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ORIGINAL RESEARCH

Technology Anxiety and Acceptance of Health Education Robots Among Patients After Abdominal Surgery: A Cross-Sectional Study

Jingya Meng[1,2], Yunyun Feng[1,2], Liping Peng[1,2], Lijuan Zhong[1,2], Qingqing Pang[1,2], Xia Feng[1,2], Jiayun Zhong[1,2]

[1]General Surgery, Cancer Center, Department of Hepatobiliary & Pancreatic Surgery and Minimally Invasive Surgery, Zhejiang Provincial People's Hospital (Affiliated People's Hospital, Hangzhou Medical College), Hangzhou, Zhejiang, 310014, People's Republic of China; [2]Nursing Department, Zhejiang Provincial People's Hospital (Affiliated People's Hospital, Hangzhou Medical College), Hangzhou, Zhejiang, 310014, People's Republic of China

Correspondence: Jiayun Zhong, General Surgery, Cancer Center, Department of Hepatobiliary & Pancreatic Surgery and Minimally Invasive Surgery, and Nursing Department, Zhejiang Provincial People's Hospital (Affiliated People's Hospital, Hangzhou Medical College), Hangzhou, Zhejiang, 310014, People's Republic of China, Tel +86 135 6717 2861, Email 1160322792@qq.com

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Background: Patients differ in their willingness to accept health education robots. This study examined the association between technology anxiety and robot acceptance among patients recovering from abdominal surgery and estimated indirect associations through negative attitudes toward robots and human–robot trust.

Methods: This cross-sectional study included 303 adults recovering from elective or emergency abdominal surgery at a tertiary hospital in Zhejiang Province, China (May–June 2026), all of whom had received at least one robot-delivered health education session. Patients with cognitive impairment, postoperative complications, or psychiatric illness were excluded. Participants completed the Robot Acceptance Questionnaire, Technophobia Scale, Negative Attitudes Toward Robots Scale, and Trust Between People and Automation Scale. PROCESS Model 6 (5,000 bias-corrected bootstrap resamples) estimated indirect associations, specifying negative attitudes before trust a priori and adjusting for age, education, employment, income, residence, and prior robot experience. Sensitivity analyses examined the reversed ordering, HC3 standard errors, Tobit regression, and an unadjusted model.

Results: Mean robot acceptance was 54.14 ± 10.66 (possible range, 9–63), and 18.8% of participants obtained the maximum score. Technology anxiety was negatively correlated with acceptance ($r = -0.511$, $p < 0.001$). The standardized direct association was −0.204 (95% CI, −0.327 to −0.081). Indirect associations were −0.077 (95% CI, −0.145 to −0.012) through negative attitudes, −0.059 (95% CI, −0.111 to −0.017) through trust, and −0.014 (95% CI, −0.035 to −0.004) for the theory-ordered serial sequence. The reversed serial sequence, with trust preceding negative attitudes, was also statistically detectable (−0.012; 95% CI, −0.031 to −0.002); therefore, their ordering could not be distinguished.

Conclusion: Higher technology anxiety was associated with lower robot acceptance, and part of this association was statistically linked to negative attitudes and trust. Because both orderings were compatible with the cross-sectional data, these findings do not establish temporal sequence, causal mediation, or intervention effects.

Plain Language Summary: Patients with greater anxiety about technology reported lower acceptance of the robot. Technology anxiety was also associated with more negative attitudes toward robots and lower trust in the ward robot. However, because all information was collected at one time point, the study cannot determine which factor occurred first or whether one factor caused another.

Many participants gave robot acceptance the highest possible score. Therefore, the questionnaire may not have clearly distinguished among patients with high levels of acceptance. These findings identify attitudes and beliefs that future studies could examine when hospitals introduce health education robots. They do not show that changing these attitudes or beliefs would necessarily increase robot acceptance.

Keywords: technology anxiety, robot acceptance, health education robot, human–robot trust, abdominal surgery, cross-sectional study

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Introduction

Robots are increasingly used in healthcare to support surgery, logistics, companionship, and health education.[1,2] Health education robots can deliver standardized information through speech, screens, and interactive content.[3,4] Their focused role may facilitate clinical implementation, although concerns about acceptability, privacy, and the quality of human–robot interaction remain. These robots may be particularly useful in abdominal surgery, where patients need repeated guidance on preoperative preparation, recovery, diet, activity, and discharge. They may also reduce nurses' repetitive educational workload.[5] However, their clinical value depends on whether patients are willing to engage with them and trust the information they provide.

Acceptance of healthcare robots varies across populations and clinical settings. Some patients prefer human professionals because robots may offer limited emotional responsiveness or educational content.[6] Moreover, 42.7% of community-dwelling older adults in one survey were unwilling to use home-care robots.[7] Such variation indicates that robot acceptance cannot be inferred from technical performance alone. Understanding the psychological factors associated with acceptance is therefore essential for implementing health education robots in surgical care.

