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Demand analysis of transitional care for patients undergoing minimally invasive cardiac interventions with AI-driven solutions: a mixed-methods approach

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Abstract

Aims Minimally invasive cardiac intervention (MICI) patients remain at high risk of readmission and mortality during their post-discharge phase, with 30-day readmission rates of up to 10%. Although technological innovations, especially AI-driven solutions, hold promise for improving outcomes, there is a pressing need to clarify the full spectrum of patient demands during the transition from hospital to home. This study aimed to systematically identify these demands to guide the development of AI-driven solutions that reduce readmission rates and improve clinical outcomes.

Methods and results A convergent parallel mixed-methods design was employed to systematically identify patient demands and inform the development of AI-driven interventions in transitional care. Quantitative and qualitative data were collected from 137 MICI patients recruited from four hospitals (June–August 2024). Quantitatively, a 23-item survey was analyzed using the Kano model, revealing no "must-be" demands—indicating that patients were accustomed to a lack of guidance post-discharge. However, health monitoring, medication guidance, symptom management, and personalized exercise plans were identified as "one-dimensional" demands that significantly impact patient satisfaction. Additionally, continuous exercise monitoring and dietary planning emerged as "attractive" features that could enhance care quality without negatively affecting satisfaction if absent. Qualitative interviews uncovered the importance of comorbidity management, psychological support and financial transparency, which were not fully captured in the survey data. The integration of these findings underscores the need for AI-driven personalized health monitoring systems and knowledge-based AI tools to revolutionize the transitional care process for MICI patients.

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Conclusion This integrated analysis highlights the significant care demands of MICI patients during the transition from hospital to home. Key recommendations include: (1) deploying AI-driven health monitoring, medication guidance, and symptom management systems, (2) designing personalized exercise and dietary tools, and (3) creating accessible, knowledge-based platforms for reliable medical information. In addition, comorbidity management, psychological support and financial transparency are areas that call for our attention. By aligning with these patient-centered demands and leveraging AI's capabilities, future transitional care interventions—particularly in China have the potential to address healthcare staffing constraints and improve patient outcomes. However, due to the limitations of our study, these insights require further validation and exploration.

Keywords Transitional care, Mixed-method, Minimally invasive cardiac interventions, Artificial intelligence

Introduction

Cardiovascular disease (CVD) is the leading cause of morbidity and mortality worldwide, contributing to a significant economic burden on healthcare systems [1]. Minimally invasive cardiac interventions (MICI) are advanced techniques for treating CVD, characterized by reduced risk and smaller incisions [2]. These interventions include cardiac catheterization-based procedures such as percutaneous coronary intervention (PCI), radiofrequency ablation, and pacemaker placement [3]. PCI, a representative of minimally invasive cardiac interventions, was performed on 1.421 million patients in China in 2022 alone [4]. With the increased popularity of MICI leading to shorter hospital stays and earlier discharges, some patients may be discharged from the hospital before they have fully recovered [5–7]. Research shows that approximately 10% of patients experience adverse events, including readmission or emergency department visits, within 30 days of discharge [8, 9]. This highlights a critical gap between hospital-based acute care and home-based recovery that transitional care aims to address [6, 10].

Transitional care is defined as a series of actions designed to ensure the coordination and continuity of health care received by patients as they transfer between different locations (e.g. from hospital to home) or levels of care [11]. Adequate transitional care not only reduces unplanned hospital readmissions and wastage of medical resources but also significantly improves patients' quality of life [12, 13]. Despite strong evidence supporting transitional care's effectiveness in western healthcare systems, its implementation in China remains limited [6]. A key barrier is the shortage of nursing staff relative to China's large population [14, 15]. However, the rapid advancement of information technology, the widespread use of mobile phones, and the emergence of artificial intelligence, present potential solutions to overcome these staffing constraints [16, 17]. This presents a critical opportunity to implement transitional care in China, given the rapid advancements in technology and the urgent need to address care gaps.

To develop effective AI-enhanced transitional care interventions, a comprehensive understanding of MICI patients' needs during the hospital-to-home transition is essential. Previous research has largely focused on general transitional care needs or specific cardiac conditions, leaving a knowledge gap regarding the unique demands of MICI patients. Additionally, few studies have examined how these needs might be addressed through AI-based solutions [18].

