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Knowledge, Belief, and Practice Study on the Use of Smart Nursing Devices by Nurses in Neurology and Rehabilitation Departments: From the Perspective of the Technology Acceptance Model (TAM)

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Abstract

Background Smart nursing devices can improve safety and quality of care for patients with neurological-rehabilitation conditions. Nevertheless, nurses' knowledge-attitude-practice (KAP) regarding these devices has rarely been explored using an integrated theoretical framework. This study aimed to investigate nurses' knowledge, attitudes and usage behaviours towards smart nursing devices based on the Technology Acceptance Model (TAM)-KAP framework, and identify influencing factors and practical barriers.

Methods A cross-sectional survey was performed among 219 registered nurses from neurology and rehabilitation departments of 20 hospitals across 16 Chinese provinces from January to May 2026. Self-administered questionnaires covered general information, knowledge, TAM-based attitude-intention, actual usage behaviour and usage barriers. Questionnaire reliability and validity were tested in a pilot survey. Statistical analyses included descriptive statistics, correlation analysis and hierarchical multiple linear regression using SPSS 26.0.

Results Nurses held positive usage attitudes (3.98 ± 0.79 per item) but showed insufficient knowledge (2.88 ± 1.08), with a notable intention-behaviour gap in device application. Perceived usefulness was the strongest predictor of usage attitude ($\beta = 0.846$, $P < 0.001$) and behavioural intention ($\beta = 0.796$, $P < 0.001$). Both behavioural intention and knowledge directly predicted actual usage behaviour. Higher training frequency was associated with higher total KAP scores ($H = 29.862$, $P < 0.001$). Major barriers included device instability (41.1%), workflow mismatch (39.7%), and poor patient cooperation caused by cognitive impairment (38.8%).

Conclusions Despite favourable attitudes, insufficient knowledge and contextual obstacles hinder nurses from translating positive intentions into practice. Targeted training and device optimisation are required to narrow the intention-behaviour gap. These findings provide evidence for training design and equipment management within neuro-rehabilitation nursing.

Introduction

With the deep integration of artificial intelligence, the Internet of Things, and big data technologies in the healthcare sector, smart nursing has emerged as a pivotal direction for enhancing clinical care quality and efficiency [1,2]. The application of intelligent nursing devices (such as smart wristbands, rehabilitation training robots, vital sign monitors, and smart mattresses) in clinical settings can assist or partially replace manual tasks in repetitive nursing procedures, thereby reducing the incidence of adverse nursing events, alleviating nurses' workload, and providing patients with safer and more precise care services [3-5]. As key departments specializing in treating neurological disorders such as stroke, Parkinson's disease, and spinal cord injuries, neurology and rehabilitation departments face distinctive challenges characterized by complex patient conditions, diverse functional impairments, prolonged rehabilitation periods, and high safety risks [6,7]. Intelligent nursing devices demonstrate unique advantages in preventing falls/wandering incidents, supporting functional rehabilitation training, and enabling continuous monitoring of vital signs, serving as critical technological support for improving care quality and patient safety in these disciplines.

However, the true clinical value of advanced devices largely depends on the acceptance and usage behaviours of frontline nurses [8]. Nurses are the direct operators of intelligent nursing devices and the primary responsible parties for their clinical outcomes; their knowledge base, attitudes toward usage, and practical behaviours directly determine the effectiveness of device application [9-10]. Currently, research on clinical nurses' awareness and utilization of intelligent nursing devices remains insufficient, particularly in specialized fields such as neurology and rehabilitation, where systematic investigations based on well-established theoretical models are lacking [11]. Therefore, this study employs the Technology Acceptance Model (TAM) [1] and the Knowledge-Attitude-Practice (KAP) framework to investigate nurses' knowledge, attitudes, and usage behaviours regarding intelligent nursing devices in neurology and rehabilitation departments, analyze key factors influencing their adoption intentions, and provide empirical evidence for targeted training programs and optimized device deployment and management in healthcare institutions, thereby facilitating the effective implementation of smart nursing care in neurological rehabilitation. Venkatesh and Davis [12] further validated the driving effects of PU and PEOU on behavioural intention within TAM2.

1 Subjects and Methods

1.1 Study subjects

This cross-sectional study was reported following the STROBE guidelines for observational studies[31].Using convenience sampling, from January to May 2026, registered nurses working in the departments of neurology and rehabilitation at over 20 hospitals across 16 provinces nationwide were selected as study subjects. Inclusion criteria: (1) possession of a nurse practice qualification certificate; (2) work experience of ≥3 months in a neurology or rehabilitation department; (3) informed consent and voluntary participation. Exclusion criteria: (1) nurses undergoing advanced training or rotation; (2) those on leave or away for further studies during the survey period.Given the convenience-sampling approach, selection bias may exist, which should be considered when interpreting the findings.

1.2 Explanation of department consolidation

The Department of Neurology and the Department of Rehabilitation share high consistency in both patient populations and nursing care content: both departments primarily serve patients with neurological disorders such as stroke, Parkinson's disease, spinal cord injury, and traumatic brain injury. Their nursing focuses encompass functional rehabilitation training, restoration of daily living skills, safety risk management for falls/wandering incidents, and cognitive function intervention. The application scenarios and nursing objectives for intelligent nursing devices (e.g., smart wristbands, rehabilitation training robots, vital sign monitors, and smart mattresses) are highly aligned across both departments. Therefore, this study combines data from nurses in both departments to increase sample size and enhance statistical power.