Technology anxiety, defined as tension, fear, or discomfort associated with technology use, is a recognized barrier to technology acceptance.[8] Patients recovering from abdominal surgery may be especially sensitive to unfamiliar technologies because they are already experiencing substantial physical and emotional demands. Higher technology anxiety may therefore be associated with less favorable evaluations of robots, weaker trust in a specific robotic system, and lower acceptance.[9] Although usefulness, ease of use, attitudes, and trust are established correlates of robot acceptance,[10–12] their joint statistical contributions remain insufficiently understood among patients who receive robot-delivered health education.

This study draws on complementary theoretical perspectives to distinguish these psychological constructs and specify their expected relationships. The Unified Theory of Acceptance and Use of Technology (UTAUT) explains behavioral intention through performance expectancy, effort expectancy, social influence, and facilitating conditions.[13] However, it provides less detail about how general technology anxiety, evaluations of robots, and trust in a specific robot are jointly associated with acceptance. The ABC model offers an organizing framework by distinguishing affective, cognitive, and behavioral components of attitudes. Within this framework, technology anxiety represents an affect-laden response, negative attitudes toward robots represent unfavorable evaluations, and robot acceptance represents behavioral intention. Human–robot trust captures expectations regarding the reliability and safety of the ward robot. Trust transfer theory further suggests that evaluations of a technology category may shape expectations about a specific system.[14] These constructs are treated as related but conceptually distinct, without assuming that the proposed ordering reflects a temporal sequence.

Technology anxiety may directly shape patients' willingness to use health education robots. In healthcare settings, patients with greater technology anxiety generally report weaker intentions to use digital health tools.[15] Postoperative pain and physical debilitation may further intensify discomfort with unfamiliar robotic systems. We therefore proposed the following hypothesis: H1. Technology anxiety is negatively associated with acceptance of health education robots among patients recovering from abdominal surgery. Negative attitudes toward robots include unfavorable beliefs that robots are cold, unreliable, or lacking in human warmth.[16] Anxiety arising during technology use may extend to robots as a specific category of technological tools.[17] Such negative attitudes may, in turn, inhibit technology adoption.[18] We therefore proposed the following hypothesis: H2. Technology anxiety is indirectly associated with acceptance of health education robots through negative attitudes toward robots. Human–robot trust refers to the expectation that relying on a robot will support goal attainment under conditions of uncertainty and vulnerability.[19] Trust is an important correlate of technology acceptance in healthcare settings. Technology anxiety may weaken trust by heightening perceived risk, thereby reducing willingness to use a robot.[20] We therefore proposed the following hypothesis: H3. Technology anxiety is indirectly associated with acceptance of health education robots through human–robot trust. Negative attitudes toward robots and human–robot trust have often been examined separately, although they may also be statistically related. Stronger negative attitudes are associated with lower trust in robotic systems,[21] whereas greater trust is associated with higher robot acceptance.[22] Consistent with trust transfer theory, these observations support a theory-driven statistical ordering from negative attitudes to trust. However, this ordering does not establish temporal precedence in cross-sectional data. We therefore proposed the following hypothesis: H4. Technology anxiety is indirectly associated with robot acceptance through a theory-ordered sequence of negative attitudes toward robots and human–robot trust.

Accordingly, this study examined the association between technology anxiety and acceptance of health education robots among patients recovering from abdominal surgery. It also estimated indirect associations through negative attitudes toward robots and human–robot trust. The serial ordering was specified a priori and evaluated alongside a reversed-order sensitivity model. Figure 1 presents the hypothesized cross-sectional serial indirect-association model.

Methods

Study Design and Participants

This cross-sectional survey was conducted at a tertiary hospital in Zhejiang Province, China, between May and June 2026. Hospitalized patients recovering from abdominal surgery were recruited using convenience sampling. Because participants completed the questionnaire on their own smartphones, patients without access to a smartphone or with limited confidence in using one may have been under-represented.

Eligible patients were aged 18 years or older and were recovering from elective or emergency abdominal surgery. They had no cognitive impairment and could understand and complete the questionnaire. They also agreed to participate, provided informed consent, and received at least one robot-delivered health education session before completing the survey. Patients were excluded if they had postoperative complications, a history of psychiatric illness, or a physical condition that prevented questionnaire completion.

Health Education Robot

The study used "Xiaomei", an OrionStar AI intelligent service robot (model OS-R-SD01; Beijing OrionStar Technology Co, Ltd, Beijing, China). This wheeled indoor service robot was certified under the China Robot Certification scheme (Certificate No. CCRCSV0100172020). It was equipped with LiDAR-based autonomous navigation, a touchscreen, a 360° microphone array, a camera module, and voice-dialogue capabilities.

Nurses assigned health education tasks using a control tablet or WeChat mini-program. The robot then navigated autonomously to the patient's bedside and delivered standardized content through speech, on-screen text, and video. The content covered admission and discharge instructions, pre-examination reminders, disease-specific knowledge, and postoperative rehabilitation. Patients could interact with the robot through voice dialogue or the touchscreen.

