Research Square

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Latent Profile Analysis of Patients' Acceptance of Companion Robots in Unaccompanied Wards: A Cross-sectional Study

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Abstract

Aims

To understand the current status of inpatients' acceptance of companion robots in no-accompanying wards through latent profile analysis, identify potential subgroups and their population characteristics, and analyze the influencing factors of different profile categories.

Design

A cross-sectional study.

Methods

The study utilized 425 inpatients from the no-accompanying ward of a tertiary hospital in Sichuan Province, China as research subjects. The study employed a number of research tools, including demographic characteristics, the Almere Technology Acceptance Questionnaire (ATAQ), the Medical Outcomes Study Social Support Survey (MOS-SSS), the PROMIS Emotional Support Short Form, the Negative Attitude towards Robots Scale (NARS), and the General Self-Efficacy Scale (GSE). A latent profile model of inpatients' companion robot acceptance was analyzed using Mplus 8.3. The influencing factors of each profile model were analyzed by multinomial logistic regression analysis.

Results

425 inpatients were finally included. Three latent profiles were identified: the wait-and-see acceptance group (n = 83, 19.53%), the cautious acceptance group (n = 139, 32.71%), and the active acceptance group (n = 203, 47.76%), with Entropy = 0.868, indicating good classification accuracy. Age, education level, and household income showed statistically significant differences among the three groups ($P < 0.001$). Medical social support, emotional support, and general self-efficacy scores showed a gradient distribution (active > cautious > wait-and-see), while negative attitudes toward robots showed the opposite trend ($P < 0.001$). Multinomial logistic regression revealed that advanced age, lower education level, lower household income, insufficient emotional support, low general self-efficacy, and negative perceptions of robots were independent risk factors for classification into the low-acceptance profile.

Conclusion

The findings revealed significant heterogeneity in inpatients' acceptance of companion robots in no-accompanying wards. Elderly patients with lower education levels, farmers, or retirees constitute high-risk groups for low acceptance. Adequate social support and higher self-efficacy can enhance patients'

willingness to accept robots. Clinical practice should implement stratified health education and optimize robot functions to better meet the needs of older adults.

Clinical trial number

Not applicable.

Background

The global shortage of nursing workforce, compounded by the deepening population aging in China, has led to a dramatic increase in care needs among older adults with chronic diseases during hospitalization [1]. The traditional family-accompanied care model faces multiple practical dilemmas: insufficient caregiving labor in one-child families, economic losses from family members taking leave to accompany patients, and imbalanced care resource allocation. A purely labor-based care system cannot simultaneously meet the full range of needs for 24-hour monitoring, rehabilitation intervention, and daily living assistance among hospitalized patients [2–4]. To address the mismatch between care supply and demand and reduce family caregiving burdens, health authorities in China have vigorously promoted the pilot implementation of no-accompanying wards, in which professional nursing teams replace family members in delivering the full-cycle inpatient care. This represents an important measure for implementing the Healthy China strategy and optimizing the allocation of clinical nursing resources [2, 3].

No-accompanying wards (also known as no-attendant care wards) do not completely prohibit family visits. Rather, under the informed and voluntary consent of patients and their families, 24-hour bedside family care is eliminated. Instead, the hospital establishes a professional "nurse + nursing assistant" team to replace family members in providing 24-hour full-process daily living care, basic nursing care, condition observation, and psychological support throughout the hospitalization period, realizing a new inpatient care model in which family members "accompany but do not provide care" [3, 5].

However, the operation of no-accompanying wards simultaneously faces prominent workforce shortages: repetitive vital sign monitoring, daily basic care, and routine health education consume a substantial amount of nurses’ working time [3]; insufficient staffing during night shifts increases safety risks for elderly and high-risk patients; and purely manual care cannot simultaneously address the real-time response needs and emotional companionship of all patients [6]. Companion robots, which integrate vital sign collection, voice interaction, safety alerts, and entertainment companionship functions, can undertake standardized basic nursing tasks, compensate for workforce gaps, and allow nurses to devote more energy to specialized clinical work [7, 8]. Embedding companion robots into the service workflow of no-accompanying wards to construct a human-robot collaborative care model represents a digital pathway for solving the long-term operational challenges of no-accompanying wards [8, 9].

Existing studies on companion robot acceptance have primarily focused on community-dwelling older adults, elderly residents in nursing homes, or healthcare professionals [10–12]. Most previous studies have adopted variable-centered analytical approaches such as regression analysis and structural equation modeling, which assume homogeneity within the study population and fail to identify attitudinal subgroups among patients. To date, no study has applied latent profile analysis to the population of inpatients in no-accompanying wards, making it difficult to develop targeted promotion strategies accordingly. Therefore, the present study employs latent profile analysis to identify potential subtypes of inpatients' companion robot acceptance from a person-centered perspective, compare the demographic and psychosocial characteristics of each subgroup, and screen for independent influencing factors associated with acceptance profile membership. The findings aim to clarify the acceptance characteristics and key influencing mechanisms of different patient groups, provide empirical evidence for stratified and precise promotion of smart nursing devices in clinical practice, and offer targeted improvement directions for age-friendly and personalized optimization of companion robots. Ultimately, this work seeks to enhance the quality and operational efficiency of no-accompanying ward services, and holds important theoretical and practical value for advancing the standardized implementation of smart nursing and constructing a modern clinical care system.

This study addresses three core research questions: (1) to determine the optimal latent profile model of inpatients' companion robot acceptance in no-accompanying wards and identify differences in robot technology perception characteristics across subgroups; (2) to explore the discriminative effects of demographic and psychosocial indicators on different acceptance subgroups; and (3) to verify the independent predictive effects of psychosocial factors on profile membership after adjusting for confounders.

Methods

Participants and sample size

Using a convenience sampling method, 425 inpatients from the cardiothoracic surgery department of a tertiary hospital's no-accompanying ward pilot program were recruited between June 2025 and March 2026. Inclusion criteria were: (1) managed under the no-accompanying care model, without 24-hour family accompaniment, and receiving care from medical nursing staff; (2) conscious and able to communicate verbally; (3) patients or nursing assistants were aware of the basic functions of the companion robot; and (4) voluntary participation with written informed consent. Exclusion criteria were: (1) cognitive impairment or severe visual/hearing impairment; (2) critical illness with altered consciousness; and (3) incomplete questionnaire responses.