1.3 Sample size estimation

The sample size was estimated using G*Power 3.1 software. This study employed two primary statistical methods: multiple linear regression analysis and one-way ANOVA, with the larger value obtained from each calculation selected as the final sample size. (1) Multiple linear regression analysis: A power of f^2 = 0.15 (moderate effect) [13], significance level α = 0.05, power (1–β) = 0.80, and 2 predictor variables were specified. Results indicated that at least 55 samples were required to achieve 80% statistical power; accounting for a 20% invalid response rate, this amounted to at least 69 samples. (2) One-way ANOVA (using five training frequency groups): A power of f = 0.25 ($\eta^2 \approx 0.06$, moderate-to-low effect) [13], significance level α = 0.05, power (1–β) = 0.80, and 5 groups were specified. Calculations showed that at least 160 samples were needed for 80% power; considering a 20% invalid response rate, this required 200 samples. To meet the sample size requirements for both methods, the study included a minimum of 200 participants. Ultimately, 219 valid questionnaires were collected, fulfilling all statistical power needs.Although we merged two departments for higher statistical power, we also performed between-group comparison in Table 1, which demonstrated no statistically significant difference in overall KAP scores between neurology and rehabilitation nurses (P=0.307).

1.4 Research tools

Most questionnaires used in this study were self-developed by our research team specifically for the present study and have not been previously published. These questionnaires were developed based on the Technology Acceptance Model (TAM) framework, combined with the clinical characteristics of neurology and rehabilitation nursing. Questionnaire items were generated through literature review, group discussion and expert consultation. Reliability and validity were examined via a pilot survey among 30 clinical nurses prior to formal data collection. Only the attitude-behaviour-intention scale was adapted from the published TAM instrument and revised for this clinical context.

The full English-language version of these self-developed questionnaires is provided as a supplementary file [32].

1.4.1 General information questionnaire: Self-designed, covering age, years of work experience, educational background, professional title, years of service in neurology/rehabilitation departments, and training frequency.

1.4.2 Knowledge questionnaire: Self-designed with five items, this questionnaire evaluates nurses' proficiency in various types of intelligent nursing devices, operational procedures, indication selection, alarm response protocols, and patient guidance. A 5-point Likert scale (1 = very unfamiliar; 5 = very familiar) is employed, where higher scores indicate greater knowledge levels. The total score ranges from 5 to 25 points.

1.4.3 The attitude and behaviour intention scale based on TAM: Adapted from Davis's TAM scale [1] with modifications tailored to the characteristics of neurology and rehabilitation medicine, this scale comprises 20 items divided into four dimensions: Perceived usefulness (PU, 7 items), Perceived ease of use (PEOU, 5 items), Use attitude (AT, 4 items), and behaviour intention (BI, 4 items). A 5-point Likert scale (1 = strongly disagree, 5 = strongly agree) is employed, where higher scores indicate more positive attitudes and stronger behavioural intentions.

1.4.4 Actual usage behaviour questionnaire: Self-designed with four items to assess nurses' frequency of actual use of smart devices. A 5-point Likert scale (1 = never; 5 = always) was employed, yielding a total score ranging from 4 to 20 points.

1.4.5 Barrier and facilitating factors survey: Multiple-choice questions and open-ended questions are included to collect information on usage barriers and improvement suggestions.

1.4.6 Reliability and validity testing: A pilot survey was conducted among 30 nurses (results were not included in the final current status analysis). The Cronbach's *α* coefficient was calculated, yielding a total Cronbach's *α* coefficient of 0.952 and dimension-specific coefficients ranging from 0.861 to 0.920, all exceeding 0.8, indicating good reliability of the questionnaire. Content validity was assessed by five experts (two nursing management specialists, two head nurses from the Department of Neurology, and one rehabilitation medicine specialist), with a scale-level content validity index (S-CVI/Ave) of 0.92 and item-level content validity indices (I-CVI) ranging from 0.80 to 1.00.

1.5 Data collection method: Questionnaires were distributed via the Wenjuanxing platform, with the informed consent form located on the first page; participants could only proceed by selecting "Agree." Each question was required to be answered, each IP address was limited to one response per question, and the response time was set at ≥3 minutes. Invalid questionnaires resulting from systematic responses or responses completed in <3 minutes were excluded after data collection.

1.6 Statistical methods: Analysis was performed using SPSS 26 software with an alpha level of $\alpha = 0.05$. (1) Descriptive statistics: Categorical data were expressed as frequency and percentage; continuous variables were presented as mean ± standard deviation, with normality assessed using the Shapiro-Wilk test. (2) Univariate analysis: For continuous variables with normal distribution and homogeneous variance, one-way ANOVA was employed; otherwise, the Kruskal-Wallis H test was used; categorical data were analyzed using the x^2 test. (3) Correlation analysis: Pearson correlation analysis was applied. (4) Factor analysis: Multiple linear regression analysis (stepwise method) was conducted, with Durbin-Watson's test to assess residual independence and the variance inflation factor (VIF) to evaluate multicollinearity. (5) Difference analysis: *t*-tests or ANOVA were utilized.