This study employs the Kano model to quantitatively assess the relative importance of various transitional care demands [19, 20]. The Kano model, developed in 1984, provides a framework for categorizing service preferences into five categories: must-be, one-dimensional, attractive, indifferent, and reverse qualities. To ensure comprehensive demand identification, we complement this quantitative approach with qualitative interviews [21, 22].

Our primary research objective is to understand the comprehensive transitional care demands of MICI patients during their hospital-to-home transition in the context of emerging AI capabilities. Specifically, we aim to: (1) identify and categorize key transitional care demands using the Kano model, (2) explore patients' lived experiences and unmet needs through qualitative inquiry, (3) generate insights to guide the development of AI-enhanced transitional care solutions.

Methods

Study design

The study adopted a convergent parallel mixed-method study design to comprehensively investigate the transitional care needs of MICI patients [23]. A cross-sectional quantitative survey identified generalizable care demands, while semi-structured qualitative interviews explored patient experiences and uncovered latent needs that structured survey items may not capture. This mixed-methods approach integrated both quantifiable trends and nuanced patient-reported needs, ensuring a comprehensive foundation for AI-driven interventions. By collecting and analyzing both quantitative and qualitative data independently but complementarily, we reduced methodological biases associated with single-method approaches, such as over-reliance on predesigned survey items in quantitative research or subjective interpretation in qualitative results.

Setting and participants

MICI patients were consecutively recruited through convenience sampling from June to August 2024 in the cardiology departments of four hospitals in southern and northern China. At each hospital, the head nurse (J.J.C., Q.M., M.L., Y.Q.Z., and Y.L.Y.) organized and supervised nurses in collecting questionnaires. When patients met the eligibility criteria, nurses invited them to scan a QR code and complete the demand survey online. The survey was discontinued once the required sample size was reached. The inclusion criteria for patients were as follows: (1) those who had undergone MICI, including cardiac stent operation, cardiac radiofrequency ablation, cardiac pacemaker implantation, cardiac occlusion and cardiac valve repair or replacement; (2) age ≥ 18 years old; (3) volunteered to participate in the study and signed the informed consent form. The exclusion criteria for patients were as follows: (1) participants with severe cognitive impairment or mental disorders who were unable to understand the study content or answer the questionnaire; (2) participants with severe complications (e.g., respiratory, circulatory, and renal diseases).

Data collection for quantitative study

Quantitative data were collected using Wenjuanxing, a widely used online survey platform in China. The questionnaire in this study consisted of two parts. The first part was a self-designed social-demographic questionnaire, including items such as age, gender, education level, income level, operation type, etc. The second part was a demand survey assessing the needs of MICI patients during the transition from hospital to home, and it includes 10 dimensions such as health monitoring service, exercise guidance service, diet guidance service, and medication guidance service, and 23 demands (Table 1).

The development of this questionnaire is as follows. First, we referred to the Expert Consensus on Home-Based Rehabilitation for Cardiovascular Disease Patients in China, where mentioned 10 key dimensions of cardiac rehabilitation [24]. Based on these dimensions, our research team conducted a brainstorming session, integrating literature reviews and clinical experiences to formulate 23 questions. Second, after completing the initial draft of the questionnaire, we conducted a pilot test involving four nursing graduate students and two MICI patients. According to their feedback, further modifications were made to refine the final version of the transitional care demand questionnaire. Third, we consulted