Sample Size Estimation

The largest regression model contained nine predictors. Based on a heuristic of at least 10 observations per predictor, the estimated minimum sample size was 90 participants. Allowing for 10% invalid responses increased the recruitment target to 99 participants. This heuristic was used because no reliable a priori effect-size estimate was available for the serial indirect association; it was not designed to estimate statistical power for indirect associations. The final analytic sample comprised 303 participants, which exceeded the planned target, but no formal power analysis for the indirect associations was conducted.

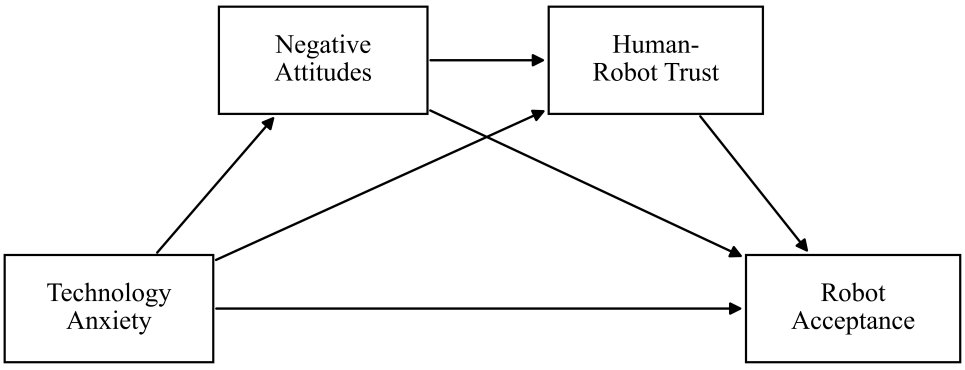

Figure 1 Hypothesized cross-sectional serial indirect-association model. Arrows represent the statistical paths estimated in process model 6 according to the ordering specified a priori; they do not imply temporal or causal precedence.

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Instruments

General Information Form

The research team developed a general information form to collect demographic and clinical characteristics. Demographic variables included gender, age, monthly income, marital status, educational level, living arrangement, place of residence, and employment status. Clinical variables included chronic disease history, time from surgery to survey completion, surgery type, surgical history, and prior experience with robots.

Robot Acceptance Questionnaire

Robot acceptance was measured using a nine-item questionnaire informed by the Almere model described by Heerink et al[23] The Chinese-language version used in this study was taken from Pei's 2023 master's thesis.[24] The questionnaire contains nine items representing acceptance-related constructs and uses a seven-point scale from 1 (completely disagree) to 7 (completely agree). Total scores range from 9 to 63, with higher scores indicating greater robot acceptance. The Chinese-language items referred specifically to the health education robot deployed in the study ward. Cronbach's α for the questionnaire in the present sample was 0.912.

Technology Anxiety Scale

Technology anxiety was assessed using the Technology Anxiety Scale, also referred to as the Technophobia Scale. Khasawneh developed the original scale in 2018,[8] and Sun translated and culturally adapted it for Chinese populations in 2022.[25] The scale contains 13 items across three dimensions: techno-anxiety, techno-fear, and privacy concerns. The first two dimensions contain five items each, whereas the privacy-concerns dimension contains three items. Items are rated from 1 (completely inconsistent) to 5 (completely consistent). Higher scores indicate greater technology anxiety. Cronbach's α for the scale in the present sample was 0.938.

Trust Between People and Automation Scale

Human–robot trust was measured using the Trust Between People and Automation Scale (TPAS). Jian developed the original scale in 2000,[26] and Cai translated and culturally adapted it in 2022.[27] The TPAS contains 12 items rated from 1 (not at all) to 7 (extremely). Higher total scores indicate greater human–robot trust. Each item referred specifically to the health education robot used in the study ward rather than to automation in general. Cronbach's α for the TPAS in the present sample was 0.926.

Negative Attitudes Toward Robots Scale

Negative attitudes toward robots were measured using the Negative Attitudes Toward Robots Scale (NARS). Nomura developed the original 14-item scale,[28] and Bi culturally adapted and validated a 13-item Chinese version in 2023.[29] The Chinese version contains three dimensions: negative attitudes toward robot-interaction situations, the social influence of robots, and emotions during robot interaction. Items are rated from 1 (strongly disagree) to 5 (strongly agree). Total scores range from 13 to 65, with higher scores indicating stronger negative attitudes toward robots. Cronbach's α for the NARS in the present sample was 0.893.

The Chinese versions of the Technophobia Scale, the TPAS, and the NARS have previously shown acceptable reliability and validity in Chinese adults.[25,27,29] The robot acceptance and trust items referred specifically to the ward robot. Cronbach's α values in the present sample ranged from 0.893 to 0.938, indicating internal consistency. Factor structure, convergent validity, and discriminant validity were not assessed in this sample; internal consistency alone does not establish construct validity.