1.7 Ethical approval

This study was conducted in accordance with the Declaration of Helsinki. The Institutional Review Board of the authors' affiliated hospital reviewed the study protocol and granted an exemption from full ethical review (the decision letter bears no specific approval number). The study was deemed exempt because it involved a survey of healthcare professionals using anonymous questionnaires, did not involve patients or vulnerable populations, and did not collect

sensitive personal information. All participants provided informed consent by selecting "Agree" before completing the online questionnaire. Participation was voluntary, and all responses were anonymised and kept confidential.

2 Results

2.1 General characteristics of the study subjects

A total of 219 questionnaires were collected, all of which were valid, resulting in a valid response rate of 100%. Among them, 120 were from neurology nurses (54.79%) and 99 from rehabilitation nursing staff (45.21%), as shown in Table 1.

Table 1 Univariate analysis of KAP scores among nurses with different characteristics (*n*=219)						
variable	classify	number of people	percentage (%)	Total Score for Knowledge, Understanding, and Practice (x ± s)	statistics	P
administrative or technical offices	neurology	120	54.79	108.15±20.22	*t*=1.023	0.307
	physiatry department	99	45.21	105.73±19.68		
sex	man	3	1.37	110.33±21.10	*t*=0.308	0.758
	woman	216	98.63	106.89±19.95		
Age (years)	18-25	31	14.16	104.52±21.10	*F*=0.712	0.546
	26-40	155	70.78	107.34±19.52		
	41-50	32	14.61	108.06±20.34		
	>50	1	0.46	115		
Education Level	Associate degree or lower	45	20.55	107.62±20.41	*F*=0.168	0.846
	undergraduate course	166	75.80	106.93±19.71		
	Master's degree or higher	8	3.65	104.13±25.13		
professional ranks and titles	nurse	65	29.68	106.68±19.97	*F*=0.315	0.814
	Nurse	40	18.26	106.33±19.30		
	nurse-in-charge	98	44.75	107.43±20.40		
	Deputy Chief Nurse or higher	16	7.31	109.38±21.80		
Years of experience in specialized training (years)	<5	82	37.44	105.38±21.14	*F*=0.634	0.594
	5-10	68	31.05	107.59±19.04		
	11-15	42	19.18	108.36±19.26		
	>15	27	12.33	108.89±20.63		
Equipment configuration of smart devices in the department	very few	61	27.85	105.18±22.27	*F*=0.710	0.585
	lesser	42	19.18	105.62±18.83		
	same as	68	31.05	108.63±18.11		
	relatively much more	33	15.07	108.48±21.59		
	a fat lot of	15	6.85	109.20±19.51		
Training Frequency	Never accepted	43	19.63	103.88±20.50	*H*=29.862	*P*<0.001
	Less than once per year	54	24.66	105.44±20.59		
	Once or twice per year	66	30.14	107.67±18.51		
	Once per quarter	25	11.42	110.88±18.13		
	Once per month or more	31	14.16	111.90±20.76		

Note: The KAP total score is the sum of scores across six dimensions: knowledge, perceived usefulness, perceived ease of use, attitude toward use, behavioural intention, and actual usage behaviour (theoretical range: 29–145 points). Univariate analysis revealed that only training frequency had a statistically significant effect on the overall knowledge-belief-action score ($P < 0.05$); higher training frequency was associated with higher overall scores. Inter-group comparisons of training frequency were conducted using the Kruskal-Wallis *H* test.

2.2 The attitudes, behavioural intentions, and practices of nurses in the department of neurology and the department of rehabilitation regarding intelligent nursing devices are shown in Table 2.

The scores and rating scales of nurses from the Department of Neurology and Rehabilitation Medicine across five dimensions—perceived usefulness, perceived ease of use, usage attitude, behavioural intention, and actual usage behaviour—of intelligent nursing devices are presented in Table 2. The results showed that the usage attitude dimension scored highest (mean score per item: 3.98 ± 0.79), while the actual usage behaviour dimension scored relatively lower (mean score per item: 3.71 ± 0.93).

Table 2 KAP scorees and severity classifications of intelligent nursing devices among nurses in the Department of Neurology and Rehabilitation (*n*=219)

project	Score (points, *x*±*s*)			Degree Classification [human being (%)]		
	total points	Divide entries equally	standard mark standardized score	difference	secondary	good
knowledge	14.41±5.38	2.88±1.08	57.63±21.80	93(42.47)	126(57.53)	0(0)
Perceived usefulness	27.65±5.63	3.91±0.77	78.20±15.40	0(0)	168(76.71)	51(23.29)
Perceptibility and Usability	19.35±3.95	3.78±0.78	75.60±15.60	0(0)	184(84.02)	35(15.98)
Usage Attitude	16.16±3.16	3.98±0.79	79.60±15.80	0(0)	155(70.78)	64(29.22)
behaviour disposition	16.45±3.09	3.96±0.78	79.20±15.60	0(0)	161(73.52)	58(26.48)
Actual Usage behaviour	14.84±3.72	3.71±0.93	74.20±18.60	0(0)	134(61.19)	85(38.81)

Note: Maximum theoretical scores for each dimension are 25 points for Knowledge, 35 points for Perceived usefulness, 25 points for Perceived ease of use, 20 points for Usage attitude, 20 points for behavioural intention, and 20 points for Actual usage behaviour. Standard score = Actual score / Maximum theoretical score × 100. Grading criteria: <60 points = Poor; 60–85 points = Average;85 points = Good.

