International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1-14

https://doi.org/10.70917/ijcisim-2026-2896
Article

The Dual Dynamics of Technology Acceptance and Psychological Reactance: Patients' Psychological Conflicts in AI-Assisted Rehabilitation and the Moderating Effects of Social Environment

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Abstract: Background Artificial intelligence (AI)-assisted rehabilitation technologies hold significant promise for improving patient outcomes, yet adoption rates remain suboptimal. Existing research has predominantly examined acceptance mechanisms in isolation, neglecting the concurrent operation of resistance pathways and social contextual influences. This study developed an integrated theoretical model combining the Technology Acceptance Model (TAM) and Psychological Reactance Theory (PRT) to examine how facilitating and inhibiting psychological mechanisms simultaneously shape patients' behavioral intentions toward AI-assisted rehabilitation, and how social environmental factors moderate these dual pathways. **Methods** A cross-sectional survey was conducted with 434 rehabilitation patients from three tertiary hospitals in eastern China between March and May 2025. Structural equation modeling was employed to test direct effects, mediation, and moderation hypotheses. **Results** Both the acceptance pathway (perceived usefulness → behavioral intention: β = 0.387, $p < 0.001$) and the reactance pathway (psychological reactance → behavioral intention: β = −0.276, $p < 0.001$) significantly influenced behavioral intentions. Perceived ease of use exerted both direct (β = 0.109, $p = 0.013$) and indirect effects on behavioral intention. Family support amplified the positive effect of perceived usefulness ($\Delta\chi^2$ = 6.847, $p < 0.01$), while physician-patient trust buffered the negative effect of psychological reactance ($\Delta\chi^2$ = 8.234, $p < 0.01$). Social norms did not significantly moderate the reactance-intention relationship. The integrated model explained 52.3% of variance in behavioral intention. **Conclusions** Patient acceptance of AI-assisted rehabilitation is shaped by concurrent facilitating and inhibiting psychological processes that are differentially moderated by social environmental factors. Implementation strategies should address both perceived usefulness and autonomy concerns through trusted physician relationships and family engagement.

Keywords: AI-assisted rehabilitation; technology acceptance model; psychological reactance; physician-patient trust; family support

1. Introduction

The evolving AI scenario has drastically impacted the medical field, with AI-assisted rehabilitation turning out to be an attractive field among medical applications [1]. The AI system uses machine learning algorithms, sensors, and feedback mechanisms to assist patients with rehabilitation exercises, track rehabilitation progress, and make real-time adjustments to rehabilitation plans [2]. The global AI rehabilitation market has witnessed tremendous growth due to an aging population, an increase in chronic diseases, and an increased need for accessible medical care [3]. In China, top medical institutions have initiated efforts to implement AI rehabilitation systems in their medical setup, focusing on stroke rehabilitation, orthopedic rehabilitation, and neurological disorders [4]. Despite significant investments in infrastructure, adoption rates among patients have been suboptimal. In a nationwide survey, it was found that 60% of American adults would be uncomfortable if their medical service providers used AI to make medical diagnoses and treatment plans [5]. Medical AI resistance studies have shown that consumers are consistently less likely to use medical care from AI service providers than from human service providers, even when performance equivalency information was provided [6].

Analyses of patient acceptance of AI-assisted rehabilitation must, therefore, take into consideration the psychological processes underlying technology adoption decisions. The Technology Acceptance Model (TAM) offers a fundamental framework for explaining the role of perceived usefulness and perceived ease of use in influencing behavioral intentions toward new technologies [7]. Systematic reviews of health information systems have shown, in fact, that the TAM remains the most widely accepted framework in explaining technology adoption in a clinical setting, with perceived usefulness and ease of use being shown to predict adoption intentions in various clinical settings [8]. Nonetheless, the classical framework of the TAM adopts an almost entirely rational process in decision-making, and researchers have called for going beyond the TAM in explaining the multifaceted process of adopting HIT in clinical settings, particularly in incorporating emotional and motivational processes in this process [9]. This becomes especially true in the context of rehabilitation, in which patients experience a sense of vulnerability and anxiety in regard to the outcome of their treatment, and in which AI adoption brings into question fundamental issues of autonomy in medical decision-making processes [10].

Psychological Reactance Theory offers a further theoretical lens for understanding patient reactance to AI-assisted rehabilitation. Psychological reactance theory suggests a person enters a state of motivated behavior aimed at restoring a sense of freedom when confronted with a threat to behavioral freedom [11]. In a mandatory/semi-mandatory healthcare technology adoption setting, patients may interpret the implementation of the AI system as a threat to their treatment autonomy, thus provoking reactance characterized by negative affective experiences and oppositional thoughts [12]. Emerging empirical support suggests the role of psychological reactance as a partial mediator of the relationship between perceived threat to freedom of choice and intentions to adopt technology, suggesting the coexistence of reactance processes with adoption processes in the technology adoption decision-making process [13]. The healthcare industry offers a set of unique factors potentially heightening reactance processes, given the strong patient-held expectations of direct involvement in healthcare decision-making, potentially threatened by the introduction of AI technology in healthcare, which can be seen as reducing the human aspects of healthcare delivery [14].