Sample size estimation followed the empirical rule for multivariate analysis, which requires at least 5 valid samples per included variable to ensure stable parameter estimation and reduce the risk of model overfitting [13]. This study included a total of 44 variables, comprising 10 sociodemographic variables, 9 dimensions of the companion robot acceptance scale, 4 dimensions of the medical social support scale,

8 items of the emotional support scale, 3 dimensions of the negative attitude toward robots scale, and 10 items of the general self-efficacy scale. Based on this rule, the minimum required sample size for multivariate analysis was 220 (44 × 5). Furthermore, given the simultaneous use of latent profile analysis (LPA), existing methodological research suggests that LPA generally requires a sample size of at least 300 to ensure stable and reliable classification [14]. To account for potential data missingness, incomplete responses, and invalid questionnaires, a 20% invalid response rate was anticipated. Combining the sample size requirements of both statistical methods, the target sample size was set at over 300. A total of 426 questionnaires were distributed, and 425 valid questionnaires were returned, yielding an effective response rate of 99.76%. The actual sample size simultaneously satisfied the sample size thresholds for both multivariate regression analysis and latent profile analysis, ensuring model convergence, subgroup identification stability, and the reliability and statistical power of the overall study findings.

Measurements

Sociodemographic characteristics

A self-developed general information questionnaire was designed by the research team to collect patients' demographic and clinical information, including 10 variables: gender, age, living arrangement, disease diagnosis, marital status, ethnicity, medical insurance type, occupation, education level, and monthly household income.

Almere Technology Acceptance Questionnaire (ATAQ)

The robot technology acceptance instrument was originally developed by Heerink et al. [15]. The Chinese version adapted by He et al. in 2022 was used in this study to measure companion robot acceptance [16]. The scale consists of 30 items across 9 dimensions: attitude toward using, intention to use, perceived adaptability, perceived enjoyment, perceived ease of use, perceived sociability, perceived usefulness, social presence, and trust. Items are rated on a 5-point Likert scale from 1 ("strongly disagree") to 5 ("strongly agree"), with higher scores indicating greater acceptance of robot technology. In this study, the Cronbach's α coefficient for the total scale was 0.908. The Cronbach's α coefficients for each dimension were: attitude toward using 0.892, intention to use 0.904, perceived adaptability 0.736, perceived enjoyment 0.827, perceived ease of use 0.832, perceived sociability 0.869, perceived usefulness 0.788, social presence 0.865, and trust 0.795, indicating good internal consistency. Permission to use the scale was obtained from the copyright holder.

Medical Outcomes Study Social Support Survey (MOS-SSS)

The medical social support scale was originally developed by Sherbourne et al. [17]. The Chinese version adapted by Li in 2012 was used in this study [18]. It comprises 20 items that reflect the social support

patients receive during the course of disease treatment. Items are scored according to established scoring procedures, with higher scores indicating higher levels of medical social support. In this study, the Cronbach's α coefficient was 0.903, indicating good internal consistency. Permission to use the scale was obtained from the copyright holder.

PROMIS Emotional Support Short Form

The Chinese version of the PROMIS Emotional Support Short Form was used for measurement [19]. It comprises 8 items that evaluate the degree of support individuals receive in areas such as confiding, understanding, trust, and emotional exchange. Items are rated on a 4-point scale, with higher scores indicating higher levels of emotional support. In this study, the Cronbach's α coefficient was 0.705, indicating acceptable internal consistency. Permission to use the scale was obtained from the copyright holder.

Negative Attitude towards Robots Scale (NARS)

The negative attitude toward robots scale was originally developed by Nomura et al. [20], and the cross-culturally adapted Chinese version was used in this study [21]. It comprises 13 items that evaluate individuals' unease, nervousness, worry, and negative attitudes during contact with, use of, and interaction with robots. Items are rated on a 5-point scale and are directly scored in this study, with higher scores indicating higher levels of negative attitude toward robots. In this study, the Cronbach's α coefficient was 0.858, indicating good internal consistency. Permission to use the scale was obtained from the copyright holder.

General Self-Efficacy Scale (GSE)

The original scale was developed by Schwarzer et al. [22]. The Chinese version of the General Self-Efficacy Scale was used to assess patients' general self-efficacy levels [23]. Permission to use the scale was obtained from the copyright holder. The scale comprises 10 items rated on a 4-point Likert scale, with total scores ranging from 10 to 40, and higher scores indicating stronger general self-efficacy. In this study, the Cronbach's α coefficient was 0.835, indicating good internal consistency. Permission to use the scale was obtained from the copyright holder.

Data collection and quality control

This study was approved by the Ethics Committee of Panzhihua Central Hospital (Approval No. 2026-39). The investigators included the first author and four cardiothoracic surgery nurses who had received standardized training. Before the survey, a standardized script was used to explain the study purpose to patients, and written informed consent was obtained. Questionnaires were primarily self-completed by patients; for patients with reading, writing, or comprehension difficulties, investigators read each item

aloud and recorded responses according to the patients' oral answers. Paper questionnaires were collected on-site, and missing items were checked and completed immediately upon collection. All data were double-entered by two independent researchers, and 5% of questionnaires were randomly selected for verification to ensure data entry accuracy.

Statistical analysis

Data were analyzed using SPSS 26.0 and Mplus 8.3 software. First, descriptive statistical analysis was performed on demographic data and main study variables using SPSS 26.0. Categorical variables were expressed as frequencies (n) and percentages (%), and continuous variables were expressed as mean ± standard deviation ($\bar{\chi} \pm s$). Cronbach's α coefficients were used to evaluate the internal consistency reliability of the scales. Harman's single-factor test was used to assess common method bias by conducting unrotated exploratory factor analysis on all measurement items, with the variance explained by the first common factor used as the criterion. Subsequently, Mplus 8.3 was used for latent profile analysis (LPA), with dimension scores of the study variables as indicator variables. Models with 1 to 5 classes were sequentially fitted, and the optimal model was determined based on comprehensive evaluation of Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), sample-size adjusted BIC (aBIC), Entropy, Lo-Mendell-Rubin Likelihood Ratio Test (LMRT), and Bootstrapped Likelihood Ratio Test (BLRT), together with class proportions and substantive interpretability. After determining the optimal class solution, chi-square tests were used to compare categorical variables across latent classes, and one-way analysis of variance (ANOVA) was used to compare continuous variables across classes. Finally, variables with statistical significance in univariate analysis were entered into multinomial logistic regression analysis to identify influencing factors of profile membership. Results were reported as B values, standard errors (SE), Wald χ^2 values, P values, odds ratios (OR), and 95% confidence intervals (95% CI). All statistical tests were two-tailed, with $P < 0.05$ considered statistically significant.

