009). Integrating the theory of planned behaviour and self-determination theory in health behaviour: A meta-analysis. British Journal of Health Psychology, 14(2), 275–302. https://doi.org/10.1348/135910708X373959

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hancock, J. T., Naaman, M., & Levy, K. (2020). AI-mediated communication: Definition, research agenda, and ethical considerations. Journal of Computer-Mediated Communication, 25(1), 89–100. https://doi.org/10.1093/jcmc/zmz022

Hayes, A. F., & Scharkow, M. (2013). The relative trustworthiness of inferential tests of the indirect effect in statistical mediation analysis: Does method really matter? Psychological Science, 24(10), 1918–1927. https://doi.org/10.1177/0956797613480187

House, J. S. (1987). Social support and social structure. Sociological Forum, 2(1), 135–146. https://doi.org/10.1007/BF01107897

Hunt, D. L., Haynes, R. B., Hanna, S. E., & Smith, K. (1998). Effects of computer-based clinical decision support systems on physician performance and patient outcomes: A systematic review. JAMA, 280(15), 1339–1346. https://doi.org/10.1001/jama.280.15.1339

Janson, A. (2023). How to leverage anthropomorphism for chatbot service interfaces: The interplay of communication style and personification. Computers in Human Behavior, 149, Article 107954. https://doi.org/10.1016/j.chb.2023.107954

Jiang, X., Xie, H., Tang, R., Du, Y., Li, T., Gao, J., Xu, X., Jiang, S., Zhao, T., Zhao, W., Sun, X., Hu, G., Wu, D., & Xie, G. (2021). Characteristics of online health care services from China’s largest online medical platform: Cross-sectional survey study. Journal of Medical Internet Research, 23(4), Article e25817. https://doi.org/10.2196/25817

Kumar, S., Nilsen, W. J., Abernethy, A., Atienza, A., Patrick, K., Pavel, M., Riley, W. T., Shar, A., Spring, B., & Swendeman, D. (2013). Mobile health technology evaluation: The mHealth evidence workshop. American Journal of Preventive Medicine, 45(2), 228–236. https://doi.org/10.1016/j.amepre.2013.03.017

Laranjo, L., Dunn, A. G., Tong, H. L., Kocaballi, A. B., Chen, J., Bashir, R., Surian, D., Gallego, B., Magrabi, F., Lau, A. Y. S., & Coiera, E. (2018). Conversational agents in healthcare: A systematic review. Journal of the American Medical Informatics Association, 25(9), 1248–1258. https://doi.org/10.1093/jamia/ocy072

Lee, I., & Hahn, S. (2024). On the relationship between mind perception and social support of chatbots. Frontiers in Psychology, 15, Article 1282036. https://doi.org/10.3389/fpsyg.2024.1282036

Lee, S., Moon, W. K., Lee, J. G., & Sundar, S. S. (2023). When the machine learns from users, is it helping or snooping? Computers in Human Behavior, 138, Article 107427. https://doi.org/10.1016/j.chb.2022.107427

Liu, W., Li, J., Tang, Y., Zhao, Y., Liu, C., Song, M., Ju, Z., Kumar, S. V., Lu, Y., Akbani, R., Mills, G. B., & Liang, H. (2025). DrBioRight 2.0: An LLM-powered bioinformatics chatbot for large-scale cancer functional proteomics analysis. Nature Communications, 16(1), Article 2256. https://doi.org/10.1038/s41467-025-57430-4

Lombard, M., & Ditton, T. (1997). At the heart of it all: The concept of presence. Journal of Computer-Mediated Communication, 3(2), Article JCMC321. https://doi.org/10.1111/j.1083-6101.1997.tb00072.x

Mackert, M., Mabry-Flynn, A., Champlin, S., Donovan, E. E., & Pounders, K. (2016). Health literacy and health information technology adoption: The potential for a new digital divide. Journal of Medical Internet Research, 18(10), Article e264. https://doi.org/10.2196/jmir.6349

Mygland, M. J., Schibbye, M., Pappas, I. O., & Vassilakopoulou, P. (2021). Affordances in human-chatbot interaction: A review of the literature. In F. Milani, N. Poels, & G. Nolte (Eds.), Proceedings of the 20th IFIP WG 6.11 Conference on e-Business, e-Services and e-Society (pp. 3–17). Springer. https://doi.org/10.1007/978-3-030-85447-8_1

Nass, C., & Moon, Y. (2000). Machines and mindlessness: Social responses to computers. Journal of Social Issues, 56(1), 81–103. https://doi.org/10.1111/0022-4537.00153

Nass, C., Steuer, J., & Tauber, E. R. (1994). Computers are social actors. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (pp. 72–78). ACM. https://doi.org/10.1145/191666.191703

Nassehi, D., Gripsrud, B. H., & Ramvi, E. (2024). Theoretical perspectives underpinning research on the physician-patient relationship in a digital health practice: Scoping review. Interactive Journal of Medical Research, 13(1), Article e47280. https://doi.org/10.2196/47280

Ng, J. Y. Y., Ntoumanis, N., Thøgersen-Ntoumani, C., Deci, E. L., Ryan, R. M., Duda, J. L., & Williams, G. C. (2012). Self-determination theory applied to health contexts: A meta-analysis. Perspectives on Psychological Science, 7(4), 325–340. https://doi.org/10.1177/1745691612447309

Nick, E. A., Cole, D. A., Cho, S. J., Smith, D. K., Carter, T. G., & Zelkowitz, R. L. (2018). The online social support scale: Measure development and validation. Psychological Assessment, 30(9), 1127–1143. https://doi.org/10.1037/pas0000558