Aside from the aforementioned individual psychological processes, the role of social environmental factors in influencing patient technology acceptance behaviors cannot be underestimated. Family support systems have been found to play highly significant roles in medical decision-making, and systematic reviews have found digital health interventions to have positive effects on family caregivers in terms of their psychological health, self-efficacy, and problem-coping capabilities in extended periods of rehabilitation programs [15]. Patient trust in physician decisions also constitutes an important social element, and recent vignette studies on AI clinical decision support systems have found general patient attitudes toward technology to impact patient perceptions of doctors who employ such technology in their practice [16]. Social norms in patient communities and society also impact acceptance intentions in establishing behavior standards and moral norms in terms of technology use [17]. While the role of social factors in influencing patient technology acceptance behavior is theoretically acknowledged, previous research on this topic has largely investigated mechanisms of acceptance and resistance in separate contexts, not accounting for the combined role of both psychological processes in social contexts [18].

The present study addresses the above-stated issues in the literature by building and testing a comprehensive theoretical framework that explores the joint effects of TAM-related acceptance mechanisms and psychological reactance on the formation of patient intentions towards AI-assisted rehabilitation. The study also investigates the moderating effects of social environmental variables, namely family support, trust between physicians and patients, and social norms. The present study employs structural equation modeling techniques in the analysis of the collected survey data from the target population of rehabilitation patients.

2. Methods

2.1. Theoretical Framework and Hypotheses

The current research anchored its theoretical foundations on the integration of the Technology Acceptance Model (TAM) and Psychological Reactance Theory to explain patients' behavior intention on AI-assisted rehabilitation. The key to understanding an individual's acceptance or adoption of new technologies lies in understanding their cognitive beliefs on perceived usefulness, which refers to performance augmentation, and perceived ease of use, which refers to ease of operation effort [7]. The critical mass of studies on healthcare has supported that perceived usefulness exerts a direct impact on behavior intention, with perceived ease of use as an important antecedent influencing perceptions on usefulness through diminishing cognitive obstacles to acknowledging benefits from new technologies [19]. The following proposition emerges from this study:

H1: Perceived usefulness positively influences behavioral intention to use AI-assisted rehabilitation.

H2: Perceived ease of use positively influences perceived usefulness of AI-assisted rehabilitation.

In addition to the indirect effect via perceived usefulness, perceived ease of use may also have a direct effect on behavioral intention. A direct effect may be supported from a theoretical perspective in three ways. Firstly, the theory of self-efficacy argues that ease of use will increase the individual's belief in his or her personal capability to perform technology-related behaviors [20]. Secondly, the technology anxiety literature argues that complex systems lead to avoidant behaviors regardless of perceived benefits [21]. Thirdly, the findings of user experience studies demonstrate that favorable interaction outcomes increase intrinsic motivation to persist in the activity [22]. Empirical support for the direct effect is provided in the meta-analytic findings, according to which the PEOU → BI relationship is significant in about 60% of the studies, and the effect is stronger in the healthcare sector [23]. Thus:

H2a: Perceived ease of use positively influences behavioral intention to use AI-assisted rehabilitation.

The Psychological Reactance Theory provides a complementary approach that may be used to explore the mechanisms of resistance that work in parallel with the mechanisms of acceptance. The theory proposes that reactance is a type of aversive motivational state that includes negative emotions and oppositional cognitions, which occur in response to perceived threats to behavioral freedom [11]. In the healthcare technology adoption process, the perceived threats to freedom occur when the patient views the adoption of AI technology as limiting treatment options or reducing decisional freedom [24]. The perceived threats trigger psychological reactance, which in turn reduces the adoption intention as the patient attempts to compensate for the perceived lack of control [13]. Thus:

H3: Perceived threat to freedom positively influences psychological reactance.

H4: Psychological reactance negatively influences behavioral intention to use AI-assisted rehabilitation.

The differential moderating effects of social environmental factors on the dual pathways can be theorized based on their distinct psychological functions.

Family support primarily operates through processes of trust-building and resource supply [25]. When patients feel a lot of support from their families, they tend to have stronger self-efficacy in dealing with new technologies. This confidence-amplification process particularly strengthens the perceived usefulness-to-behavioral commitment process. Yet, family support does not operate on autonomy-related issues of psychological reactance directly.

Trust in the physician-patient relationship operates through legitimization processes and the transfer of authority [26]. As patients display a strong level of trust in the healthcare providers, the recommendations received in the trustworthy relationships are perceived as professional advice in the best interest of the patients rather than as constraints imposed from outside [10]. Trust therefore translates the AI technology from a threat of autonomy to a physician-recommended therapeutic tool, thus immediately reducing the psychological reactance response.

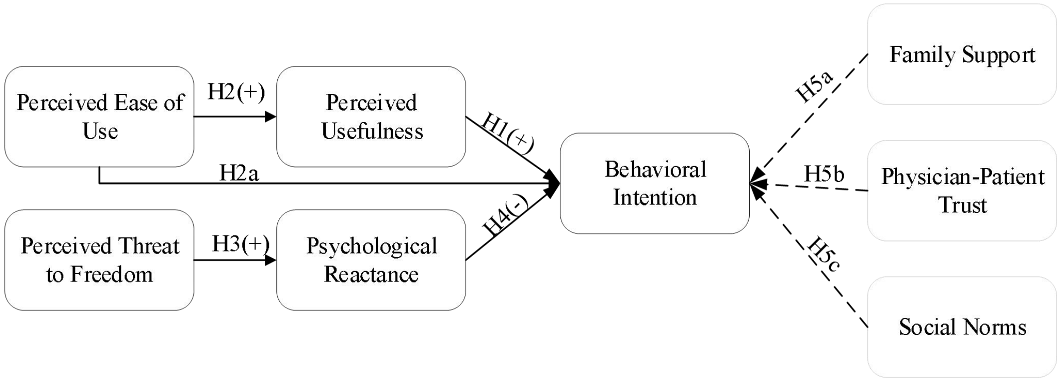
Social norms function through behavioral expectation mechanisms, establishing what is considered appropriate within one's social reference group [27]. When strong social norms favor AI rehabilitation adoption, patients experiencing psychological reactance face normative pressure that may counteract their resistance tendencies.