Table 1 Translational care demand questionnaire

Dimension	Description of translational care demand
Health monitoring and checkup reminders service	D1. Provide reminders about upcoming follow-up visits and examinations after discharge.
	D2. Provide repeated reminders about upcoming follow-up visits and examinations after discharge.
	D3. Provide a personalized health monitoring plan tailored to your individual needs (e.g., measuring blood sugar levels before and after meals, taking blood pressure and heart rate twice daily, and measuring weight once a week).
	D4. Provide reminders or guidance when you experience any health abnormalities.
Exercise guidance service	D5. Provide a personalized exercise plan based on your individual circumstances (such as treatment method, discharge time, symptoms, comorbidities, etc.).
	D6. Provide continuous health monitoring and guidance each time you exercise.
	D7. Provide weight loss guidance for you.
Diet guidance service	D8. Provide a personalized dietary plan based on your individual circumstances (such as comorbidities, weight, blood lipids, etc.).
	D9. Provide an adjusted dietary plan based on your physical condition or dietary preferences.
	D10. Provide supervision in quitting smoking and limiting alcohol consumption.
	D11. Provide guidance on quitting smoking and limiting alcohol consumption.
Medication guidance service	D12. Provide reminds to take your medication on time and in the correct dosage as prescribed.
	D13. Provide guidance when you encounter confusion about your medication.
Sleep guidance service	D14. Provide evaluation and guidance on your sleep quality.
	D15. Provide monitoring on your sleep quality.
Symptom management service	D16. Provide assistance in managing symptoms such as fatigue and pain.
Fundamental nursing service	D17. Provide fundamental nursing from a nurse.
Skill learning service	D18. Provide training and guidance on medical or nursing skills, such as CPR.
Psychological support service	D19. Provide evaluation and guidance on your psychological well-being.
	D20. Provide psychological therapy (such as meditation, mindfulness therapy, etc.) when needed.
Social support service	D21. Provide additional assistance from the community hospital when needed.
	D22. Provide connection with the cardiovascular disease patient support group.
	D23. Provide assistance in better searching for health-related information.

Abbreviation: D: demand, CPR: Cardiopulmonary resuscitation six experts in relevant fields (including four researchers specializing in chronic disease management and two experienced clinical cardiovascular nurses) to evaluate the content validity of the questionnaire. The average age of the experts was 40.67 ± 9.67 years, with four holding a master's degree or above and four having associate senior professional titles or above. The experts assessed the content validity of each item using a 4-point rating scale (1–4 points, representing inappropriate, somewhat inappropriate, somewhat appropriate, appropriate, respectively) to determine whether the items appropriately represented the intended contents. The results indicated good content validity with Item-level Content Validity Index (I-CVI): 0.833-1.000, Scale-level Content Validity Index using the Universal Agreement method (S-CVI/UA): 0.957, and Scale-level Content Validity Index using the Average method (S-CVI/Ave): 0.993.

We designed the phrasing of the questionnaire questions and response options based on the Kano model [25]. For each demand, two opposing questions were asked. For example, "How would you feel about receiving reminders for your upcoming follow-up visits and examinations after discharge?" (functional question), followed by "How would you feel about not receiving reminders for your upcoming follow-up visits and examinations after discharge?" (dysfunctional question). Respondents selected the most appropriate answer from the following options: "I like it that way", "It must be that way", "I am neutral", "I can live with it that way", and "I dislike it that way". There were 25 (5*5) possible results, each corresponding to a specific Kano attribute (Table 2).

Based on sample size estimation methods commonly used in medical statistics, the sample size for a cross-sectional survey should be 5 to10 times the number of independent variables [26]. Our study included 23 independent variables, and we considered a maximum loss to follow-up rate of 10%. Therefore, the minimum required sample size was calculated as (23*5)/0.9 = 128. The quality control of the online survey was as followed. (1) The online questionnaire was set to require answers for both the positive and negative questions for the 23 needs (a total of 46 questions), so no answers were missed, (2) the online system recorded the time taken to complete the questionnaire. Questionnaires completed in less than 2 min were considered invalid and removed during the data cleaning process, (3) manual checks were performed, and questionnaires with obvious logical errors or contradictions (e.g., selecting "Strongly Agree" or "Strongly Disagree" for all 46 questions on the 23 needs) were deemed anomalous and removed during the data cleaning process.

Table 2 The kano model attribute classification criteria

Functional (If the service is provided, how do you feel?)	Dysfunctional (If the service is absent, how do you feel?)				
	I like it	I expect it	I am neutral	I can live with it	I dislike it
I like it	Q	A	A	A	O
I expect it	R	I	I	I	M
I am neutral	R	I	I	I	M
I can live with it	R	I	I	I	M
I dislike it	R	R	R	R	Q

Abbreviation: A = attractive attribute, O = one-dimensional attribute, R = reverse attribute, I = indifferent attribute, M = must-be attribute, Q = questionable results