Research hypotheses

This study aimed to investigate the latent profiles of companion robot acceptance among inpatients in no-accompanying wards and their associated factors, to inform the development of targeted intervention strategies. Specifically, it tested the following hypotheses:

(1) There are distinct latent profile categories of companion robot acceptance among inpatients in no-accompanying wards.

(2) Demographic characteristics including age, education level, and occupation are associated with latent profile membership.

(3) Psychosocial variables including medical social support, emotional support, general self-efficacy, and negative attitudes toward robots are associated with latent profile membership.

(4) Demographic and psychosocial variables independently or jointly predict profile membership of companion robot acceptance.

Ethical approval

This study was approved by the Ethics Committee of Panzhihua Central Hospital (Approval No. 2026-39). Adhering to the ethical guidelines, protocols, and regulations outlined in the Declaration of Helsinki, the study ensured that informed consent was obtained from all participants. Participation was entirely voluntary, with individuals having the freedom to withdraw from the study at any point without facing any consequences. All procedures followed relevant ethical standards.

Results

Sociodemographic characteristics

A total of 425 inpatients were included in the analysis. Descriptive statistics showed that 245 (57.6%) were male, and the largest age group was 41–59 years (n=200, 47.1%). Most participants were not living alone (n=408, 96.0%). Pulmonary nodules was the most common diagnosis (n=97, 22.8%). The majority were married (n=371, 87.3%) and of Han ethnicity (n=393, 92.5%). The primary medical insurance type was the New Rural Cooperative Medical Scheme (n=218, 51.3%). Occupations were distributed as self-employed (n=83, 19.5%) and retired (n=81, 19.1%). The most common education level was junior college or above (n=144, 33.9%). Monthly household income was primarily concentrated in the range of 5,000–6,999 RMB (n=216, 50.8%). Detailed characteristics are presented in Table 1.

Table 1 Sociodemographic characteristics of the participants (n = 425)

Variable	Category	Number(n)	Constituent ratio (%)
Gender	Male	245	57.6
	Female	180	42.4
Age (years)	≤40	48	11.3
	41–59	200	47.1
	≥60	177	41.6
Living arrangement	Living alone	17	4.0
	Not living alone	408	96.0
Disease diagnosis	Lung cancer supportive care	83	19.5
	Esophageal cancer	25	5.9
	Pulmonary nodule	97	22.8
	Pulmonary occupying lesion	47	11.1
	Pneumothorax	46	10.8
	Rib fracture	69	16.2
	Mediastinal tumor	19	4.5
	Valvular heart disease	13	3.1
	Coronary heart disease	13	3.1
	Atrial septal defect	2	0.5
	Ventricular septal defect	4	0.9
	Aortic dissection	7	1.6
Marital status	Married	371	87.3
	Single	11	2.6
	Divorced	24	5.6
	Widowed	19	4.5
Ethnicity	Han	393	92.5
	Ethnic minority	32	7.5
Medical insurance	New Rural Cooperative Scheme	218	51.3
	Urban employee insurance	179	42.1

	Self-pay	14	3.3
	Work injury	14	3.3
Occupation	Farmer	70	16.5
	Teacher	28	6.6
	Freelancer	68	16.0
	Self-employed	83	19.5
	Retired	81	19.1
	Student	4	0.9
	Worker	29	6.8
	Civil servant	35	8.2
	Office worker	27	6.4
Education level	Illiterate	35	8.2
	Primary school	50	11.8
	Junior high school	31	7.3
	Senior high school	43	10.1
	Secondary vocational school	122	28.7
	Junior college or above	144	33.9
Monthly household income (RMB)	1,000–2,999	6	1.4
	3,000–4,999	131	30.8
	5,000–6,999	216	50.8
	>7,000	72	16.9

Common method bias

Harman's single-factor test was conducted to assess common method bias. The results showed that the variance explained by the first common factor in the unrotated factor analysis was 17.816%, which is below the 40% critical threshold. This indicates that the data in this study did not exhibit serious common method bias, and the questionnaire measurement results were minimally affected by common method variance, meeting the requirements for subsequent statistical analysis.

Descriptive statistics of main variables

Descriptive statistical analysis was performed on the overall levels of the study variables. The total score for robot technology acceptance was 100.44 ± 10.09. Among the dimensions, perceived usefulness (4.09 ± 0.49), trust (3.99 ± 0.61), and attitude toward using (3.99 ± 0.68) had relatively higher mean scores, while perceived sociability (2.73 ± 0.55) and perceived enjoyment (2.78 ± 0.48) had relatively lower mean scores. The total scores for medical social support, emotional support, negative attitude toward robots, and general self-efficacy were 54.23 ± 10.56, 22.18 ± 3.72, 30.48 ± 6.82, and 25.47 ± 5.40, respectively. Detailed results are presented in Table 2.

Table 2 Descriptive statistics of study variables (n = 425)

Variable	Mean score (M ± SD)	Total score (M ± SD)
Attitude toward using	3.99 ± 0.68	11.96 ± 2.04
Intention to use	3.27 ± 0.63	13.07 ± 2.52
Perceived adaptability	3.55 ± 0.47	10.64 ± 1.40
Perceived enjoyment	2.78 ± 0.48	11.12 ± 1.91
Perceived ease of use	3.50 ± 0.54	10.49 ± 1.61
Perceived sociability	2.73 ± 0.55	10.94 ± 2.20
Perceived usefulness	4.09 ± 0.49	12.26 ± 1.46
Social presence	2.99 ± 0.53	11.97 ± 2.12
Trust	3.99 ± 0.61	7.99 ± 1.22
Robot technology acceptance (total)	3.35 ± 0.34	100.44 ± 10.09
Medical social support	2.71 ± 0.53	54.23 ± 10.56
Emotional support	2.77 ± 0.47	22.18 ± 3.72
Negative attitude toward robots	2.34 ± 0.52	30.48 ± 6.82
General self-efficacy	2.55 ± 0.54	25.47 ± 5.40

Latent profile analysis

Model fit indices

The results of latent profile analysis are presented in Table 3. As the number of classes increased from 1 to 5, AIC, BIC, and aBIC generally decreased, indicating progressive improvement in model fit. The 2-class model had an Entropy of 0.825, and both LMRT (P = 0.002) and BLRT (P < 0.001) were significant, indicating improvement over the 1-class model. For the 3-class model, AIC, BIC, and aBIC decreased to 5333.677, 5487.656, and 5367.069, respectively. Entropy increased to 0.868, and both LMRT and BLRT were significant (both P < 0.001). The class proportions were 19.53%, 32.71%, and 47.76%, showing a reasonable distribution. The 4-class model showed a slight decrease in AIC (5331.749), but BIC and aBIC

rebounded, Entropy decreased to 0.829, and both LMRT (P = 0.556) and BLRT (P = 0.333) were non-significant. The 5-class model also showed no improvement in fit, with Entropy dropping to 0.807 and non-significant tests, and yielded a small class comprising only 1.97% of the sample. Considering the comprehensive fit indices, class distribution, and model parsimony, the 3-class model was finally determined to be the optimal latent profile model.