2.3 Correlation analysis between intelligent nursing equipment and nurses in neurology and rehabilitation departments

Table 3 Pearson correlation analysis matrices for each dimension (*r*-values)

dimension	knowledge	Perceived usefulness	Perceptibility and Usability	Usage Attitude	behavioural disposition	Actual Action
knowledge	1.00	0.20**	0.29**	0.22**	0.17*	0.34**
Perceived usefulness	-	1.00	0.85**	0.85**	0.80**	0.57**
Perceptibility and Usability	-	-	1.00	0.84**	0.77**	0.62**
Usage Attitude	-	-	-	1.00	0.94**	0.65**
behavioural disposition	-	-	-	-	1.00	0.67**
Actual Action	-	-	-	-	-	1.00

Pearson correlation analysis revealed positive correlations among all six dimensions—knowledge, perceived usefulness, perceived ease of use, usage attitude, behavioural intention, and actual usage behaviour (r = 0.17–0.94, P < 0.05 or P < 0.01). Among these, usage attitude showed the strongest correlation with behavioural intention (r = 0.94), followed by perceived usefulness (r = 0.85); see Table 3 for details.

*Note:**P<0.01; *P<0.05

2.4 Multivariate linear regression analysis of factors influencing behavioural intentions toward intelligent nursing devices among nurses in the Department of Neurology and Rehabilitation Medicine

To address the multicollinearity between perceived usefulness and perceived ease of use (r = 0.848, VIF = 83.1), this study employed a hierarchical regression approach: in the first step, a simplified model was constructed (including only perceived usefulness). The results demonstrated that perceived usefulness was the strongest predictor of usage attitude (β=0.846, P<0.001), accounting for 71.5% of the variance independently; it also served as the strongest predictor of behavioural intention (β=0.796, P<0.001), explaining 63.2% of the variance independently. In the second step, perceived ease of use was added to the model. Although the R^2 values increased to 77.3% and 67.5%, respectively (both with P-values <0.001), the VIF reached 83.1—far exceeding the conventional acceptable threshold (VIF < 10)—causing the standardized coefficient of perceived usefulness to plummet from 0.846 to 0.516 and rendering parameter estimates highly unstable. Therefore, the simplified model from Step 1 was adopted as the final explanatory model. For actual usage behaviour, behavioural intention (β=0.630) and knowledge (β=0.237) were included in the model together, explaining 50.3% of the variance without collinearity issues (VIF=1.029), thus allowing direct application of the full model. Although knowledge showed a weak correlation with behavioural intention (r=0.17, P<0.05), it did not enter the regression models for attitude or intention after controlling for core TAM variables, indicating its direct effect on actual behaviour rather than an indirect pathway mediated by attitude/intention. The simple regression analysis with knowledge as the independent variable and behavioural intention as the dependent variable demonstrated that knowledge significantly predicts behavioural intention (β = 0.17, P <0.05). However, when perceived usefulness was included, the effect of knowledge became fully mediated (β decreased to 0.03, P> 0.05), confirming the mediating role of the TAM core variables in the knowledge-intention pathway. Specific regression coefficients and model fit indices are presented in Table 4.

We acknowledge that such high multicollinearity prevents simultaneous interpretation of both perceived usefulness and perceived ease-of-use coefficients. Therefore, we selected the simplified model (only perceived usefulness) as our final model. The step-2 model including both variables was only treated as sensitivity analysis rather than for direct coefficient interpretation.

Table 4: Multivariate hierarchical regression analysis of influencing factors on nurses' attitudes, behavioural intentions, and actual usage behaviours rega

dependent variable	step	argument	*B*	*SE*	*β*	*t*	*P*	*VIF*
make use of manner	Step 1	(constant)	1.593	0.245		6.498	<0.001	
		Perceived usefulness	0.527	0.023	0.846	23.312	<0.001	1
	Step 2	(constant)	0.493	0.133		3.701	<0.001	
		Perceived usefulness	0.508	0.06	0.516	8.438	<0.001	83.1
		Perceptibility and Usability	0.398	0.061	0.397	6.494	<0.001	83.1
action Intention	Step 1	(constant)	2.184	0.28		7.798	<0.001	
		Perceived usefulness	0.516	0.027	0.796	19.312	<0.001	1
	Step 2	(constant)	0.878	0.156		5.628	<0.001	
		Perceived usefulness	0.503	0.07	0.524	7.145	<0.001	83.1
		Perceptibility and Usability	0.322	0.072	0.329	4.489	<0.001	83.1
Actual Usage behaviour	Step 1	(constant)	0.998	0.438		2.278	0.024	
		behavioural disposition	0.842	0.064	0.668	13.221	<0.001	1
	Step 2	(constant)	-0.17	0.266		-0.641	0.522	
		behavioural disposition	0.791	0.061	0.630	12.957	<0.001	1.02
		knowledge	0.214	0.044	0.237	4.883	<0.001	1.02

*Note: [1] $F(1, 217)$; [2] $F(2, 216)$; [3] $F(1, 217)$; [4] $F(2, 216)$; [5] $F(1, 217)$; [6] $F(2, 216)$. All models showed P <0.001. Bold values represent the standard regression coefficients of the final recommended model.