Data collection for qualitative study

A semi-structured interview was conducted to collect qualitative data. The development of interview questions was as follows. First, we conducted a literature review on transitional care needs and organized a brainstorming session within the research team [24, 27–30]. Based on this, five key questions were formulated. Next, two rounds of pilot interviews were conducted, revealing that participants needed additional prompts to help them recall specific aspects of their transitional care experiences. To address this, we incorporated core components of transitional care, including wound, medication, diet, exercise, and mental health as prompts to facilitate more engaged and comprehensive interviews. The final five key questions were: (1) "How have you been recovering since returning home?" (2) "What precautions do you find important regarding wound, medication, diet, exercise, and mental health after discharge?" (3) "When managing your wound, medication, diet, exercise, or psychological well-being after discharge, what assistance from healthcare providers have you found necessary?" (4) "What other concerns do you have that healthcare providers could help you with?" (5) "What is your attitude toward the involvement of healthcare providers in your transitional care, and how do you feel about incorporating technology, such as smartphones, into this process?".

Patients for the qualitative study were purposefully selected and included after obtaining their consent for both the interview and recording. The interviews were conducted by one author (S.J.L.), a master's student in nursing with completed coursework in qualitative research. Given that the interviewees were from both the southern and northern areas in China, the interviews were conducted by phone. Given that the interviews were conducted online, we invited participants to review the transcribed texts and findings to avoid any potential misinterpretation of their responses. They were asked to provide feedback on whether the interpretations accurately reflected their perspectives, thereby enhancing the reliability of the qualitative results. Data saturation was achieved when no new themes emerged [31]. The interview took place in August 2024 and January 2025, with each interview lasting between 20 and 30 min.

Data analysis
The authors (J.Y., W.Q.L. and Q.T.L.) downloaded quantitative data from the online Wenjuanxing platform, and imported it to the IBM SPSS version 20.0. and Excel software. The authors (Y.W.L. and S.J.L.) analyzed the data. Descriptive statistics were used to summarize the socio-demographic information. Continuous variables that follow a normal distribution were presented as means ± standard deviations (mean ± SD), while those that do not follow a normal distribution were reported as the median (25th percentile, 75th percentile) [Median (P25, P75)]. Categorical variables were expressed as frequencies and percentages. The Kano model was utilized to analyze the relative importance of different demands from the perspective of customer satisfaction, using the Better-Worse coefficient [25]. A higher better coefficient refers to a higher Satisfaction Index (SI), calculated as SI = $(A + O)/ (A + O + M + I)$. Conversely, a higher worse coefficient is linked to a higher Dissatisfaction Index (DSI), calculated as DSI = $(O + M)/ (A + O + M + I)$. We Performed correlation analysis between one-dimensional needs and patients' demographic data (e.g., age and sex). For categorical demographic variables, chi-square test was used; for continuous variables, Spearman's rank correlation was applied. A two-tailed test was conducted, with $P < 0.05$ indicating statistical significance.

Qualitative data were analyzed using thematic analysis [32]. All recordings were initially transcribed verbatim into Word documents using NetEase Jianwai, a transcription tool developed by the Chinese company NetEase within 24 h after each interview. To prevent errors in the software's transcription, the interviewer then listened to the recordings and revised the text based on the audio to ensure the accuracy of the final transcription. To ensure a thorough understanding of the data, each transcript was read three times by two researchers (Y.W.L. and S.J.L.). Initially, two researchers independently coded the first six transcripts, then compared and discussed their findings to reach a consensus and establish the initial codes. The interviewer continued coding the remaining transcripts and collaborated with the second researcher to reach a consensus when new codes emerged. Two authors induced the coded data into themes after the coding process was completed. The themes were subsequently reviewed and discussed by the entire research team to reach a consensus.

Results
Quantitative results
Characteristics of participants
From June 2024 to August 2024, we surveyed a total of 160 participants. However, 23 questionable answers were removed after data cleaning, resulting in 137 valid questionnaires being included in the data analysis. The effective response rate was 85.6%. The characteristics of the participants were summarized in Table 3. Among the included 137 participants, the average age was 58.54 years, with a majority being male (75.2%). High school education was the most common level of education (39.4%) and 92.7% of the participants were married. More than two-thirds (73.7%) of the participants had two or more children. The majority of participants reported a monthly income of less than 6,000 Renminbi. Most participants had good visual and hearing condition. The number of patients from northern and southern China was roughly equal. The types of surgeries included cardiac stent operation (77.4%) and radiofrequency ablation operation (12.4%), etc. The mean length of hospital stay after operation was 4 days, and 46.7% participants had a normal weight.