Data Collection and Quality Control

Data were collected using the Questionnaire Star platform (https://www.wjx.cn/). After each participant received at least one robot-delivered health education session, a trained investigator provided an individual survey QR code at the bedside. Participants completed the questionnaire on their smartphones after providing electronic informed consent.

All questions required a response, and the platform permitted one submission per IP address. Bedside distribution by trained investigators provided additional verification of participant identity. However, the IP restriction could not prevent

submissions across different networks or distinguish participants sharing the same network. No additional electronic deduplication procedures were applied. Questionnaires completed within three minutes or showing invariant response patterns were excluded according to predefined quality-control criteria.

Ethical Considerations

The Ethics Committee of Zhejiang Provincial People's Hospital, Hangzhou, China, approved the study on May 11, 2026 (Approval No. KY2026094). The study was conducted in accordance with the Declaration of Helsinki. Recruitment began only after ethical approval had been granted. Before participation, all participants provided electronic informed consent on the first page of the online questionnaire. The ethics committee reviewed and approved the electronic consent procedure. Study data were used solely for academic research and were maintained confidentially.

Statistical Analysis

Data were analyzed using IBM SPSS Statistics version 26.0 and PROCESS macro version 3.5. Three erroneous age entries were corrected using verified values from the original survey records. Score distributions were examined for skewness and ceiling effects. Descriptive statistics and Pearson correlation coefficients were then calculated.

Independent-samples *t*-tests, one-way analyses of variance, and Pearson correlations were used, as appropriate, to examine associations between participant characteristics and robot acceptance. Age, educational level, employment status, monthly income, place of residence, and prior experience with robots were included as covariates because they were associated with robot acceptance in these univariate analyses. This data-driven approach was a pragmatic adjustment strategy for observed sociodemographic differences in acceptance; it was not derived from a causal model and does not ensure control of confounding. An unadjusted model was therefore also estimated. Employment status, place of residence, and prior robot experience were entered as binary indicator variables. Educational level and monthly income, each with three categories, were entered as ordinal variables according to their coded categories, and both were dummy-coded in a sensitivity analysis. All variables included in the regression models were standardized before analysis; therefore, coefficients for binary covariates represent standardized rather than raw group differences.

Serial indirect associations were estimated using PROCESS Model 6 with 5000 bias-corrected bootstrap resamples. Negative attitudes toward robots and human–robot trust occupied the first and second "mediator" positions of the model; this term describes the statistical specification only and does not imply causal mediation. An indirect association was considered statistically detectable when its 95% bootstrap confidence interval did not include zero. The ratio of each estimate to the total association was reported descriptively and was not interpreted as a proportion mediated. Variance inflation factors were examined to assess multicollinearity. Model diagnostics included residual skewness, the Shapiro–Wilk test, and the Breusch–Pagan test.

Because robot acceptance is a bounded score (9–63) and showed a ceiling effect, three additional sensitivity analyses were conducted. First, all regression models were estimated using HC3 heteroscedasticity-consistent standard errors. Second, robot acceptance was analyzed using a Tobit model with right censoring at the maximum score of 63. Third, an unadjusted model was estimated because covariates had been selected from univariate associations with robot acceptance. The HC3 and Tobit analyses were applied to the regression paths, whereas the bootstrap indirect estimates were derived from the linear models. Given the cross-sectional design, the reversed ordering of negative attitudes and trust was also evaluated. Neither ordering was interpreted as evidence of temporal precedence.

Results

Assessment of Common Method Variance

All study variables were measured using self-report questionnaires administered at a single time point. Harman's single-factor analysis of the item-level responses identified nine factors with eigenvalues greater than 1.0. The first unrotated factor explained 33.57% of the total variance, below the prespecified threshold of 40%. Because Harman's test is an insensitive diagnostic, this result does not indicate that common method variance was absent, and common method bias cannot be excluded.

Participant Flow and Characteristics

A total of 320 questionnaires were distributed, of which 303 passed the predefined quality-control checks. Seventeen questionnaires were excluded because they were completed within three minutes or showed invariant response patterns.

Three records initially contained an age of 15 years, which conflicted with the eligibility criteria. Verification against the original Questionnaire Star records confirmed that these values resulted from data-entry errors. All three participants were aged 18 years at enrollment. The verified values were substituted, and the three records were retained. No other anomalies were identified in these records.

The final analytic sample comprised 303 participants, representing 94.7% of the distributed questionnaires. The numbers approached, assessed for eligibility, and declining participation were not recorded. Therefore, 94.7% represented the questionnaire completion proportion rather than a true response rate.

Participants had a mean age of 47.38 years (SD = 15.63; range, 18–82), and 56.4% were female. Robot acceptance differed by educational level, employment status, monthly income, place of residence, and prior experience with robots. Robot acceptance was also negatively correlated with age (all $p < 0.05$; Table 1).