Table 3 Fit indices of latent profile models (n = 425)

Model	AIC	BIC	aBIC	Entropy	LMRT	BLRT	Class proportion (%)
1-class	6277.951	6350.889	6293.768	—	—	—	100
2-class	5622.85	5736.309	5647.455	0.825	0.002	<0.001	42.12 / 57.88
3-class	5333.677	5487.656	5367.069	0.868	<0.001	<0.001	19.53 / 32.71 / 47.76
4-class	5331.749	5526.249	5373.928	0.829	0.556	0.333	19.53 / 4.00 / 32.94 / 43.53
5-class	5332.833	5567.854	5383.799	0.807	0.264	0.685	19.53 / 33.88 / 34.82 / 9.88 / 1.88

Profile characteristics and naming

Based on the 3-class model, inpatients' robot technology acceptance could be classified into three profiles: wait-and-see acceptance, cautious acceptance, and active acceptance (Fig. 1). The wait-and-see acceptance group comprised 83 patients (19.53%), with relatively low scores across all dimensions. Although they had a certain cognitive foundation, their intention to use, confidence, and trust were relatively conservative, and they maintained a wait-and-see attitude toward robots entering healthcare settings. The cautious acceptance group comprised 139 patients (32.71%), with moderate scores across all dimensions. They showed some recognition of robot usefulness and ease of use, but remained cautious regarding practical application and trust, exhibiting a pattern of "accept but be cautious." The active acceptance group comprised 203 patients (47.76%), with the highest scores across all dimensions. They evaluated robot usefulness, adaptability, ease of use, social interaction, and trust highly, representing the primary latent type in this study.

Fig. 1 Distribution characteristics of the three latent acceptance profiles among inpatients in no-accompanying wards

Note: ATT = Attitude; ITU:Intention to use; PA = Perceived adaptability; PE = Perceived enjoyment; PEOU = Perceived ease of use; PS = Perceived sociability; PU = Perceived usefulness; SP = Social presence; TR = Trust. The Y-axis represents mean scores on a 5-point Likert scale. Three distinct acceptance profiles are depicted: wait-and-see acceptance (square solid line, n = 83, 19.53%), cautious acceptance (triangle solid line, n = 139, 32.71%), and active acceptance (circle dashed line, n = 203, 47.76%).

Average latent class posterior probabilities

The average posterior probabilities for individuals assigned to their own class were 0.963, 0.932, and 0.947 for the three profiles, all exceeding 0.90, indicating good classification accuracy. The misclassification probabilities were generally low (Table 4): patients in the wait-and-see group had misclassification probabilities of 0.036 and 0.001 into the cautious and active groups, respectively; patients in the cautious group had misclassification probabilities of 0.015 and 0.053 into the wait-and-see and active groups; and patients in the active group had misclassification probabilities of 0.000 and 0.052 into the wait-and-see and cautious groups. The discriminability and classification stability across the three profiles were good, further supporting the use of the 3-class model for subsequent influencing factor analysis.

Table 4 Average latent class posterior probabilities for the 3-class model

Most likely class	Wait-and-see acceptance	Cautious acceptance	Active acceptance
Wait-and-see acceptance	0.963	0.036	0.001
Cautious acceptance	0.015	0.932	0.053
Active acceptance	0.000	0.052	0.947

Univariate analysis of latent profiles

Chi-square tests and one-way ANOVA were used to compare sociodemographic characteristics and related variables across the three robot acceptance profiles (Table 5). The results showed that the three latent profiles differed significantly in terms of age ($\chi^2 = 35.758$, $P < 0.001$), education level ($\chi^2 = 94.240$, $P < 0.001$), and household income ($\chi^2 = 47.078$, $P < 0.001$). No statistically significant differences were observed for gender, living arrangement, disease diagnosis, marital status, ethnicity, medical insurance, or occupation (all $P > 0.05$).

Furthermore, the three profiles showed statistically significant differences in medical social support ($F = 48.329$, $P < 0.001$), emotional support ($F = 27.132$, $P < 0.001$), negative attitude toward robots ($F = 57.650$, $P < 0.001$), and general self-efficacy ($F = 76.409$, $P < 0.001$).

Table 5 Comparison of sociodemographic and psychosocial variables across latent acceptance profiles (n = 425)

Variable	Category/Indicator	Wait-and-see (n=83)	Cautious (n=139)	Active (n=203)	χ^2/F	P
Gender	Male	46 (55.4)	73 (52.5)	126 (62.1)	3.292	0.193
	Female	37 (44.6)	66 (47.5)	77 (37.9)		
Age (years)	≤40	2 (2.4)	17 (12.2)	29 (14.3)	35.758	<0.001
	41–59	23 (27.7)	75 (54.0)	102 (50.2)		
	≥60	58 (69.9)	47 (33.8)	72 (35.5)		
Living arrangement	Living alone	3 (3.6)	9 (6.5)	5 (2.5)	3.498	0.174
	Not living alone	80 (96.4)	130 (93.5)	198 (97.5)		
Disease diagnosis	Lung cancer supportive care	17 (20.5)	24 (17.3)	42 (20.7)	26.888	0.216
	Esophageal cancer	7 (8.4)	7 (5.0)	11 (5.4)		
	Pulmonary nodule	13 (15.7)	34 (24.5)	50 (24.6)		
	Pulmonary occupying lesion	6 (7.2)	14 (10.1)	27 (13.3)		
	Pneumothorax	12 (14.5)	20 (14.4)	14 (6.9)		
	Rib fracture	12 (14.5)	25 (18.0)	32 (15.8)		
	Mediastinal tumor	3 (3.6)	7 (5.0)	9 (4.4)		
	Valvular heart disease	7 (8.4)	1 (0.7)	5 (2.5)		
	Coronary heart disease	3 (3.6)	3 (2.2)	7 (3.4)		
	Atrial septal defect	0 (0.0)	0 (0.0)	2 (1.0)		
	Ventricular septal defect	1 (1.2)	1 (0.7)	2 (1.0)		
	Aortic dissection	2 (2.4)	3 (2.2)	2 (1.0)		