Regarding the handling of multicollinearity: Perceived usefulness and perceived ease of use are highly correlated (r=0.848, P<0.001). When both variables were included in the model simultaneously, the variance inflation factor (*VIF*) reached 83.1, far exceeding the acceptable threshold (VIF < 10), leading to unstable parameter estimates. This collinearity is a common phenomenon anticipated in TAM research—when users perceive a device as useful, they typically invest effort to master its operation, resulting in close interdependence between these two constructs in practical contexts [1,12]. To address this issue, our study employed a hierarchical regression approach: Step 1 established a simplified model (including only perceived usefulness); Step 2 incorporated perceived ease of use to test incremental effects. Given that *VIF*=83.1 in Step 2 caused the standardized coefficient for perceived usefulness to plummet from 0.846 to 0.516, resulting in highly unstable parameter estimates, we adopted the simplified model from Step 1 as the final explanatory model for usage attitude and behavioural intention. This model accounted for 71.5% and 63.2% of the variance, respectively, with robust parameter estimates (*VIF*=1.0). The results from Step 2 serve as a sensitivity analysis reference: even after controlling for perceived ease of use, perceived usefulness remained statistically significant (P<0.001), demonstrating that its core effect was unaffected by collinearity. For actual usage behaviour, no collinearity issues were observed between behavioural intention and knowledge (*VIF*=1.029), thus Step 2 was selected as the final model.

2.5 Main barriers faced by nurses in the department of neurology and rehabilitation in using intelligent nursing devices are shown in table 5.

Table 5 Main barriers to the use of smart nursing devices by nurses in neurology and rehabilitation departments (*n*=219, multiple-choice question)

Obstructive factors	Number of selections (*n*)	selectance (%)
Insufficient training	81	37.0
The device exhibits poor stability and frequently malfunctions.	90	41.1
The patient has difficulty operating the device due to cognitive or consciousness impairments.	85	38.8
Increase work burden	66	30.1
The device operation is complex.	79	36.1
Concerns regarding data security or patient privacy	46	21.0
Concerns that device usage may affect patients' motivation for active rehabilitation	39	17.8
The support provided by the department is insufficient.	38	17.4
Does not match the existing workflow	87	39.7
The device exhibits poor integration with specialized neurological assessment tools.	28	12.8
Other factors (small venue size, insufficient funding, etc.)	12	5.5

2.6 Effective measures to promote the use of smart nursing devices by nurses in neurology and rehabilitation departments are shown in Table 6.

Table 6 Effective Measures to Promote Nurses' Use of Smart Nursing Devices (*n*=219, multiple-choice question)

Promotion Measures	Number of selections (*n*)	Percentage (%)
Provide systematic and regular training.	133	60.7
Improve equipment stability and reliability	148	67.6
Simplify device operation procedures	120	54.8
Enhance manufacturers' technical support and maintenance services	116	53
Integrate the use of smart nursing devices more closely with rehabilitation care plans.	112	51.1
Optimize the workflow to integrate better with the device	138	63.0
Provide training on device operation techniques for patients with impaired consciousness or poor cooperation.	108	49.3
Incorporate equipment usage into performance evaluations or incentive mechanisms.	85	38.8
The leadership values this practice and leads by example in its use.	89	40.6
Other (data interoperability, increased investment, etc.)	15	6.8

2.7 Qualitative analysis of open-ended questions is shown in Table 7.

Qualitative thematic analysis was conducted for open-ended items, which served as supplementary interpretation for quantitative findings instead of formal qualitative research. A thematic analysis of the 29 valid responses to Question 39 ("Other Opinions or Suggestions") identified a total of 55 specific recommendations, as shown in Table 7. The most frequent theme was "increasing equipment investment" (12 instances), with typical statements such as "Hospitals currently have limited smart nursing equipment; additional investment is needed." Followed by "simplifying operational procedures" (10 instances) and "data interoperability" (8 instances). Additionally, some nurses expressed the expectation that "smart devices should truly be intelligent to significantly reduce nursing workload," reflecting their desire for tangible benefits from such equipment in alleviating labor burdens.

Table 7 Summary of suggested topics for open-ended questions (*n*=29 participants; a total of 55 valid suggestions were identified)

theme	occurrence number	Representative Original Sentence
Increase equipment investment	12	The hospital currently has limited intelligent nursing equipment and may require additional investment.
Simplify the workflow	10	Operations can be simpler, and processes are streamlined.
Data Interconnectivity	8	Integrate data systems to ensure automatic transmission of data into the hospital's electronic medical record system.
Leadership's attention and support	7	"Active support from leadership is essential," "Promote it as soon as possible."
The device truly reduces the burden.	6	We hope smart devices will truly be intelligent and significantly reduce the need for nursing staff.
Optimize workflow matching	4	The device matches the actual workflow
Space and Location Constraints	2	The ward is too small to accommodate all these facilities.
Other specific recommendations	6	"Promote mobile nursing vehicles" and "use electronic wristbands to open doors"