Table 1 Participant Characteristics and Their Associations with Robot Acceptance (N = 303)

Characteristic	Category or Sample Value	Robot Acceptance, mean ± SD	t, F, or r	p value
Gender			1.737	0.083
	Male, 132 (43.6)	52.93 ± 12.35		
	Female, 171 (56.4)	55.07 ± 9.07		
Age, years	47.38 ± 15.63	–	−0.336	<0.001
Education level			23.808	<0.001
	Junior high school or below, 108 (35.6)	50.25 ± 11.51		
	Senior high school, 66 (21.8)	51.64 ± 14.46		
	Undergraduate degree or above, 129 (42.6)	58.67 ± 3.79		
Marital status			−0.589	0.556
	Unmarried/ Divorced/ Widowed, 66 (21.8)	53.45 ± 16.21		
	Married, 237 (78.2)	54.33 ± 8.53		
Employment status			−5.448	<0.001
	Retired / Unemployed, 138 (45.5)	50.65 ± 13.31		
	Employed, 165 (54.5)	57.05 ± 6.52		
Monthly income			3.814	0.023
	<¥5000, 108 (35.6)	52.00 ± 10.70		
	¥5000–10,000, 66 (21.8)	54.41 ± 12.71		
	>¥10000, 129 (42.6)	55.79 ± 9.15		
Place of residence			−2.440	0.015
	Rural, 111 (36.6)	52.19 ± 14.07		
	Urban, 192 (63.4)	55.27 ± 7.89		
Living arrangement			−1.972	0.050
	Living alone, 42 (13.9)	51.14 ± 16.02		
	Living with others, 261 (86.1)	54.62 ± 9.48		
Time from surgery to survey			1.083	0.280
	<24h, 198 (65.3)	54.62 ± 6.45		
	≥24h, 105 (34.7)	53.23 ± 15.81		
Type of surgery			0.525	0.592
	Hepatobiliary surgery, 150 (49.5)	54.68 ± 10.93		
	Gastrointestinal surgery, 111 (36.6)	53.32 ± 11.40		
	Pancreatic surgery, 42 (13.9)	54.36 ± 7.17		

(*Continued*)

Table 1 (Continued).

Characteristic	Category or Sample Value	Robot Acceptance, mean ± SD	t, F, or r	p value
Surgical history			0.501	0.616
	No, 222 (73.3)	54.32 ± 8.63		
	Yes, 81 (26.7)	53.63 ± 14.93		
History of chronic diseases			−0.576	0.565
	No, 183 (60.4)	53.85 ± 9.37		
	Yes, 120 (39.6)	54.58 ± 12.40		
Previous robot use experience			−4.012	<0.001
	No, 153 (50.5)	51.76 ± 12.93		
	Yes, 150 (49.5)	56.56 ± 6.93		

Notes: Values in the second column are presented as n (%) unless otherwise indicated. Age is presented as mean ± standard deviation. The third column reports the mean robot acceptance score and standard deviation for each category. The reported test statistic is Student's t for variables with two categories, one-way analysis of variance F for variables with three categories, and Pearson's correlation coefficient *r* for age.

Descriptive Statistics and Bivariate Correlations

The mean scores were 35.50 (SD = 11.90) for technology anxiety and 32.00 (SD = 9.87) for negative attitudes toward robots. The corresponding means were 49.00 (SD = 13.94) for human–robot trust and 54.14 (SD = 10.66) for robot acceptance. Robot acceptance scores were negatively skewed (skewness = −2.03). Fifty-seven participants (18.8%) attained the maximum score of 63, indicating a ceiling effect.

All pairwise correlations among the four study variables were statistically significant (all $p < 0.01$; Table 2). Technology anxiety correlated negatively with robot acceptance and human–robot trust, but positively with negative attitudes toward robots. Robot acceptance correlated positively with human–robot trust and negatively with negative attitudes toward robots.

Serial Indirect-Association Analysis

Regression Models

Three regression models were estimated with negative attitudes toward robots, human–robot trust, and robot acceptance as the respective dependent variables (Table 3). All reported coefficients were standardized.

In Model 1, technology anxiety was positively associated with negative attitudes toward robots ($\beta = 0.640$, $p < 0.001$). This model explained 45.4% of the variance in negative attitudes. In Model 2, technology anxiety ($\beta = -0.497$, $p < 0.001$) and negative attitudes ($\beta = -0.183$, $p = 0.002$) were negatively associated with human–robot trust. Model 2 explained 42.5% of the variance in trust.

In Model 3, technology anxiety ($\beta = -0.204$, $p = 0.001$) and negative attitudes ($\beta = -0.120$, $p = 0.035$) were negatively associated with robot acceptance. Human–robot trust was positively associated with robot acceptance ($\beta = 0.119$, $p = 0.030$). Model 3 explained 50.3% of the variance in robot acceptance. The maximum variance inflation factor across the regression models was 2.46.