Demand analysis based on the Kano model
A total of 23 demands were included in the Kano model analysis, with each demand having its own better-worse coefficient. The detailed attributes of these demands were shown in Table 4. The satisfaction index ranged from 0.678 to 0.857, while the dissatisfaction index ranged from 0.203 to 0.289. To distinguish different attributes of these demands (including one-dimensional, attractive, indifferent, and must-be), we categorized them into four quadrants based on the mean values of the satisfaction and dissatisfaction indices (average SI: 0.750 and average DI: 0.237) across all demands. The classification was visually presented in the scatter plot shown in Fig. 1.

One-dimensional demands (high priority) All demands related to health monitoring services, such as reminders about upcoming follow-up visits and examinations after discharge, were classified as one-dimensional. Additionally, demands related to medication guidance, symptom management, and personalized exercise plan were also categorized as one-dimensional. These demands showed consistently high satisfaction indices (SI: 0.758–0.857) and dissatisfaction indices (DI: 0.246–0.289).

Attractive demands (innovation opportunities) Demand such as providing continuous health monitoring and guidance each time you exercise (demand 6), providing adjusted dietary plan based on your physical condition or dietary preferences (demand 9), and providing assistance in better searching for health-related infor-

Table 3 Characteristics of the participants in quantitative study ($n=137$)

Variables	Mean ± SD/ *n* (%)/ Median
Age (years, mean ± SD)	58.54 ± 14.43
Sex [n (%)]	
Male	103 (75.2)
Female	34 (24.8)
Education level [n (%)]	
Primary school or below	42 (30.7)
Middle school	54 (39.4)
High school	21 (15.3)
Bachelor's degree or above	20 (14.6)
Marital status [n (%)]	
Unmarried	2 (1.5)
Married	127 (92.7)
Divorced	2 (1.5)
Widowed	6 (4.4)
Number of children [n (%)]	
0	4 (2.9)
1	32 (23.4)
2	67 (48.9)
3	29 (21.2)
4	5 (3.6)
Residence [n (%)]	
Living with family	123 (89.8)
Living with caregiver	3 (2.2)
Living alone	11 (8.0)
Monthly household income [n (%)]	
< 3000 RMB	52 (38.0)
3,000 ~ 5,999 RMB	47 (34.3)
6,000 ~ 8,999 RMB	14 (10.2)
> 9000 RMB	24 (17.5)
Visual condition [n (%)]	
Good	107 (78.1)
Some impact on daily life	20 (14.6)
Poor	10 (7.3)
Hearing condition [n(%)]	
Good	124 (90.5)
Some impact on daily life	7 (5.1)
Poor	6 (4.4)
City for medical treatment [n (%)]	
Southern region	70 (51.1)
Northern region	67 (48.9)
Type of operation [n (%)]	
Cardiac stent operation	106 (77.4)
Cardiac radiofrequency ablation operation	17 (12.4)
Cardiac pacemaker implantation operation	10 (7.3)
Cardiac occlusion operation	2 (1.5)
Cardiac valve repair or replacement operation	2 (1.5)
Length of hospital stay after operation [day, Median (P25, P75)]	4.0 (2.5, 5.5)
BMI [n (%)]	
BMI < 18.5	4 (2.9)
18.5 ≤ BMI < 24	64 (46.7)
24 ≤ BMI < 28	48 (35.0)
28 ≤ BMI ≤ 34	18 (13.1)
BMI > 34	3 (2.2)
Comorbidity [n (%)]	
Yes	83 (60.6)
No	54 (39.4)

Abbreviation: RMB, Renminbi

mation (demand 23) were classified as attractive. These elements demonstrated high satisfaction potential (SI: 0.764–0.768) with lower dissatisfaction risk (DI: 0.228–0.234).

Indifferent demands Demand such as providing weight loss guidance for you, providing supervision and guidance on quitting smoking and limiting alcohol consumption, and providing evaluation and monitoring on your sleep quality were classified as indifferent. These services had relatively lower satisfaction indices (SI: 0.678–0.744) and dissatisfaction indices (DI: 0.203–0.228) compared to other demands, indicating that patients were generally neutral about their inclusion in transitional care programs. This finding is particularly noteworthy given that these aspects are traditionally emphasized in cardiac rehabilitation programs, indicating a potential mismatch between standard care practices and patient preferences during the transition period.