3 Discussion

3.1 Theoretical contributions: development and validation of the TAM-KAP integrated framework

This study integrates the TAM framework with the KAP framework and conducts empirical validation within the context of neurorehabilitation nursing care. Davis's classical TAM hypothesis posits that external variables indirectly influence behavioural intention and actual use behaviour through perceived usefulness (PU) and perceived ease of use (PEOU) [1]. However, our study identified a more complex pathway: knowledge, as an exogenous variable, directly predicts actual use behaviour (β= 0.237, P <0.001), yet shows no significant effect on attitudes or behavioural intention. This finding deviates from the linear assumption of classical TAM. From a theoretical perspective, this direct pathway through which knowledge acts as an exogenous variable on actual behaviour aligns closely with Bandura's self-efficacy theory [14], which states that "belief in competence directly influences behavioural performance"—nurses may exhibit positive attitudes toward smart devices but still struggle to translate intention into action due to a lack of operational knowledge and clinical judgment skills. Additionally, this pathway contrasts with the "effort expectancy" concept in the UTAUT model [15], where effort expectancy refers to "the level of effort required to use a system." In this study, we conceptualize this notion as domain-specific knowledge reserves, indicating that knowledge proficiency determines whether nurses can exert effective effort in clinical settings rather than merely their willingness to do so.

The parallel pathway models we identified—the Attitude Path (PU/PEOU → Attitude → Intention → Practice) and the Knowledge Path (Knowledge Directly → Practice)—suggest that in high-risk clinical settings, behaviour adoption requires not only positive attitudinal tendencies but also an adequate knowledge base. This aligns closely with the theoretical perspective of knowledge as a foundation for competence [14] and offers significant implications for training design: when attitudes are already positive, knowledge-focused interventions alone can still effectively promote behavioural change. This finding complements rather than challenges the linear assumption inherent in traditional KAP theory. Thus, this study provides a more refined theoretical framework for understanding how cognitive and affective factors jointly shape technology adoption behaviours in nursing practice, thereby enriching the theoretical framework of the Technology Acceptance Model (TAM) in the healthcare domain [16,17].

3.2 Dominance of perceived usefulness: the specific nature of neurorehabilitation specialties

Consistent with Davis's classic TAM [1] and Venkatesh and Davis's TAM2 [12], the simplified model demonstrates that perceived usefulness (β = 0.846–0.796) is the strongest predictor of usage attitude and behavioural intention, independently explaining 71.5% and 63.2% of the variance, respectively. Although both variables remain statistically significant when perceived ease of use is included (P <0.001), severe multicollinearity (VIF = 83.1) causes the coefficient for perceived usefulness to plummet from 0.846 to 0.516, resulting in unstable parameter estimates and making it impossible to reliably assess the relative contributions of the two variables. This "usefulness prioritizes ease of use" pattern aligns with recent findings from studies conducted in Pakistan [18] and Shanghai [19]. However, this finding differs from some studies focusing on comprehensive care populations, where perceived ease of use has sometimes proven equally important or even more critical than perceived usefulness [20].

We believe this disparity may stem from the unique clinical context of neurorehabilitation care. When managing critically ill patients with conditions such as stroke, Parkinson's disease, or spinal cord injuries, nurses' clinical decisions often directly impact patient safety, making the functional value of smart devices—such as fall prevention, continuous monitoring, and rehabilitation assistance—far more critical than considerations of interface complexity. The integrative systematic review by Jarvis et al. [21] supports this interpretation: in neurorehabilitation, staff adoption of digital health technologies is primarily driven by "perceived patient benefits" and "evidence-based practice empowerment," rather than interface simplicity. This finding provides important guidance for device development and procurement—smart devices tailored for neurorehabilitation should prioritize ensuring the clinical efficacy and reliability of core functions over excessive emphasis on minimalist interface design.

It is noteworthy that the strong correlation (r = 0.848) between perceived usefulness and perceived ease of use in this study, along with the resulting multicollinearity (VIF = 83.1), aligns with the findings of Davis [1] and Venkatesh & Davis's [12] original TAM research and represents a theoretical expectation of the TAM framework. Hierarchical regression results demonstrate that even after controlling for multicollinearity, the core effect of perceived usefulness

remains robustly significant, further confirming its dominant role in the adoption of neurorehabilitation nursing technologies. While this statistical finding necessitates caution regarding individual regression coefficients, it also reflects a fundamental reality in clinical technology adoption: when nurses perceive a device as useful, they are typically willing to invest effort in mastering its operation, thereby closely interconnecting these two constructs in practical contexts [19].

3.3 Knowledge-behaviour gap: the key bottleneck to implementing smart nursing care

The most concerning finding of this study is the significant gap between nurses' positive attitudes (mean score: 3.98 ± 0.79) and their actual usage behaviour (3.71 ± 0.93), with knowledge level (2.88 ± 1.08) emerging as the weakest link in the knowledge-belief-action chain. This "intention-behaviour gap" [22] is not unique to this study; a large-scale survey involving 1,395 nursing professionals in Shanghai similarly revealed that although 78.9% of nurses expressed intention to use digital information technologies, only 44.9% actually used them frequently [19]. However, the gap appears more pronounced in the neurorehabilitation sample, likely attributable to additional patient-related barriers specific to this specialty.