Ntoumanis, N., Ng, J. Y. Y., Prestwich, A., Quested, E., Hancox, J. E., Thøgersen-Ntoumani, C., Deci, E. L., Ryan, R. M., Lonsdale, C., & Williams, G. C. (2021). A meta-analysis of self-determination theory-informed intervention studies in the health domain: Effects on motivation, health behavior, physical, and psychological health. Health Psychology Review, 15(2), 214–244. https://doi.org/10.1080/17437199.2020.1718529

Pham Thi, T. D., & Duong, N. T. (2025). Intrinsic motivations in health and fitness app engagement: A mediation model of entertainment. Digital Health, 11, Article 20552076251326151. https://doi.org/10.1177/20552076251326151

Raees, M., Meijerink, I., Lykourentzou, I., Khan, V. J., & Papangelis, K. (2024). From explainable to interactive AI: A literature review on current trends in human-AI interaction. International Journal of Human-Computer Studies, 189, Article 103301. https://doi.org/10.1016/j.ijhcs.2024.103301

Rafikova, A., & Voronin, A. (2025). Human–chatbot communication: A systematic review of psychological studies. AI & Society, 40(7), 5389–5408. https://doi.org/10.1007/s00146-025-02277-y

Reeves, B., & Nass, C. (1996). The media equation: How people treat computers, television, and new media like real people. Cambridge University Press.

Ryan, R. M. (1995). Psychological needs and the facilitation of integrative processes. Journal of Personality, 63(3), 397–427. https://doi.org/10.1111/j.1467-6494.1995.tb00501.x

Ryan, R. M., & Connell, J. P. (1989). Perceived locus of causality and internalization: Examining reasons for acting in two domains. Journal of Personality and Social Psychology, 57(5), 749–761. https://doi.org/10.1037/0022-3514.57.5.749

Ryan, R. M., & Deci, E. L. (2002). Overview of self-determination theory: An organismic dialectical perspective. In E. L. Deci & R. M. Ryan (Eds.), Handbook of self-determination research (pp. 3–33). University of Rochester Press.

Ryan, R. M., & Deci, E. L. (2006). Self-regulation and the problem of human autonomy: Does psychology need choice, self-determination, and will? Journal of Personality, 74(6), 1557–1586. https://doi.org/10.1111/j.1467-6494.2006.00420.x

Scherr, S., Cao, B., Jiang, L. C., & Kobayashi, T. (2025). Explaining the use of AI chatbots as context alignment: Motivations behind the use of AI chatbots across contexts and culture. Computers in Human Behavior, 172, Article 108738. https://doi.org/10.1016/j.chb.2025.108738

Schunk, D. H., & DiBenedetto, M. K. (2021). Self-efficacy and human motivation. In A. J. Elliot (Ed.), Advances in motivation science (Vol. 8, pp. 153–179). Elsevier. https://doi.org/10.1016/bs.adms.2020.10.001

Shneiderman, B. (2020). Human-centered artificial intelligence: Three fresh ideas. AIS Transactions on Human-Computer Interaction, 12(3), 109–124. https://doi.org/10.17705/1thci.00131

Singh, B., Olds, T., Brinsley, J., Dumuid, D., Virgara, R., Matricciani, L., Bobrovskaya, L., Rocke, K., & Maher, C. (2023). Systematic review and meta-analysis of the effectiveness of chatbots on lifestyle behaviours. NPJ Digital Medicine, 6(1), Article 118. https://doi.org/10.1038/s41746-023-00856-1

Sundar, S. S. (2020). Rise of machine agency: A framework for studying the psychology of human–AI interaction (HAII). Journal of Computer-Mediated Communication, 25(1), 74–88. https://doi.org/10.1093/jcmc/zmz026

Thoits, P. A. (2011). Mechanisms linking social ties and support to physical and mental health. Journal of Health and Social Behavior, 52(2), 145–161. https://doi.org/10.1177/0022146510395592

Waddell, T. F. (2019). Can an algorithm reduce the perceived bias of news? Testing the effect of machine attribution on news readers' evaluations of bias, anthropomorphism, and credibility. Journalism & Mass Communication Quarterly, 96(1), 82–100. https://doi.org/10.1177/1077699018815891

Wegner, D. M., Sparrow, B., & Winerman, L. (2004). Vicarious agency: Experiencing control over the movements of others. Journal of Personality and Social Psychology, 86(6), 838–848. https://doi.org/10.1037/0022-3514.86.6.838

Williams, G. C., Grow, V. M., Freedman, Z. R., Ryan, R. M., & Deci, E. L. (1996). Motivational predictors of weight loss and weight-loss maintenance. Journal of Personality and Social Psychology, 70(1), 115–126. https://doi.org/10.1037/0022-3514.70.1.115

Williams, G. C., McGregor, H. A., Sharp, D., Levesque, C., Kouides, R. W., Ryan, R. M., & Deci, E. L. (2006). Testing a self-determination theory intervention for motivating tobacco cessation: Supporting autonomy and competence in a clinical trial. Health Psychology, 25(1), 91–101. https://doi.org/10.1037/0278-6133.25.1.91

Williams, G. C., McGregor, H. A., Zeldman, A., Freedman, Z. R., & Deci, E. L. (2004). Testing a self-determination theory process model for promoting glycemic control through diabetes self-management. Health Psychology, 23(1), 58–66. https://doi.org/10.1037/0278-6133.23.1.58

Yardley, L., Spring, B. J., Riper, H., Morrison, L. G., Crane, D. H., Curtis, K., Kellers, G., Blandford, A., & Blandford, A. (2016). Understanding and promoting effective engagement with digital behavior change interventions. American Journal of Preventive Medicine, 51(5), 833–842