H5a: Family support positively moderates the relationship between perceived usefulness and behavioral intention.

H5b: Physician-patient trust negatively moderates the relationship between psychological reactance and behavioral intention (i.e., attenuates the negative effect).

H5c: Social norms negatively moderate the relationship between psychological reactance and behavioral intention.

As illustrated in Figure 1, the integrated framework captures dual psychological mechanisms operating simultaneously under social environmental conditions.



Note: Solid lines indicate direct effects; dashed lines indicate moderating effects. (+) positive relationship; (−) negative relationship.

Figure 1. Research Model: Dual Mechanisms of Technology Acceptance and Psychological Reactance in AI-Assisted Rehabilitation.

2.2. Research Design and Sample

This study employed a cross-sectional survey design to examine the proposed hypotheses. This study was approved by the Institutional Review Board of [University/Hospital Name] (Approval No.XXX-2025-XXX). All participants provided written informed consent. Data collection was conducted through both online and offline channels between March and May 2025 in rehabilitation departments of three tertiary hospitals located in eastern China. Participants were required to meet the following inclusion criteria: aged 18 years or above, currently undergoing or having completed rehabilitation treatment within the past six months, and having used AI-assisted rehabilitation technologies at least twice during their treatment process.

A convenience sampling approach was adopted due to the specialized nature of the study population. Research assistants distributed questionnaires to eligible patients in hospital waiting areas and rehabilitation wards. The survey instrument underwent pilot testing with 35 patients to assess item clarity and completion time.

A total of 486 questionnaires were obtained, but 52 were eliminated because they were incomplete, had too many missing values, and/or failed attention checks. The remaining 434 valid questionnaires provided an effective response rate of 89.3 percent. The sample size is adequate because the minimum requirement for structural equation modeling analysis is at least ten observations for each estimated parameter [28].

2.3. Measures

All constructs were measured using validated scales adapted from prior research, with minor modifications to fit the AI-assisted rehabilitation context. Responses were recorded on a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

Usefulness perception was measured using four items based on Davis' scale [7], which assessed patients' perceptions on whether they believe that AI-supported rehabilitation systems increase their treatment outcomes. Ease of use perception was also assessed using four items based on Davis' scale. Freedom threat perception was conceptualized using three items based on Dillard & Shen's scale [13], which assessed patients' perceptions on whether their treatment autonomy is being threatened by AI system implementation. Psychological reactance was assessed using four items that include both affective and cognitive components.

The three moderating variables were measured as follows. Family support was assessed using four items from the Multidimensional Scale of Perceived Social Support [29]. Physician-patient trust was measured with five items adapted from the Trust in Physician Scale [30]. Social norms were captured using three items derived from Venkatesh et al.[19].

Behavioral intention, the dependent variable, was assessed using three items adapted from Venkatesh and Davis [21]. All scales demonstrated acceptable internal consistency, with Cronbach's alpha coefficients ranging from 0.82 to 0.91.

2.4. Data Analysis

Data analysis was conducted using SPSS 26.0 and AMOS 24.0 following a two-stage analytical approach recommended for structural equation modeling [28]. The measurement model was assessed through confirmatory factor analysis evaluating reliability (Cronbach's α > 0.70, CR > 0.70) and validity (AVE > 0.50, Fornell-Larcker criterion) [31]. The structural model was examined using multiple fit indices (χ^2 /df < 3.0, CFI/TLI > 0.90, RMSEA < 0.08, SRMR < 0.08) [32].

The hypotheses related to mediation were tested using a bootstrap resample with 5,000 iterations to yield bias-corrected 95% confidence intervals [33]. For moderation analysis, a multi-group approach was conducted where high and low groups were derived from median splits in the sample. Prior to examining structural paths between groups, a standard assessment of invariance was performed [34].

Given that all variables were collected using self-report measures at a single point in time, common method bias was assessed using both procedural remedies (anonymity assurance, scale separation, item randomization) and statistical techniques (Harman's single-factor test, unmeasured latent method construct approach) [35].

3. Results

3.1. Demographic Characteristics

Table 1 presents the demographic profile of the 434 participants. The sample comprised 189 males (43.5%) and 245 females (56.5%), with ages ranging from 22 to 78 years (M = 51.37, SD = 12.84). Regarding education level, 98 participants (22.6%) had completed junior high school or below, 127 (29.3%) had completed senior high school, 156 (35.9%) held a college or bachelor's degree, and 53 (12.2%) had obtained a postgraduate degree. The rehabilitation types included stroke recovery (*n* = 168, 38.7%), orthopedic rehabilitation (*n* = 142, 32.7%), neurological disorders (*n* = 89, 20.5%), and other conditions (*n* = 35, 8.1%). Most participants had used AI-assisted rehabilitation services 2-5 times (*n* = 247, 56.9%).