Marital status	Married	71 (85.5)	116 (83.5)	184 (90.6)	4.957	0.549
	Single	3 (3.6)	5 (3.6)	3 (1.5)		
	Divorced	5 (6.0)	11 (7.9)	8 (3.9)		
	Widowed	4 (4.8)	7 (5.0)	8 (3.9)		
Ethnicity	Han	75 (90.4)	129 (92.8)	189 (93.1)	0.670	0.716
	Ethnic minority	8 (9.6)	10 (7.2)	14 (6.9)		
Medical insurance	New Rural Cooperative Scheme	43 (51.8)	76 (54.7)	99 (48.8)	10.705	0.098
	Urban employee insurance	33 (39.8)	59 (42.4)	87 (42.9)		
	Self-pay	1 (1.2)	3 (2.2)	10 (4.9)		
	Work injury	6 (7.2)	1 (0.7)	7 (3.4)		
Occupation	Farmer	11 (13.3)	22 (15.8)	37 (18.2)	20.978	0.179
	Teacher	9 (10.8)	10 (7.2)	9 (4.4)		
	Freelancer	10 (12.0)	22 (15.8)	36 (17.7)		
	Self-employed	18 (21.7)	31 (22.3)	34 (16.7)		
	Retired	21 (25.3)	24 (17.3)	36 (17.7)		
	Student	0 (0.0)	2 (1.4)	2 (1.0)		
	Worker	5 (6.0)	10 (7.2)	14 (6.9)		
	Civil servant	6 (7.2)	5 (3.6)	24 (11.8)		
	Office worker	3 (3.6)	13 (9.4)	11 (5.4)		
Education level	Illiterate	19 (22.9)	4 (2.9)	12 (5.9)	94.240	<0.001
	Primary school	23 (27.7)	14 (10.1)	13 (6.4)		
	Junior high school	10 (12.0)	7 (5.0)	14 (6.9)		
	Senior high school	14 (16.9)	8 (5.8)	21 (10.3)		

	Secondary vocational school	13 (15.7)	43 (30.9)	66 (32.5)		
	Junior college or above	4 (4.8)	63 (45.3)	77 (37.9)		
Monthly household income (RMB)	1,000–2,999	4 (4.8)	0 (0.0)	2 (1.0)	47.078	<0.001
	3,000–4,999	46 (55.4)	29 (20.9)	56 (27.6)		
	5,000–6,999	30 (36.1)	83 (59.7)	103 (50.7)		
	>7,000	3 (3.6)	27 (19.4)	42 (20.7)		
Medical social support (M ± SD)		2.33 ± 0.49	2.63 ± 0.45	2.92 ± 0.49	48.329	<0.001
Emotional support (M ± SD)		2.50 ± 0.50	2.73 ± 0.41	2.91 ± 0.43	27.132	<0.001
Negative attitude toward robots (M ± SD)		2.77 ± 0.44	2.41 ± 0.49	2.13 ± 0.45	57.650	<0.001
General self-efficacy (M ± SD)		2.05 ± 0.45	2.48 ± 0.47	2.79 ± 0.47	76.409	<0.001

Multicollinearity assessment

Before conducting multinomial logistic regression, the categorical variables included in the model were coded. With "robot technology acceptance latent profile" as the dependent variable and "wait-and-see acceptance" as the reference category, age, education level, and household income were entered as ordinal independent variables, while medical social support, emotional support, negative attitude toward robots, and general self-efficacy were entered as continuous variables using their actual mean scores. The variable coding is summarized in Table 6.

Table 6 Coding scheme for independent variables in regression analysis

Variable	Coding scheme
Robot acceptance latent profile	1 = wait-and-see; 2 = cautious; 3 = active
Age group	1 = ≤40; 2 = 41–59; 3 = ≥60
Education level	1 = illiterate; 2 = primary school; 3 = junior high; 4 = senior high; 5 = secondary vocational; 6 = junior college or above
Household income (RMB)	1 = 1,000–2,999; 2 = 3,000–4,999; 3 = 5,000–6,999; 4 = >7,000
Medical social support	Actual mean score used
Emotional support	Actual mean score used
Negative attitude toward robots	Actual mean score used
General self-efficacy	Actual mean score used

Before regression analysis, multicollinearity among the independent variables was assessed (Table 7). Generally, tolerance values > 0.10 and variance inflation factor (VIF) values < 10 indicate no serious multicollinearity; VIF < 5 indicates low collinearity risk. The results showed that tolerance values ranged from 0.650 to 0.948, all greater than 0.10. VIF values ranged from 1.055 to 1.537, all well below 5. Education level had the relatively highest VIF at 1.537, which remained at a low level. Therefore, no significant multicollinearity was observed among the independent variables, and they could be entered into the multinomial logistic regression model for further analysis.

Table 7 Multicollinearity diagnostics (Tolerance and VIF)

Variable	Tolerance	VIF
Age	0.948	1.055
Education level	0.650	1.537
Household income	0.689	1.450
Medical social support	0.754	1.327
Emotional support	0.764	1.310
Negative attitude toward robots	0.872	1.147
General self-efficacy	0.834	1.200

Multinomial logistic regression analysis

Using the wait-and-see acceptance group as the reference, multinomial logistic regression was performed (Table 8). In the comparison between the cautious and wait-and-see groups, age, education level, household income, negative attitude toward robots, and general self-efficacy were all significant.

Age had a negative effect (B = -0.986, P = 0.003, OR = 0.373, 95% CI: 0.197–0.707), indicating that older patients were less likely to be classified into the cautious group. Education level (B = 0.477, P < 0.001, OR = 1.611, 95% CI: 1.243–2.089) and household income (B = 0.744, P = 0.026, OR = 2.104, 95% CI: 1.092–4.054) both had positive effects, with higher levels corresponding to greater likelihood of being in the cautious group.