Table 2 Descriptive Statistics and Correlations Among the Study Variables (N = 303)

Variable	Mean ± SD	1	2	3	4
1. Robot acceptance	54.14 ± 10.66	1	—	—	—
2. Technology anxiety	35.50 ± 11.90	−0.511***	1	—	—
3. Human–robot trust	49.00 ± 13.94	0.433***	−0.632***	1	—
4. Negative attitudes	32.00 ± 9.87	−0.441***	0.657***	−0.513***	1

Notes: Values below the diagonal represent Pearson correlation coefficients. ***p < 0.001.

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Table 3 Regression Models for the Prespecified Serial Indirect-Association Analysis

Predictor	Model 1 β	Model 1 t	Model 2 β	Model 2 t	Model 3 β	Model 3 t
Age	0.161*	2.407	0.024	0.346	−0.181**	−2.800
Education level	0.001	0.016	0.029	0.427	0.219***	3.482
Previous robot use experience	−0.076	−1.731	0.007	0.157	0.204***	4.808
Employment status	0.113	1.891	0.058	0.937	0.142*	2.470
Place of residence	0.033	0.709	0.059	1.238	0.088*	1.977
Monthly income	−0.030	−0.590	0.003	0.063	0.355***	7.370
Technology anxiety	0.640***	14.085	−0.497***	−8.217	−0.204**	−3.271
Negative attitudes toward robots	–	–	−0.183**	−3.065	−0.120*	−2.115
Human–robot trust	–	–	–	–	0.119*	2.187
R^2	0.454		0.425		0.503	
F	35.098		27.189		32.966	

Notes: Model 1 predicted negative attitudes toward robots. Model 2 predicted human–robot trust. Model 3 predicted robot acceptance. β represents the standardized regression coefficient. *p < 0.05, **p < 0.01, and ***p < 0.001. Full regression coefficients, standard errors, exact p values, and 95% confidence intervals are reported in Supplementary Table S1.

Direct and Indirect Associations

PROCESS Model 6 estimated the prespecified indirect associations between technology anxiety and robot acceptance. Negative attitudes toward robots were entered in the first intermediate position, and human–robot trust was entered in the second.

The standardized total association between technology anxiety and robot acceptance was −0.354. After both intermediate variables and the covariates were included, the direct association was −0.204. The total indirect association was −0.150 (95% bootstrap CI, −0.239 to −0.076).

Each prespecified indirect association had a 95% bootstrap confidence interval that excluded zero (Table 4). The association through negative attitudes was −0.077 (95% bootstrap CI, −0.145 to −0.012). The association through human–robot trust was −0.059 (95% bootstrap CI, −0.111 to −0.017). The theory-ordered serial association through negative attitudes and then human–robot trust was −0.014 (95% bootstrap CI, −0.035 to −0.004). The standardized path coefficients for this theory-ordered serial indirect-association model are shown in Figure 2.

Model Diagnostics and Sensitivity Analyses

Residuals from the robot acceptance model were non-normal and heteroscedastic. Residual skewness was −1.22, the Shapiro–Wilk test had p < 0.001, and the Breusch–Pagan test had p < 0.001. These findings were consistent with the observed ceiling in robot acceptance scores.

Table 4 Bootstrap Estimates of Direct and Indirect Associations Between Technology Anxiety and Robot Acceptance

Association	Estimate	SE	95% CI, lower Limit	95% CI, Upper Limit	Ratio to Total Association (%)
Direct association	−0.204	0.062	−0.327	−0.081	57.71
Indirect association through negative attitudes toward robots	−0.077	0.033	−0.145	−0.012	21.67
Indirect association through human–robot trust	−0.059	0.024	−0.111	−0.017	16.67
Theory-ordered serial indirect association	−0.014	0.007	−0.035	−0.004	3.94
Total indirect association	−0.150	0.041	−0.239	−0.076	42.29
Total association	−0.354	0.044	−0.441	−0.267	100.00

Notes: Estimates are standardized and were obtained from linear regression models adjusted for age, educational level, employment status, monthly income, place of residence, and prior robot experience. SE denotes standard error: bootstrap SEs are reported for indirect associations, and ordinary least-squares SEs for the direct and total associations. Bias-corrected 95% bootstrap confidence intervals for indirect associations used 5000 resamples; confidence intervals for the direct and total associations used ordinary least-squares standard errors. Given the ceiling effect in robot acceptance, the focal regression paths were separately examined using HC3 heteroscedasticity-consistent standard errors and a Tobit model right-censored at 63. These analyses supported the direction and statistical significance of the focal regression associations (Model Diagnostics and Sensitivity Analyses); the indirect-association estimates remained based on the linear models. Ratios to the total association are descriptive and should not be interpreted as proportions mediated.