Table 1. Demographic Characteristics of Respondents (N = 434)

Variable	Category	*n*	%
Gender	Male	189	43.5
	Female	245	56.5
Age (years)	18-35	52	12.0
	36-50	148	34.1
	51-65	167	38.5
	>65	67	15.4
	M = 51.37, SD = 12.84		
Education	Junior high school or below	98	22.6
	Senior high school	127	29.3
	College/Bachelor's degree	156	35.9
	Postgraduate degree	53	12.2
Rehabilitation Type	Stroke recovery	168	38.7
	Orthopedic	142	32.7
	Neurological disorders	89	20.5
	Others	35	8.1
AI Rehabilitation Experience	2-5 times	247	56.9
	6-10 times	112	25.8
	>10 times	75	17.3

3.2. Measurement Model Evaluation

3.2.1. Reliability and Validity

Confirmatory factor analysis was conducted to assess the measurement model. As shown in Table 2, all factor loadings exceeded 0.60, ranging from 0.714 to 0.893. Internal consistency was established with Cronbach's alpha coefficients ranging from 0.827 to 0.912. Composite reliability values ranged from 0.841 to 0.918. Convergent validity was confirmed as all average variance extracted values exceeded 0.50, ranging from 0.528 to 0.693. The measurement model demonstrated acceptable fit: χ^2 /df = 2.136, CFI = 0.954, TLI = 0.947, RMSEA = 0.051, SRMR = 0.042.

Table 2. Measurement Items and Factor Loadings

Construct	Item	Loading	α	CR	AVE
Perceived Usefulness (PU)			0.891	0.894	0.679
	PU1: AI rehabilitation improves my treatment effectiveness	0.842			
	PU2: AI rehabilitation helps me recover faster	0.867			
	PU3: AI rehabilitation enhances my rehabilitation outcomes	0.823			
	PU4: AI rehabilitation is beneficial for my recovery	0.762			
Perceived Ease of Use (PEOU)			0.865	0.869	0.625
	PEOU1: Learning to use AI rehabilitation is easy	0.798			
	PEOU2: Operating AI rehabilitation equipment is straightforward	0.812			
	PEOU3: The AI rehabilitation interface is clear and understandable	0.786			
	PEOU4: I find it easy to follow AI rehabilitation instructions	0.764			
Perceived Threat to Freedom (PTF)			0.847	0.852	0.591
	PTF1: AI rehabilitation limits my treatment choices	0.782			
	PTF2: Using AI rehabilitation reduces my control over treatment	0.806			
	PTF3: AI rehabilitation constrains my decision-making autonomy	0.714			
Psychological Reactance (PR)			0.882	0.887	0.612
	PR1: I feel frustrated when AI makes decisions for me	0.793			
	PR2: I feel annoyed when my freedom is restricted by AI	0.824			
	PR3: I resist recommendations imposed by AI systems	0.756			
	PR4: I feel uncomfortable when AI controls my rehabilitation	0.752			
Family Support (FS)			0.878	0.883	0.654
	FS1: My family encourages me to use AI rehabilitation	0.837			
	FS2: My family helps me understand AI rehabilitation technology	0.812			
	FS3: My family supports my decisions about AI rehabilitation	0.793			
	FS4: My family provides emotional support during AI rehabilitation	0.791			
Physician-Patient Trust (PPT)			0.912	0.918	0.693
	PPT1: I trust my physician's recommendations about AI rehabilitation	0.856			
	PPT2: My physician has my best interests in mind	0.893			
	PPT3: I believe my physician is competent in AI rehabilitation guidance	0.824			
	PPT4: My physician is honest about AI rehabilitation benefits and risks	0.789			
	PPT5: I can rely on my physician's advice regarding AI treatment	0.812			
Social Norms (SN)			0.827	0.841	0.528
	SN1: People important to me think I should use AI rehabilitation	0.748			
	SN2: Other patients recommend using AI rehabilitation	0.726			
	SN3: Society generally approves of AI-assisted medical treatment	0.719			
	SN4: Using AI rehabilitation is becoming common in hospitals	0.714			
Behavioral Intention (BI)			0.904	0.908	0.687
	BI1: I intend to use AI rehabilitation if available	0.847			
	BI2: I plan to continue using AI rehabilitation services	0.863			
	BI3: I would recommend AI rehabilitation to other patients	0.824			

Note. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted. All factor loadings significant at $p < 0.001$.

Discriminant validity was established as the square root of AVE for each construct exceeded its correlations with other constructs (Table 3).