The knowledge dimension has become the "weak link" in the KAP chain, with 42.47% of nurses scoringng below the "medium" level in knowledge proficiency. This finding aligns with the mixed-method systematic review by Li et al. [23], which synthesized 28 studies and concluded that although nursing students hold positive attitudes toward AI applications, there remains a significant knowledge gap regarding usability and practicality. Similarly, the reviews by Labrague and Al Sabei [16] also highlighted inadequate systematic dissemination of AI-related knowledge in nursing education. The mechanisms underlying these knowledge deficiencies can be understood at three levels: First, content related to smart nursing in China's nursing education curriculum remains underdeveloped and outdated [24-26], resulting in a lack of systematic theoretical foundation among practicing nurses; Second, data indicate that 38.2% of nurses receive training less than once annually. The Kruskal-Wallis test revealed that training frequency was the only demographic variable with statistically significant differences in total KAP scores (H = 29.862, P <0.001), with higher training frequencies correlating with higher total KAP scores—a finding consistent with Jarvis et al.' s [21] identification of "insufficient skills and knowledge" as the most frequently reported barrier for staff implementing digital health technologies in neurorehabilitation; Third, rapid iterations of intelligent devices in neurorehabilitation—including wearable sensors, rehabilitation robots, and AI monitoring systems—have continuously shifted knowledge update targets beyond the capacity of institutional training programs to keep pace [27].

3.4 The underlying mechanism of knowledge-action separation: transcending individual volition

The discrepancy between behavioural intention (4.11±0.77) and actual behaviour (3.70±0.97) in this study reflects the "intention-behaviour gap" phenomenon proposed by Sheeran [22] in health psychology, a phenomenon that has not yet received sufficient attention in research on nursing technology adoption. Our regression model accounts for 50.3% of the variation in actual behaviour, indicating that nearly half of behavioural differences remain unexplained—suggesting significant contextual barriers that hinder the translation of positive intentions into actual actions.

Barrier analysis revealed the specific manifestations of these barriers. "Poor equipment stability and frequent malfunctions" (41.1%) and "incompatibility with existing workflows" (39.7%) ranked as the top two obstacles, which are highly consistent with findings from recent international studies [21,27,28]. A qualitative investigation by Mitchell et al. [27] into factors influencing rehabilitation technology adoption identified insufficient technical reliability and difficulties in integrating with clinical workflows as core barriers commonly reported by interdisciplinary teams (including nurses, physical therapists, and occupational therapists). Additionally, 38.8% of respondents identified "patient cooperation difficulties due to cognitive or awareness impairments" as a significant barrier, highlighting a specialty-specific challenge rarely encountered in comprehensive care settings. Even when nurses possess the necessary willingness and knowledge, equipment deployment may become impractical or even unsafe when dealing with patients exhibiting agitation, aphasia, or cognitive impairments. This finding expands the Technology Acceptance Model (TAM) framework, suggesting that patient-mediated barriers should be incorporated as an independent category of external variables within technology acceptance frameworks in neurorehabilitation contexts.

3.5 Training: a key leverage for system improvement

The significant correlation between training frequency and the total KAP score (P = 0.047), combined with "providing systematic, regular training" being identified as the most anticipated promotional measure (60.7%), establishes training as the most actionable intervention target identified in this study. This finding aligns with emerging evidence that structured training programs addressing both technical competencies and clinical integration significantly improve healthcare professionals' technology adoption and sustained usage behaviours [21,27,29]. However, our data suggest potential efficacy limitations in current training models: even nurses receiving monthly training exhibited suboptimal knowledge scores, indicating that merely increasing training frequency may not be sufficient to address the issue, underscoring the urgent need for innovative teaching methodologies.ies.

Drawing on the disciplinary teaching knowledge (TPACK) framework for integrated technology proposed by Koehler and Mishra [30], we propose that effective training for intelligent neurorehabilitation nursing devices should integrate three knowledge domains: (1) technical knowledge—device operation and troubleshooting; (2) pedagogical knowledge—how to guide patients and their families in using the devices; and (3) content knowledge—the indications, contraindications, and expected therapeutic outcomes specific to neurorehabilitation. The current training model, which primarily focuses on "how to operate" [24], lacks sufficient emphasis on "when to use" and "why to use," which may be the fundamental reason why knowledge acquisition fails to translate into confident, autonomous practice. Future training programs should incorporate scenario-based simulation learning, interdisciplinary case discussions, and competency-based assessment to ensure that knowledge acquisition truly leads to behavioural change [29].

3.6 Special challenges in specialty practice: balancing "High Technology" and "High Contact" in neurorehabilitation

This study reveals a unique tension in neurorehabilitation nursing: the coexistence of enthusiasm for technological innovation and concerns about therapeutic relationships. Among nurses, 17.8% expressed worry that equipment usage might diminish patients' motivation for active rehabilitation, reflecting

a profound understanding of the principles of neural plasticity [6]. In neurorehabilitation, patient participation is not only ideal but also a neurobiologically essential prerequisite for cortical reorganization and functional recovery [6]. Overly automated intelligent devices may inadvertently undermine patient engagement and compromise the very rehabilitation goals they are intended to support. This "automation paradox" underscores that neurorehabilitation devices should prioritize auxiliary rather than substitutive functions, while nurse training should focus on equipping practitioners to use technology as a "support structure" for active patient engagement rather than a substitute for manual care. Device manufacturers should collaborate with clinical nurses to develop "smart-human" switchable modes that allow graduated automation adjustments tailored to patients' cognitive states and rehabilitation stages [21,27].