Negative attitude toward robots had a negative effect (B = -0.118, P < 0.001, OR = 0.888, 95% CI: 0.835–0.945), indicating that higher negative attitudes decreased the likelihood of being classified into the cautious group. General self-efficacy had a positive effect (B = 0.174, P < 0.001, OR = 1.190, 95% CI: 1.094–1.294), indicating that higher self-efficacy increased the likelihood of being in the cautious group. Neither medical social support nor emotional support reached statistical significance (both P > 0.05).

In the comparison between the active and wait-and-see groups, age, education level, household income, medical social support, negative attitude toward robots, and general self-efficacy were all significant. Age had a negative effect (B = -0.921, P = 0.008, OR = 0.398, 95% CI: 0.202–0.784). Education level (B = 0.378, P = 0.008, OR = 1.459, 95% CI: 1.106–1.926) and household income (B = 0.754, P = 0.033, OR = 2.125, 95% CI: 1.062–4.253) had positive effects, with higher levels corresponding to greater likelihood of being in the active group.

Medical social support had a positive effect (B = 0.084, P < 0.001, OR = 1.088, 95% CI: 1.039–1.139), indicating that higher social support increased the likelihood of being in the active group. Negative attitude toward robots had a negative effect (B = -0.200, P < 0.001, OR = 0.819, 95% CI: 0.766–0.876). General self-efficacy had a positive effect (B = 0.297, P < 0.001, OR = 1.346, 95% CI: 1.228–1.474). Emotional support was not significant (P = 0.222).

In summary, age, education level, household income, negative attitude toward robots, and general self-efficacy showed stable effects across both comparisons: lower age, higher education and income, lower negative attitudes, and higher self-efficacy were associated with greater acceptance. Medical social support was only significant for the active group comparison, suggesting that high levels of social support are associated with more positive acceptance tendencies.

Table 8 Multinomial logistic regression analysis of influencing factors for robot acceptance profiles (n = 425)

Variable	*B*	*SE*	*Wald* χ^2	*P*	*OR*	*95% CI*
Cautious acceptance vs. wait-and-see acceptance						
Intercept	-3.417	2.174	2.471	0.116		
Age group	-0.986	0.326	9.138	0.003	0.373	0.197–0.707
Education level	0.477	0.133	12.960	<0.001	1.611	1.243–2.089
Household income	0.744	0.335	4.946	0.026	2.104	1.092–4.054
Medical social support	0.032	0.022	2.108	0.147	1.033	0.989–1.078
Emotional support	0.047	0.057	0.683	0.408	1.048	0.938–1.171
Negative attitude toward robots	-0.118	0.032	14.088	<0.001	0.888	0.835–0.945
General self-efficacy	0.174	0.043	16.324	<0.001	1.190	1.094–1.294
Active acceptance vs. wait-and-see acceptance						
Intercept	-7.135	2.360	9.138	0.003		
Age group	-0.921	0.346	7.101	0.008	0.398	0.202–0.784
Education level	0.378	0.142	7.133	0.008	1.459	1.106–1.926
Household income	0.754	0.354	4.533	0.033	2.125	1.062–4.253
Medical social support	0.084	0.023	13.007	<0.001	1.088	1.039–1.139
Emotional support	0.075	0.061	1.494	0.222	1.078	0.956–1.216
Negative attitude toward robots	-0.200	0.034	33.872	<0.001	0.819	0.766–0.876
General self-efficacy	0.297	0.047	40.723	<0.001	1.346	1.228–1.474

Note: Reference category = wait-and-see acceptance group. B = regression coefficient, SE = standard error, OR = Exp(B), 95% CI = 95% confidence interval for OR. P < 0.05 indicates statistical significance.

Discussion

Latent profile analysis confirms significant heterogeneity in robot acceptance among inpatients in no-accompanying wards

Based on nine technology perception indicators of robot acceptance, this study identified three latent profiles: wait-and-see acceptance (19.53%), cautious acceptance (32.71%), and active acceptance (47.76%), with an Entropy value of 0.868. The average posterior probabilities for all latent classes exceeded 0.90, indicating that the 3-class model had good classification accuracy and class discriminability. This result supports Hypothesis H1, namely that inpatients' acceptance of companion robots in no-accompanying wards is not a single homogeneous construct but comprises identifiable latent subgroups.

In terms of profile shape, the three patient groups exhibited a clear gradient distribution across the nine technology perception indicators. The wait-and-see acceptance group had relatively low scores across all dimensions, particularly in intention to use, perceived sociability, social presence, and trust. The cautious acceptance group had moderate scores across dimensions, showing some recognition of robot technology and intention to use, but remained cautious regarding practical application and trust. The active acceptance group had the highest scores across all dimensions, demonstrating strong recognition and acceptance of robot technology in healthcare settings, and was the primary latent type in this study.

This finding has two important implications. First, it methodologically addresses the limitation of previous studies that adopted variable-centered approaches assuming population homogeneity. Most prior studies on companion robot acceptance used regression analysis or structural equation modeling, which can reveal average effects among variables but cannot identify attitudinal subgroups. The present study uses a person-centered approach to demonstrate that attitudinal stratification exists among inpatients in no-accompanying wards, providing a reproducible quantitative stratification basis for individualized interventions in the field of smart nursing. Second, it suggests that clinical promotion strategies cannot rely on a "one-size-fits-all" approach. The wait-and-see and cautious acceptance groups together account for 52.24% of the sample, nearly half, indicating that a substantial proportion of inpatients in no-accompanying wards still hold reserved or cautious attitudes toward companion robots. Neglecting this population heterogeneity may result in limited effectiveness of uniform education interventions, and information overload may even exacerbate technology anxiety among the low-acceptance group.

Demographic stratification patterns and scenario specificity in no-accompanying settings

Univariate analysis showed that the three latent profiles differed significantly in age, education level, and household income, while no significant differences were observed for gender, living arrangement, disease diagnosis, marital status, ethnicity, medical insurance, or occupation. Multinomial logistic regression further demonstrated that age, education level, household income, negative attitude toward

robots, and general self-efficacy showed relatively stable significant effects across both the cautious vs. wait-and-see and active vs. wait-and-see comparisons. This result partially supports Hypothesis H2, namely that demographic variables are associated with latent profile membership, although the discriminative effects of different variables are not uniform.