Table 3. Descriptive Statistics and Correlations

Variable	M	SD	1	2	3	4	5	6	7	8
1. PU	4.82	1.21	(0.824)							
2. PEOU	4.67	1.18	0.524***	(0.791)						
3. PTF	3.45	1.34	-0.312***	-0.287***	(0.769)					
4. PR	3.28	1.29	-0.356***	-0.298***	0.583***	(0.782)				
5. FS	4.93	1.15	0.412***	0.378***	-0.245***	-0.268***	(0.809)			
6. PPT	5.14	1.08	0.467***	0.398***	-0.324***	-0.352***	0.456***	(0.833)		
7. SN	4.56	1.22	0.389***	0.342***	-0.198***	-0.215***	0.412***	0.387***	(0.727)	
8. BI	4.71	1.25	0.586***	0.478***	-0.367***	-0.412***	0.398***	0.445***	0.356***	(0.829)

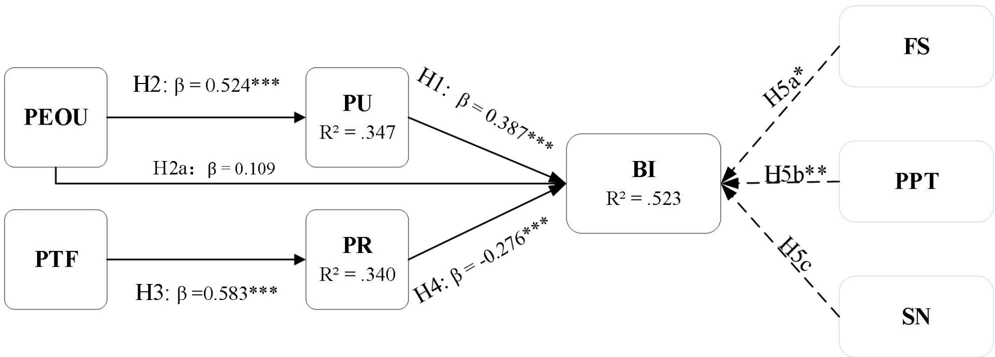
Note. N = 434. Diagonal values in parentheses represent the square root of AVE. ***p < 0.001.

3.2.2. Common Method Bias Assessment

Harman's single-factor test revealed that the first unrotated factor explained 31.24% of the variance. This is less than the 50% cut-off. Results from the assessment of the construct of the latent method factor indicated that the common method variance explained only 8.7% of the variance of the indicators. Moreover, there were no significant changes in the factor loadings (mean $\Delta\lambda$ = 0.024) and path coefficients (mean $\Delta\beta$ = 0.021). This implies that common method variance does not pose a significant threat to the validity of the results.

3.3. Structural Model and Hypothesis Testing

The structural model demonstrated acceptable fit indices: χ^2 /df = 2.284, CFI = 0.946, TLI = 0.938, RMSEA = 0.054, SRMR = 0.048. Table 4 presents the results of hypothesis testing. The model explained 52.3% of the variance in behavioral intention (R^2 = 0.523) and 34.7% of the variance in perceived usefulness (R^2 = 0.347). The structural model results are presented in Figure 2.



Note: N = 434. Standardized path coefficients (β) are displayed on paths. R^2 values are shown within endogenous variables. Model fit: χ^2 /df = 2.284, CFI = 0.946, TLI = 0.938, RMSEA = 0.054, SRMR = 0.048. *p < .05; **p < .01; ***p < 0.001.

Figure 2. Structural Model Results with Standardized Path Coefficients.

Table 4. Structural Model Results and Hypothesis Testing

Hypothesis	Path	β	S.E.	C.R.	p	95% CI	Result
H1	PU → BI	0.387	0.052	7.442	<0.001	[0.285, 0.489]	Supported
H2	PEOU → PU	0.524	0.048	10.917	<0.001	[0.430, 0.618]	Supported
H2a	PEOU → BI	0.109	0.044	2.477	<0.05	[0.023, 0.195]	Supported
H3	PTF → PR	0.583	0.046	12.674	<0.001	[0.493, 0.673]	Supported
H4	PR → BI	-0.276	0.058	-4.759	<0.001	[-0.390, -0.162]	Supported

Note. β = standardized coefficient; S.E. = standard error; C.R. = critical ratio; CI = confidence interval (bootstrap 5000 samples). Model fit: χ^2 /df = 2.284, CFI = 0.946, TLI = 0.938, RMSEA = 0.054, SRMR = 0.048. R^2 (BI) = 0.523; R^2 (PU) = 0.347; R^2 (PR) = 0.340.

Regarding the technology acceptance pathway, perceived usefulness exerted a significant positive effect on behavioral intention (β = 0.387, $p < 0.001$), supporting H1. Perceived ease of use significantly influenced perceived usefulness (β = 0.524, $p < 0.001$), supporting H2. Consistent with H2a, perceived ease of use also exerted a significant direct effect on behavioral intention (β = 0.109, $p = .013$, 95% CI [0.023, 0.195]).

The psychological reactance pathway was also confirmed: perceived threat to freedom positively influenced psychological reactance (β = 0.583, $p < 0.001$), supporting H3, and psychological reactance negatively influenced behavioral intention (β = -0.276, $p < 0.001$), supporting H4.

3.3.1. Measurement Invariance Assessment

The invariance of measurements was evaluated before performing multi-group path analyses. For each of the three groupings of moderators: family support, physician-patient trust, and social norms, configural invariance was established using acceptable fit indices, and metric invariance was confirmed by non-significant chi-square difference test and Δ CFI < 0.01 (Table 5). This implies that the measurement model is equal across groups for both high and low groups, allowing for comparison of structural path coefficients.