Must-be demands No demands were categorized as "must-be".

Associations between demographic factors and one-dimensional demands

Detailed associations were shown in Table 5. Among the included patient characteristics, one-dimensional demands were mainly associated with age (D1, D2, D5), residence status (D1, D3, D13) and body mass index (BMI) (D1, D2, D3, D4) with $P<0.05$, and the differences were statistically significant. In addition, the number of children ($P=0.005$) and hearing condition ($P=0.007$) were also related to the demand of checkup reminder (D1). However, the three one-dimensional demands of D4, D12 and D16 did not show associations with demographic data ($P>0.05$), which, to some extent, reflected that these three demands were universal for patients. No associations were found between other demographic factors (i.e., sex, educational level, marital status, monthly household income, visual condition, city of medical treatment, type of operation, length of hospital stay

Table 4 Demand attributes based on the Kano model

Demand	Kano model attribute						Category	Better-worse coefficient		Rank	
	A	O	M	I	Q	R		SI	DI	SI	DI
D1	66	34	1	20	15	1	One-dimensional	0.826	0.289	2	1
D2	61	33	1	24	17	1	One-dimensional	0.790	0.286	5	2
D3	66	34	0	25	11	1	One-dimensional	0.800	0.272	4	4
D4	73	35	0	18	10	1	One-dimensional	0.857	0.278	1	3
D5	63	31	0	30	11	2	One-dimensional	0.758	0.250	11	7
D6	66	29	0	29	12	1	Attractive	0.766	0.234	9	9
D7	55	27	0	39	11	5	Indifferent	0.678	0.223	23	16
D8	66	26	0	31	13	1	Indifferent	0.748	0.211	12	19
D9	66	28	0	29	12	2	Attractive	0.764	0.228	10	14
D10	60	24	1	36	14	2	Indifferent	0.694	0.207	20	21
D11	57	27	0	37	13	3	Indifferent	0.694	0.223	20	16
D12	63	30	1	26	16	1	One-dimensional	0.775	0.258	6	5
D13	66	31	0	23	16	1	One-dimensional	0.808	0.258	3	5
D14	65	25	0	31	13	3	Indifferent	0.744	0.207	14	21
D15	61	25	0	37	11	3	Indifferent	0.699	0.203	18	23
D16	64	30	0	28	12	3	One-dimensional	0.770	0.246	7	8
D17	62	27	0	33	13	2	Indifferent	0.730	0.221	16	18
D18	64	28	0	31	13	1	Indifferent	0.748	0.228	12	12
D19	57	28	1	38	10	3	Indifferent	0.685	0.234	22	9
D20	58	28	0	37	10	4	Indifferent	0.699	0.228	18	12
D21	62	26	0	36	12	1	Indifferent	0.710	0.210	17	20
D22	63	28	0	33	11	2	Indifferent	0.734	0.226	15	15
D23	67	29	0	29	11	1	Attractive	0.768	0.232	8	11

Abbreviation: A = attractive attribute, O = one-dimensional attribute, M = must-be attribute, I = indifferent attribute, Q = questionable results, R = reverse attribute, SI = satisfaction index, DI = dissatisfaction index