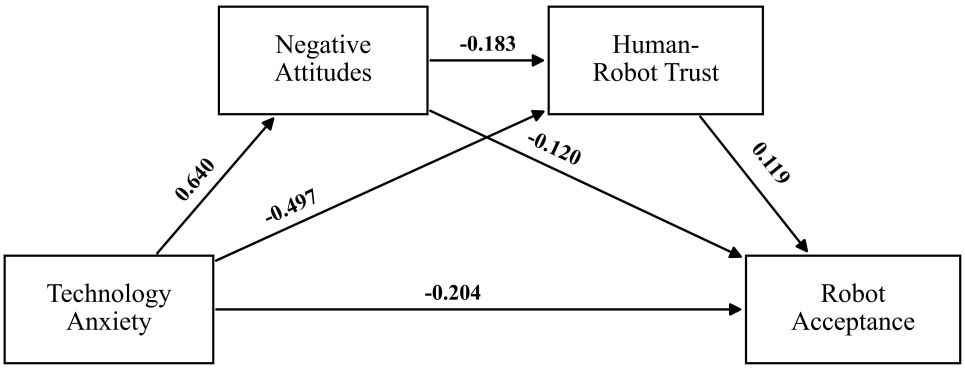

Figure 2 Theory-ordered serial indirect-association model showing standardized path coefficients. Coefficients were estimated from linear regression models adjusted for age, educational level, employment status, monthly income, place of residence, and prior robot experience (covariates not shown). A statistically detectable reversed-order model is reported in Model Diagnostics and Sensitivity Analyses.

With HC3 heteroscedasticity-consistent standard errors, all three focal associations remained statistically significant. The p values were < 0.001 for technology anxiety, 0.019 for negative attitudes, and 0.011 for human–robot trust. In the Tobit model, robot acceptance was treated as right-censored at 63, with 57 censored observations. Technology anxiety remained negatively associated with acceptance (b = −2.11, p = 0.006), as did negative attitudes (b = −1.73, p = 0.014). Human–robot trust remained positively associated with acceptance (b = 1.41, p = 0.034). These estimates represented the change per standard deviation of each predictor. Because the bootstrap indirect estimates were derived from the linear models, their magnitudes should be regarded as approximate in the presence of this ceiling effect.

When educational level and monthly income were dummy-coded, all prespecified indirect associations retained bootstrap confidence intervals that excluded zero. The estimates were −0.075 through negative attitudes (95% CI, −0.140 to −0.011) and −0.052 through trust (95% CI, −0.107 to −0.010). The theory-ordered serial estimate was −0.012 (95% CI, −0.032 to −0.003). However, the association between human–robot trust and robot acceptance was attenuated to β = 0.106 (p = 0.051).

In the unadjusted model, all three indirect associations retained bootstrap confidence intervals that excluded zero. The estimates were −0.104 through negative attitudes (95% CI, −0.182 to −0.023) and −0.081 through trust (95% CI, −0.143 to −0.029). The serial indirect estimate was −0.018 (95% CI, −0.042 to −0.006).

The reversed-order model placed human–robot trust before negative attitudes toward robots. Its serial indirect association was −0.012 (bias-corrected 95% CI, −0.031 to −0.002). Because both serial orderings were statistically compatible with the data, the analyses did not establish the temporal order of negative attitudes and trust. The prespecified ordering was retained solely as a theory-based representation.

Discussion

Among patients who received health education from a ward robot, greater technology anxiety was associated with lower robot acceptance. Specific indirect associations were detected through negative attitudes toward robots and human–robot trust, both separately and in the prespecified serial ordering. However, the reversed serial ordering was also statistically detectable. These findings support an interrelated set of psychological constructs but do not establish a temporal or causal sequence.

Association Between Technology Anxiety and Robot Acceptance

Technology anxiety was negatively associated with robot acceptance, consistent with Hypothesis 1. For patients recovering from surgery, unfamiliar technology may represent an additional cognitive and emotional demand.[30,31] Greater discomfort with technology could therefore coexist with less willingness to engage with a health education robot.

Alternative explanations should also be considered. The observed association may partly reflect differences in digital experience, health literacy, perceived usefulness, pain, or other unmeasured characteristics. The findings support assessing technology-related concerns during implementation studies. However, they do not establish that reducing technology anxiety would increase robot acceptance.

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Indirect Association Through Negative Attitudes Toward Robots

The indirect association through negative attitudes toward robots was statistically detectable, consistent with Hypothesis 2. This pattern accords with evidence that general discomfort with technology coexists with unfavorable evaluations of robots.[32,33] Negative attitudes may therefore help characterize why patients with similar robot exposure report different levels of acceptance.

However, technology anxiety and negative attitudes were measured concurrently using self-report questionnaires. Their association may partly reflect common method variance or conceptual overlap between the two constructs. Longitudinal studies and item-level measurement models are needed before negative attitudes can be considered a modifiable intermediate target.

Indirect Association Through Human–Robot Trust

The indirect association through human–robot trust was also statistically detectable, consistent with Hypothesis 3. Technology anxiety may coexist with stronger perceptions of technological risk and lower confidence in a robot's reliability.[10,34] Lower trust may then accompany reduced willingness to rely on the robot for health information.