In terms of age, a high proportion of elderly patients were concentrated in the low-acceptance profile. In no-accompanying settings, patients need to independently operate robots and respond to device alarms without immediate family assistance. Elderly patients commonly experience digital operation anxiety and worry that no one will be available to handle robot malfunctions, which may further intensify their rejection. In terms of education level, patients with lower educational attainment lack experience with smart devices and have difficulty understanding safety mechanisms such as robot data encryption and fault alerts, making them more susceptible to forming negative stereotypes. In terms of occupation, farmers and retirees have less daily exposure to smart devices and are more likely to be classified into the low-acceptance group, while professional groups such as teachers and civil servants show relatively higher acceptance. This stratification pattern is not entirely consistent with findings from community-based elderly care robot research, reflecting the unique stratification characteristics of the inpatient no-accompanying setting: patients are in a disease state, removed from their family support systems, and must immediately accept and operate new technology during hospitalization. Their acceptance is more influenced by assessments of "whether I can independently cope right now" rather than general technology attitudes.

Notably, although household income and disease type showed some statistical significance in specific profile comparisons in the multinomial logistic regression, disease diagnosis showed no significant between-group differences in univariate analysis, and the effect of household income was not entirely consistent across profile comparisons. Given the unified management and standardized care processes in no-accompanying wards, the core contradiction affecting patient attitudes may stem more from safety anxiety due to caregiving absence than from economic conditions or the disease itself. This finding suggests that in no-accompanying settings, economic stratification is not the primary determinant of robot acceptance; clinical screening should prioritize high-risk characteristics such as advanced age, low education level, farmer/retired occupation, rather than simply using income or disease type to identify intervention targets.

Psychosocial pathways: from external support to self-efficacy and negative attitudes

Combining the results of univariate analysis and multinomial logistic regression, this study suggests a clinically modifiable psychological pathway: sufficient medical and emotional social support may enhance patients’ general self-efficacy, thereby reducing their negative attitudes toward companion robots and ultimately improving robot acceptance. This result partially supports Hypotheses H3 and H4, namely that psychosocial variables are associated with latent profile membership, and some variables have independent predictive effects.

In the comparison between the active and wait-and-see groups, medical social support had a significant positive effect (B = 0.084, P < 0.001, OR = 1.088), indicating that higher medical social support increased the likelihood of being classified into the active acceptance group. Emotional support showed significant between-group differences in univariate analysis (F = 27.132, P < 0.001), but did not demonstrate independent predictive effects in multinomial logistic regression (P = 0.222). This discrepancy warrants careful interpretation: emotional support may share variance with medical social support and general self-efficacy, and its effects may be mediated indirectly through enhancing self-efficacy or reducing negative attitudes rather than directly determining profile membership. Medical social support, because it includes informational and instrumental support components, may more directly help patients understand robot emergency response and privacy protection mechanisms, thereby independently promoting active acceptance.

General self-efficacy showed stable positive effects across both comparisons: cautious vs. wait-and-see (B = 0.174, P < 0.001, OR = 1.190) and active vs. wait-and-see (B = 0.297, P < 0.001, OR = 1.346). This indicates that patients' subjective judgment of their ability to independently operate robots is a key psychological variable distinguishing acceptance profiles. In no-accompanying conditions, without family members to assist with operation, the influence of self-efficacy may be stronger than in community home settings. Patients with low self-efficacy may pre-judge themselves as unable to complete operations such as calling for help, checking vital signs, or responding to alarms, thereby avoiding robot use.

Negative attitude toward robots showed significant negative effects across both comparisons: cautious vs. wait-and-see (B = -0.118, P < 0.001, OR = 0.888) and active vs. wait-and-see (B = -0.200, P < 0.001, OR = 0.819). Primary concerns include robots' inability to replace humanistic care, delays in treatment due to malfunctions, and leakage of personal health information; the absence of family backup may further amplify these concerns. Stronger negative attitudes were associated with a greater likelihood of being classified into the wait-and-see group rather than the cautious or active group.

Overall, psychosocial variables do not operate in isolation but may form a chain pathway of "external support → self-efficacy → negative attitudes → acceptance." Medical and emotional social support constitute external sources of patients' sense of security; general self-efficacy represents patients' subjective judgment of their independent operational capability; and negative attitudes toward robots reflect concerns about technological risks and the absence of humanistic care. These three factors jointly influence patients' classification into different acceptance profiles. All of these variables can be intervened through nursing process optimization without requiring hardware modification, and thus have high clinical translation value.

Theoretical implications: complementing variable-centered research paradigms with a person-centered approach

Existing theories related to nursing robot technology acceptance have largely been constructed with community-dwelling older adults, nursing home residents, or healthcare professionals as study

populations, and empirical evidence specific to inpatients in no-accompanying wards is lacking. The present study introduces latent profile analysis into this specific research context, constructing a multi-layer influence model encompassing demographic characteristics, dual social support, self-efficacy, negative attitudes toward robots, and acceptance subgroups.

The theoretical contributions of this study are threefold. First, it confirms the existence of latent classification characteristics in robot acceptance among inpatients in no-accompanying wards, supplementing person-centered research evidence in this specific setting. Second, it suggests that traditional variable-centered analytical approaches may mask differences in underlying mechanisms across subgroups. For example, emotional support was significant in univariate analysis but not in multinomial logistic regression, indicating that its effects may be mediated or shared with other psychological variables; relying solely on average effects may overestimate or underestimate its independent contribution. Third, it constructs a modifiable psychological pathway that provides a testable hypothesis framework for future longitudinal studies or intervention trials.

Clinical practice implications for no-accompanying wards: stratified screening and precise intervention

Targeting the three latent profiles, stratified intervention strategies can be proposed.

For the wait-and-see acceptance group: conduct pre-admission screening to identify high-risk characteristics such as advanced age, low education level, and farmer/retired occupation. Implement one-to-one bedside hands-on training. Simplify the functional interface, retaining only core modules such as calling nurses, fall alerts, and vital sign viewing. Provide targeted psychological counseling and demonstrations of fault alarm mechanisms and data encryption. Guide patients to gradually trial the robot to enhance operational self-efficacy.

For the cautious acceptance group: treat this group as key conversion targets. Education should emphasize how robots solve no-accompanying pain points, such as nighttime monitoring and medication reminders. Introduce peer sharing from high-acceptance patients in the same ward to correct negative cognitions and promote conversion toward the higher acceptance group.

For the active acceptance group: leverage their role as peer promoters by encouraging them to share their usage experiences with other patients, conserving nursing education manpower.