3.7 Implications for practice, policy, and future research

The clinical practice implications encompass three key aspects: First, hospital administrators are advised to prioritize implementing a tiered training system—where the foundational module targets novice users, advanced troubleshooting and teaching skills workshops are designed for core staff, and micro-learning formats (e.g.,5-minute pre-shift briefings) facilitate knowledge updates without disrupting clinical workflows; second, equipment selection committees must evaluate not only technical specifications but also workflow compatibility and reliability records, given that device instability and process incompatibility represent the two primary challenges identified in this study; Third, nursing managers should establish specialized protocols for smart device use by patients with cognitive impairments, including phased implementation strategies, caregiver engagement plans, and clear criteria for device discontinuation when patient safety or rehabilitation participation is compromised. A systematic review by Walzer et al. further highlights that leadership support, organizational readiness, and user engagement are critical facilitators for successful adoption of digital nursing technologies, emphasizing that device integration should be incorporated into broader organizational digital strategy planning rather than being treated as isolated departmental procurement decisions[29].

The core implication at the policy level lies in establishing national competency standards for intelligent neurological rehabilitation care. Currently, China lacks standardized certification or a competency framework for the use of smart nursing devices. This study suggests that such standards should specify minimum training hours, competency assessment indicators, and continuing education requirements, with regulatory authorities mandating that device manufacturers provide evidence-based implementation support upon product sales [27,28].

Future research directions include: (1) employing a mixed-method longitudinal design to track the evolution of the intention-behaviour gap over time and identify the optimal window for intervention; (2) conducting randomized controlled trials to compare the effects of TPACK-oriented training versus traditional "operational training" on knowledge retention and behavioural outcomes; (3) conducting qualitative ethnographic studies to examine in-depth the real-time decision-making processes of nurses regarding the use or abandonment of smart devices in complex clinical settings; (4) utilizing multilevel structural equation modeling that incorporates organizational-level variables (leadership support, resource availability) and patient-level variables (cognitive state, functional independence) to test the impact of cross-level moderating effects on the TAM-KAP pathway [19,21,28].

3.8 Limitations

This study has the following limitations: First, the cross-sectional design cannot establish causal relationships, and the directional pathways within the TAM-KAP framework require validation through longitudinal studies; Second, convenience sampling may introduce selection bias, and since the sample primarily consists of tertiary hospitals, caution is warranted when generalizing the findings to secondary or primary healthcare institutions; Third, self-report questionnaires may exhibit social desirability bias, particularly regarding attitude and intention items; Fourth, organizational-level variables (e.g.,leadership support, institutional digital maturity) were not included—these variables may moderate TAM relationships at the individual level and represent an important area for future multi-level research; Finally, while high multicollinearity between PU and PEOU is expected in TAM studies, it compromises the precision of individual coefficient estimates, suggesting that future research could employ latent variable analysis methods such as structural equation modeling to better separate these constructs [18].

In addition, this study did not measure organisational-level variables such as department-level digital resources and leadership support, which may moderate nurses' technology-adoption behaviours.Self-reported questionnaires may bring social-desirability bias, where participants may over-report positive attitudes and intention towards smart devices.

Abbreviations

KAP
Knowledge-Attitude-Practice
TAM
Technology Acceptance Model
TPACK
Technological Pedagogical Content Knowledge
PU
Perceived usefulness
PEOU
Perceived ease of use
AT
Attitude toward use
BI

Behavioural intention
VIF
Variance inflation factor
S-CVI/Ave
Scale-level content validity index/Average
I-CVI
Item-level content validity index
UTAUT
Unified Theory of Acceptance and Use of Technology

Declarations

Ethics approval and consent to participate

This study was performed in accordance with the principles of the Declaration of Helsinki. The Institutional Review Board of the Affiliated Hospital of Nanjing University of Chinese Medicine reviewed this study protocol and granted an exemption from full ethical review. No formal reference number was assigned because this study was an anonymous questionnaire-based survey targeting healthcare professionals; it did not recruit patients or vulnerable populations and no sensitive personal identifying information was collected. Electronic informed consent was obtained from all participants before questionnaire completion. Participation was voluntary, and all responses were anonymised and kept strictly confidential.

Consent for publication

Not applicable.

Availability of data and materials

The datasets supporting the conclusions of this study are available from the corresponding author upon reasonable request. The raw data will not be deposited in a public repository, as full anonymisation cannot completely rule out the risk of indirect participant identification.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

HC and YC contributed equally to this work and should be regarded as co-first authors. HC: Conceptualization, Investigation, Writing-original draft. YC: Formal analysis, Writing-review & editing. XB: Investigation. HF: Conceptualization, Methodology, Supervision, Writing-review & editing. All authors read and approved the final version of the manuscript.

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Conflict of Interest Statement:

The authors declare no conflict of interest.

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