Table 5. Measurement Invariance Testing Results

Moderator	Model	χ^2	df	CFI	TLI	RMSEA	$\Delta\chi^2$	Δdf	p	ΔCFI	Decision
Family Support	Configural	876.45	406	.951	.943	.052	—	—	—	—	Supported
	Metric	894.79	428	.948	.942	.053	18.34	22	.687	.003	Supported
Physician-Patient Trust	Configural	882.67	406	.949	.941	.053	—	—	—	—	Supported
	Metric	904.23	428	.945	.939	.055	21.56	22	.487	.004	Supported
Social Norms	Configural	879.23	406	.950	.942	.053	—	—	—	—	Supported
	Metric	899.05	428	.947	.941	.054	19.82	22	.593	.003	Supported

Note. Metric invariance criterion: $\Delta\chi^2$ $p > .05$ and Δ CFI < .010. All three moderator groupings demonstrated acceptable metric invariance, supporting valid cross-group path comparisons.

3.3.2. Mediation Analysis

Bootstrap analysis confirmed both hypothesized mediation pathways. For the acceptance pathway, perceived usefulness significantly mediated the PEOU-BI relationship (indirect effect β = 0.203, 95% CI [0.145, 0.267]), with 65.1% of the total effect mediated. The significant direct effect indicates partial mediation. For the resistance pathway, psychological reactance fully mediated the PTF-BI relationship (indirect effect β = -0.161, 95% CI [-0.219, -0.109]), accounting for 65.7% of the total effect, with the direct effect becoming non-significant when controlling for the mediator. Table 6 presents the results of the mediation analysis for both the acceptance and resistance pathways.

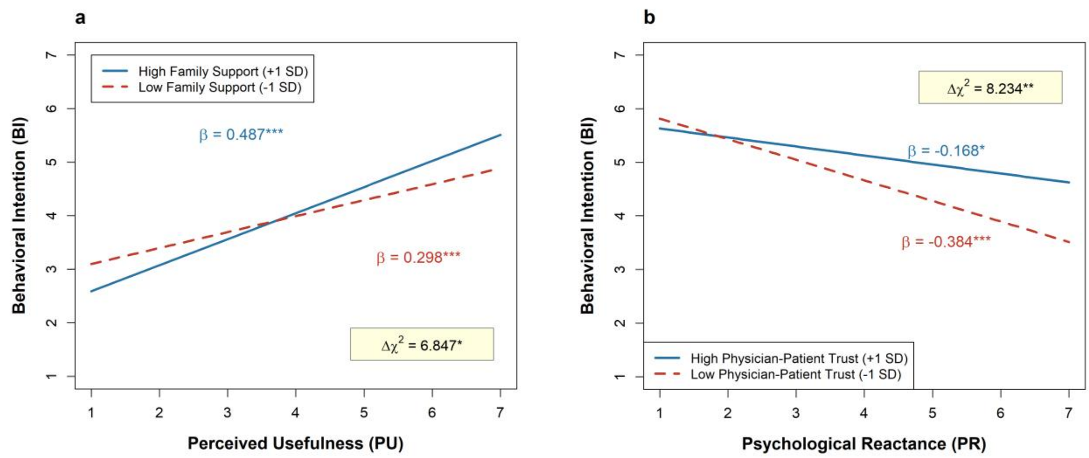
Table 6. Mediation Analysis Results

Pathway	Indirect Effect (β)	95% CI	Mediation Type	PM
PEOU → PU → BI	0.203***	[0.145, 0.267]	Partial	65.1%
PTF → PR → BI	-0.161***	[-0.219, -0.109]	Full	65.7%

Note. Bootstrap sample = 5,000. *** $p < 0.001$. PM = proportion mediated.

3.4. Moderation Effects

Moderation effects were examined using multi-group structural equation modeling. Table 7 presents the complete results. As shown in Figure 3, the relationship between perceived usefulness and behavioral intention was stronger for patients with high family support compared to those with low family support. Similarly, the negative effect of psychological reactance on behavioral intention was attenuated for patients with high physician-patient trust.



Panel (a) illustrates the moderating effect of family support on the relationship between perceived usefulness (PU) and behavioral intention (BI).

Panel (b) illustrates the moderating effect of physician-patient trust on the relationship between psychological reactance (PR) and behavioral intention (BI).

Note: High and low groups represent median split. Standardized coefficients (β) are displayed for each simple slope. *p < .05; **p < .01; ***p < 0.001.

Figure 3. Simple Slope Analysis of Significant Moderating Effects

Table 7. Moderation Effects Analysis

Moderator	Path	Group	β	S.E.	p	$\Delta\chi^2$	Δdf	p(diff)	Result
Family Support (H5a)	PU → BI	High FS (n=224)	0.456	0.067	<0.001	6.847	1	0.009	Supported
		Low FS (n=210)	0.298	0.072	<0.001				
Physician-Patient Trust (H5b)	PR → BI	High PPT (n=231)	-0.167	0.071	0.018	8.234	1	0.004	Supported
		Low PPT (n=203)	-0.378	0.068	<0.001				
Social Norms (H5c)	PR → BI	High SN (n=219)	-0.241	0.069	<0.001	1.892	1	0.169	Not Supported
		Low SN (n=215)	-0.298	0.073	<0.001				

Note. β = standardized coefficient; S.E. = standard error; $\Delta\chi^2$ = chi-square difference; p(diff) = significance of path difference between groups. Groups divided by median split.

3.4.1. Family Support Moderation (H5a)

The moderating effect of family support on the PU-BI relationship was significant ($\Delta\chi^2$ = 6.847, Δdf = 1, p = 0.009). In the high family support group, the effect of perceived usefulness on behavioral intention was stronger (β = 0.456, p < 0.001) compared to the low family support group (β = 0.298, p < 0.001). Thus, H5a was supported.