Trust was assessed after participants had encountered the ward robot. This timing increased the specificity of the trust measure to the system under study but did not resolve directionality. Experimental studies are needed to determine whether transparent demonstrations or guided interaction can change trust and subsequent robot use.[35,36]

Theory-Ordered Serial Indirect Association

The prespecified serial indirect association through negative attitudes and then human–robot trust was statistically detectable, consistent with Hypothesis 4. This ordering was compatible with the trust transfer rationale that category-level evaluations may shape expectations about a specific system.[14] However, compatibility with a theoretical model does not confirm its temporal sequence.

The reversed serial ordering was also statistically detectable. Negative attitudes and human–robot trust should therefore be interpreted as interrelated correlates rather than an empirically established sequence. Longitudinal measurements before and after robot exposure could help examine their temporal ordering.[37] Experimental manipulation of information or interaction would provide a stronger test of the proposed sequence.

Implications for Research and Practice

Technology anxiety, negative attitudes toward robots, and human–robot trust may help characterize heterogeneity in patients' responses to health education robots.[38] Future implementation studies could evaluate transparent demonstrations, supervised practice, accessible interfaces, and opportunities to consult clinicians.[39] These approaches may address different sources of concern without assuming that a single strategy will benefit all patients.

Such strategies should be evaluated prospectively before routine stratified intervention is recommended. Because the present associations are cross-sectional, it should not be assumed that interventions designed to reduce technology anxiety, modify attitudes, or increase trust will necessarily increase robot acceptance. Relevant outcomes include actual robot use, sustained engagement, knowledge acquisition, patient experience, and clinical workflow measures. Recording the frequency, duration, and content of robot exposure would also clarify how implementation conditions relate to acceptance.

Limitations

Several limitations should be considered. First, the cross-sectional design precludes conclusions about temporal order or causality; the statistically detectable reversed-order model further indicates that the proposed sequence was theory-driven rather than temporally verified. Second, all participants completed the measures after receiving at least one robot-delivered education session. Technology anxiety, negative attitudes, and trust may therefore have been influenced by this experience, and the study cannot determine whether technology anxiety reflected a stable, pre-existing disposition or a response shaped by the robot encounter. Third, all variables were self-reported at one time point. Harman's single-factor test cannot exclude common method bias, which may have inflated the observed associations.[40] Fourth, internal consistency was high for all instruments, but confirmatory factor analysis was not conducted; factor structure, convergent validity, and discriminant validity were

therefore not assessed in this sample. Fifth, robot acceptance showed a ceiling effect, which may have restricted variability. Although the focal regression paths remained statistically significant in robust and Tobit analyses, the bootstrap indirect estimates were derived from linear models and may be less accurate near the upper bound of the scale. Sixth, convenience sampling from a single tertiary hospital and the requirement to complete the questionnaire on a smartphone may have favored patients with greater technological access or confidence. In addition, patients with postoperative complications or psychiatric illness were excluded; therefore, the findings may not apply to more clinically vulnerable surgical populations. Seventh, covariates were selected on the basis of univariate associations with robot acceptance. This pragmatic strategy does not ensure adequate control of confounding, and residual confounding remains possible.[41] Finally, the a priori sample-size estimate relied on a simple observations-per-predictor heuristic that was not designed for indirect associations. Although the final sample substantially exceeded the planned target, statistical power for the specified indirect associations was not established a priori.[42]

Conclusion

In this single-center cross-sectional study, greater technology anxiety was associated with lower robot acceptance among patients recovering from abdominal surgery who had received robot-delivered health education. Negative attitudes toward robots and human–robot trust showed separate and serial indirect associations, although the data did not distinguish their temporal ordering. These constructs may inform variable selection in prospective studies of health education robot implementation. Longitudinal and experimental studies incorporating behavioral outcomes are required before these associations are interpreted causally or used to define intervention targets.

Disclosure of Artificial Intelligence Use

During the preparation and revision of this manuscript, the authors used Claude Opus 5.5 (Anthropic) and OpenAI Codex (Codex CLI version 0.163.0-alpha.10.2) to assist with writing, language editing, translation, and checking the manuscript content and references, because the authors are non-native English speakers. The authors reviewed and verified all content, confirm the originality and accuracy of all manuscript content, and take full responsibility for the integrity of the whole content, including the accuracy of references. The authors checked the terms of use of these tools and confirm their suitability for publication.

Data Sharing Statement

The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

Consent for Publication

Not applicable; the manuscript contains no identifiable individual data or images.

Author Contributions

Jingya Meng: conceptualization, methodology, investigation, data curation, formal analysis, and writing – original draft. Yunyun Feng, Liping Peng, Lijuan Zhong, Qingqing Pang, and Xia Feng: investigation, data curation, and writing – review and editing. Jiayun Zhong: conceptualization, supervision, project administration, and writing – review and editing.

All authors made a significant contribution to the work reported, whether in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

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