Simultaneously advance age-friendly hardware iteration of robots: amplify voice volume, simplify interfaces, add dialect-based entertainment modules, and strengthen multi-layer fault alarms. Robot acceptance stratification can be incorporated into admission nursing assessments to proactively deliver psychological and operational training. Establish a "nurse + nursing assistant + companion robot" collaborative care model, delegating repetitive monitoring and reminders to robots and freeing nurses to deliver specialized nursing care.

Limitations

Several limitations should be acknowledged. First, this study used convenience sampling from a single cardiothoracic surgery department, which limits the generalizability of findings to other specialties such as internal medicine or oncology. Second, as a cross-sectional study, it can only demonstrate variable associations and cannot establish causal relationships; follow-up studies are needed to verify the predictive effects of profile membership on long-term actual usage behavior. Third, the study relied entirely on quantitative self-report scales without incorporating semi-structured interviews, which limits the depth of understanding of the genuine concerns of low-acceptance patients. Fourth, as an observational study, it did not conduct a stratified education intervention trial, and the actual effectiveness of the proposed stratified intervention strategies remains to be verified.

Conclusion

This study employed a person-centered latent profile analysis approach to reveal the intrinsic heterogeneity of companion robot acceptance among inpatients in no-accompanying wards. The 3-class model provided the optimal fit, with scores across nine technology perception indicators showing a clear gradient distribution. Advanced age, lower education level, and farmer/retired occupation were demographic high-risk factors for low acceptance, while gender, disease type, household income, and medical insurance type showed limited discriminative effects. Medical social support, emotional support, and general self-efficacy positively facilitated robot acceptance, while negative cognitive attitudes toward robots were important psychological barriers. All of these variables independently predicted profile membership. Clinical practice should implement differentiated education and psychological interventions based on patients' acceptance stratification, while simultaneously optimizing age-friendly robot functions to advance the implementation of human-robot collaborative care models in no-accompanying wards.

Declarations

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Authors' contributions

Jing Ren: Conceptualization, Methodology, Writing – Original Draft. Chenxi Gao: Conceptualization, Writing – Review & Editing. Jun Zhang: Methodology. Mingzhu Feng: Investigation, Data Curation. Jinrong Fu: Investigation, Data Curation. Zhengjuan Shi: Formal Analysis. All authors read and approved the final manuscript.

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Data availability

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

Ethics approval and consent to participate

This study was approved by the Ethics Committee of Panzhihua Central Hospital (Approval No. 2026-39). The study was conducted in accordance with the Declaration of Helsinki. All participants provided written informed consent. All procedures followed relevant ethical standards.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

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Figures

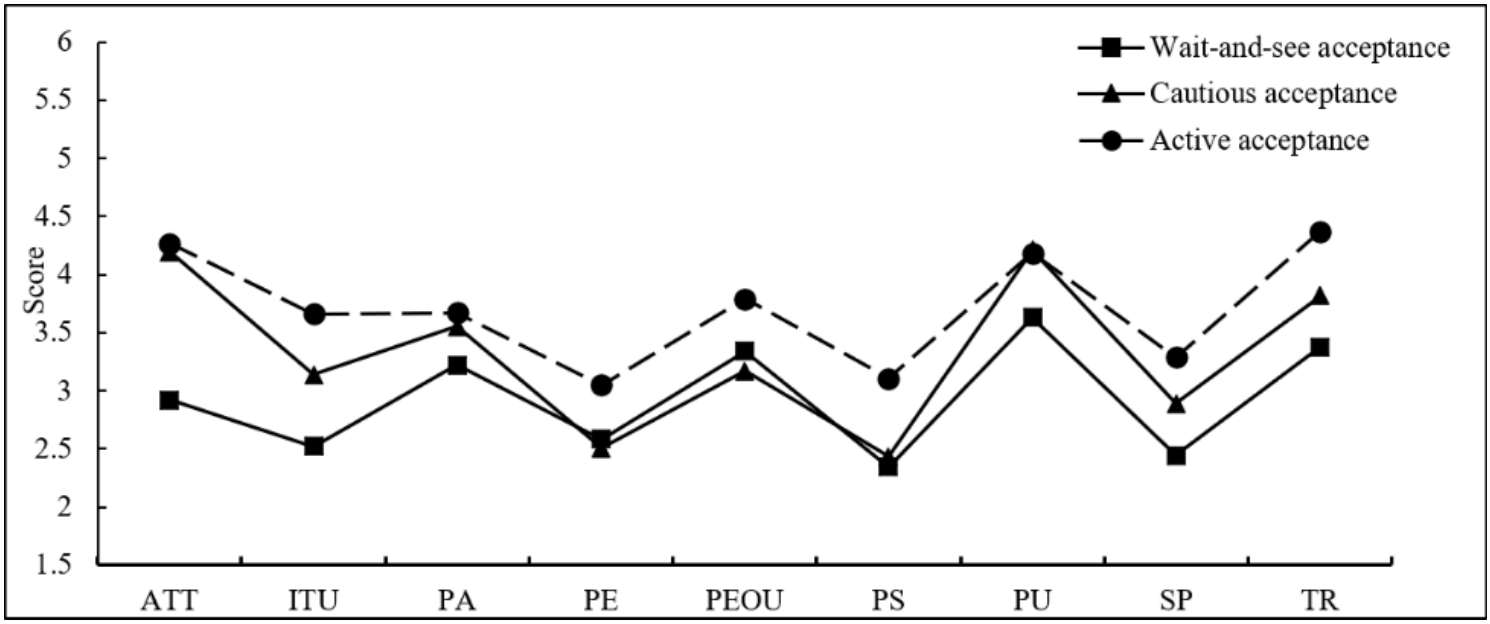

Figure 1

Distribution characteristics of the three latent acceptance profiles among inpatients in no-accompanying wards

Note: ATT = Attitude; ITU:Intention to use; PA = Perceived adaptability; PE = Perceived enjoyment; PEOU = Perceived ease of use; PS = Perceived sociability; PU = Perceived usefulness; SP = Social presence; TR = Trust. The Y-axis represents mean scores on a 5-point Likert scale. Three distinct acceptance profiles are depicted: wait-and-see acceptance (square solid line, n = 83, 19.53%), cautious acceptance (triangle solid line, n = 139, 32.71%), and active acceptance (circle dashed line, n = 203, 47.76%).