3.4.2. Physician-Patient Trust Moderation (H5b)

The moderating effect of physician-patient trust on the PR-BI relationship was significant ($\Delta\chi^2$ = 8.234, Δdf = 1, p = 0.004). In the high trust group, the negative effect of psychological reactance on behavioral intention was attenuated (β = -0.167, p = 0.018) compared to the low trust group (β = -0.378, p < 0.001). H5b was supported.

3.4.3. Social Norms Moderation (H5c)

The moderating effect of social norms on the PR-BI relationship was not significant ($\Delta\chi^2$ = 1.892, Δdf = 1, p = 0.169). Although the negative effect of psychological reactance was slightly weaker in the high social norms group (β = -0.241) compared to the low social norms group (β = -0.298), this difference did not reach statistical significance. H5c was not supported.

3.4.4. Robustness Check

Supplementary analyses treating moderators as continuous variables using the product indicator method confirmed the multi-group findings (Table 8). The interaction terms PU × FS (β = .089, p = .012) and PR × PPT (β = .076, p = .028) were significant, while PR × SN remained non-significant (β = .034, p = .241).

Table 8. Robustness Check: Continuous Moderator Analysis Results

Interaction Term	β	SE	t	p	Result
PU × Family Support → BI	.089	.035	2.543	.012*	Significant
PR × Physician-Patient Trust → BI	.076	.034	2.235	.028*	Significant
PR × Social Norms → BI	.034	.029	1.172	.241	Non-significant

Note. Product indicator method with mean-centered indicators. β = standardized coefficient; SE = standard error. *p < .05. Results are consistent with multi-group SEM findings.

3.5. Summary of Hypothesis Testing

Table 9 summarizes all hypothesis testing results. Of the eight hypotheses proposed, seven were supported. The dual psychological mechanisms—technology acceptance pathway (H1-H2a) and psychological reactance pathway (H3-H4)—were fully confirmed. Regarding social environmental moderation, family support and physician-patient trust demonstrated significant moderating effects (H5a, H5b), while social norms did not significantly moderate the reactance-intention relationship (H5c).

Table 9. Summary of Hypothesis Testing Results

Hypothesis	Description	Result
H1	Perceived usefulness → Behavioral intention (+)	Supported
H2	Perceived ease of use → Perceived usefulness (+)	Supported
H2a	Perceived ease of use → Behavioral intention (+)	Supported
H3	Perceived threat to freedom → Psychological reactance (+)	Supported
H4	Psychological reactance → Behavioral intention (−)	Supported
H5a	Family support moderates PU → BI (strengthening)	Supported
H5b	Physician-patient trust moderates PR → BI (buffering)	Supported
H5c	Social norms moderate PR → BI (buffering)	Not Supported

4. Discussion

This research examines the two simultaneous psychological processes of technology acceptance and psychological reactance in patients' behavioral intentions toward AI-assisted rehabilitation. Through the combination of the Technology Acceptance Model and Psychological Reactance Theory with the inclusion of social-environmental factors, the results of the study provide empirical support for the complex psychological processes underlying patients' reactions to AI-supported healthcare treatments.

4.1. The Facilitating Pathway: Validation of TAM in AI-Assisted Rehabilitation

This study further confirms the strength and explanatory power of the Technology Acceptance Model (TAM) in predicting the adoption of AI-assisted rehabilitation technologies by patients. The strong and positive relationship between perceived usefulness and behavioral intention (β = 0.387, p < 0.001) is in line with the fundamental postulates of the Technology Acceptance Model and supports the most recent findings from a meta-analysis regarding the adoption of health technologies. The strong relationship between perceived ease of use and perceived usefulness (β = 0.524, p < 0.001) is particularly evident in the context of rehabilitation, in which patients, who are frequently elderly and less tech-savvy, are likely to consider ease of use when evaluating the potential advantages offered by AI technologies.

The integrated model explained 52.3% of the variance in behavioral intention, representing a substantial improvement over single-framework approaches. This enhanced explanatory power underscores the theoretical value of incorporating psychological reactance as a complementary mechanism.

However, the direct effect of perceived ease of use on behavioral intention remains large (β = 0.109, H2a supported). For patients undergoing physical and psychological rehabilitation, the potential for physical limitations, cognitive tiredness, and technological anxiety exists, and therefore, the ease-of-use aspect of the system could have a direct and indirect (via perceived usefulness) effect on perceived competence and control, irrespective of the perceived efficacy of the system for the treatment process. The result of the partial mediation analysis shows that 65.1% of the effect is mediated by perceived usefulness (PU). This implies that the implementation strategy for AI-assisted rehabilitation must include both the benefits of the system and the user interaction process.

4.2. The Inhibiting Pathway: Psychological Reactance as a Barrier to AI Acceptance

One of the key roles of this research is to identify the inhibitory process through which psychological reactance negatively influences patients' acceptance of AI-assisted rehabilitation. The positive relationship between perceived threat to freedom and psychological reactance (β = 0.583, $p < 0.001$), as well as the negative impact of psychological reactance on behavioral intention (β = -0.276, $p < 0.001$), indicate a psychological factor that has not been adequately explored in studies on health technology acceptance.

These findings extend Brehm and Brehm’s [14] original reactance theory to the emerging domain of AI-mediated healthcare. The effect size of the PTF→PR relationship substantially exceeds those typically reported in health communication contexts [36], suggesting that AI technologies may represent particularly potent autonomy threats in patients’ perceptions.

The co-existence of facilitation and inhibition paths indicates that patients are indeed ambivalent about AI rehabilitation systems when they are aware of the possible benefits as well as the possible limits to their freedom imposed by these systems. The relative strength of the facilitation path (β = 0.387) to the inhibition path (β = -0.276) indicates that facilitation is greater than inhibition at the present time.

The overall mediation pattern indicated that the threat of freedom does not have a direct inhibiting effect on adoption intentions, but rather it only exerts its effect through the arousal of reactance. This finding has significant theoretical implications, in that the harmful effects of perceived autonomy restrictions could be diminished or negated through the use of interventions aimed at preventing or reducing the arousal of reactance, regardless of whether the threat of freedom can be completely removed or not.

4.3. Social Environmental Moderators: Differential Effects on Dual Pathways

The examination of social environmental moderators yielded theoretically meaningful patterns. Family support significantly amplified the positive relationship between perceived usefulness and behavioral intention ($\Delta\chi^2$ = 6.847, $p < 0.05$). This finding resonates with research on digital health interventions emphasizing the catalytic role of family caregivers [15]. Patients embedded in supportive family environments may experience greater confidence in their capacity to leverage AI technologies effectively, thereby strengthening the translation of perceived usefulness into behavioral commitment.

Physician-patient trust emerged as a significant buffer against reactance’s negative effects ($\Delta\chi^2$ = 8.234, $p < 0.01$). For patients reporting high trust, the detrimental impact of psychological reactance on behavioral intention was substantially attenuated (β = -0.167 vs. β = -0.378 for low trust). When patients maintain strong trust in their healthcare providers, AI recommendations conveyed through these trusted relationships may be interpreted as supportive guidance rather than autonomy-threatening directives [26].

In contrast to expectations based on theory, social norms played little part in moderating the relationship between reactance and intentions. Some possible explanations include that decisions regarding rehabilitation may be sufficiently personalized and health-relevant compared to preventive health behaviors to resist normative influences to a greater degree than health concerns on an individual level. Also, cultural context may play a role in this phenomenon in that family support systems based on collectivist ideologies prevalent in Chinese culture may act in a manner not based on social norms.

Furthermore, while we hypothesized moderation effects that are specific to specific pathways due to the unique psychological function of each social factor, we did not test the empirical hypotheses of the moderating effects across the pathways (for example, the moderating role of family support between perceived risk and intention). Future studies should examine the alternative hypotheses of the moderating effects.

4.4. Practical Implications

Implications for healthcare professionals, AI system developers, and policymakers can be drawn from these results. The strong effect of perceived threat to freedom implies that it is necessary for AI system design and its use in healthcare to focus on preserving the patient's autonomy. Healthcare professionals can use AI system output as informational resources that can assist but not dictate patient decision-making. Multiple treatment alternatives can be provided by interface design that allows customization by the patient.

The strong moderating effect of trust between physicians and patients highlights the importance of human healthcare practitioners in AI-facilitated healthcare. Education should emphasize communication practices that promote trust by portraying AI technology as a tool that assists healthcare practitioners rather than replacing them. The reinforcing effect on family support suggests that involving families in healthcare practices through practices such as involving family members in technology introduction and maintaining a communication channel to update families on patient progress may be effective.

4.5. Limitations and Future Directions

There are a few limitations that are worth noting. The design does not lend itself to making definitive claims about causation. While there are hypothetical directional relationships that are grounded in established theory, it must not be overlooked that reverse causality may also be a possibility. Longitudinal studies could assess changes in psychological reactions to AI technologies over time.

The sample population, which was collected from three tertiary care institutions in Eastern China, might limit the generalizability of the results to other healthcare settings, regions, and contexts. Cross-cultural comparison studies would help understand the role of contextual factors in influencing the psychological processes uncovered in the current study. Although the integrated model explained a good amount of the variance in behavioral intention, the well-documented intention-behavior gap suggests a need to be cautious in generalizing the results to actual use patterns of technology.

5. Conclusion

This paper describes and tests an integrated theoretical framework explaining how technology acceptance and psychological reactance co-occur in shaping patients' behavioral intentions toward AI-assisted rehabilitation. The main findings are as follows: (1) The Technology Acceptance Model (TAM) technology acceptance process (perceived ease of use (PEOU) → perceived usefulness (PU) → behavioral intention (BI)) and psychological reactance process (perceived threat to freedom (PTF) → psychological reactance (PR) → BI) and their integrated model are significant predictors of BI, explaining 52.3% of variance in BI; (2) Perceived ease of use has a direct and an indirect effect on BI; (3) The impact of the technology acceptance process is strengthened by family support, while physician-patient trust mitigates the impact of psychological reactance; and (4) Social norms are not significant moderators of psychological reactance effects.

In terms of contribution to theory, this study helps to further elucidate technology acceptance in healthcare by showing that both facilitative and inhibitory psychological processes occur simultaneously and in different ways due to social environmental factors. From a practical perspective, this suggests that to successfully implement AI-supported rehabilitation, one must simultaneously increase perceptions of usefulness and manage autonomy issues through trusted physician relationships and family engagement strategies.

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