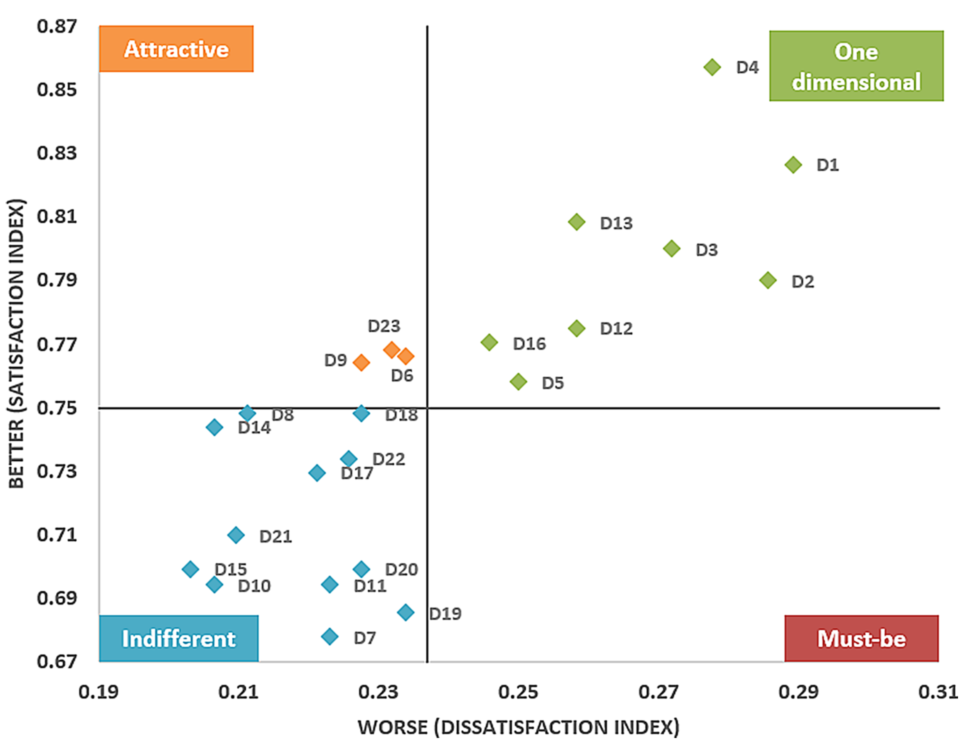

Fig. 1 Demand quadrant scatter diagram based on better-worse coefficient

Table 5 Association between demographic factors and one-dimensional demands

Demands	D1		D2		D3		D4		D5		D12		D13		D16	
Characteristics	r/χ^2 value	*P* value	r/χ^2 value	*P* value	r/χ^2 value	*P* value	r/χ^2 value	*P* value	r/χ^2 value	*P* value	r/χ^2 value	*P* value	r/χ^2 value	*P* value	r/χ^2 value	*P* value
Age	0.222	**0.009***	0.223	**0.009***	0.096	0.263	0.084	0.327	0.229	**0.007***	0.053	0.539	0.026	0.763	0.126	0.144
Sex	9.394	0.094	3.067	0.690	7.426	0.115	3.575	0.467	2.287	0.683	7.662	0.176	7.497	0.112	6.159	0.188
Education level	11.405	0.723	8.583	0.898	7.736	0.805	10.163	0.602	5.415	0.943	14.115	0.517	9.056	0.698	6.364	0.897
Marital status	5.196	0.990	7.743	0.934	6.910	0.863	9.324	0.675	8.743	0.725	6.984	0.958	5.668	0.932	7.289	0.838
Number of children	40.168	**0.005***	15.360	0.755	15.340	0.500	8.174	0.944	13.462	0.639	14.045	0.828	15.950	0.456	14.033	0.596
Residence	21.255	**0.019***	8.914	0.540	17.915	**0.022***	13.684	0.090	16.495	**0.036***	12.214	0.271	16.069	**0.041***	10.209	0.251
Monthly household income	13.063	0.597	10.156	0.810	10.055	0.611	5.750	0.928	5.778	0.927	19.711	0.183	14.777	0.254	14.755	0.255
Visual condition	16.445	0.088	9.281	0.506	10.746	0.216	9.618	0.293	4.319	0.827	10.881	0.367	10.771	0.215	5.845	0.665
Hearing condition	24.220	**0.007***	2.186	0.995	9.468	0.304	2.377	0.967	4.752	0.784	4.373	0.929	3.833	0.872	11.773	0.162
City for medical treatment	7.634	0.178	6.239	0.284	4.239	0.375	3.639	0.457	2.882	0.578	8.961	0.111	9.458	0.051	4.737	0.315
Type of operation	22.491	0.314	24.857	0.207	10.787	0.822	10.684	0.829	13.080	0.667	10.405	0.960	10.289	0.851	9.606	0.886
Length of hospital stay after operation	0.054	0.532	0.060	0.485	-0.059	0.493	-0.120	0.164	-0.041	0.634	-0.029	0.734	-0.057	0.506	-0.060	0.486
Body mass index	637.805	**0.001***	610.603	**0.009***	489.728	**0.015***	484.296	**0.023***	430.927	0.346	552.591	0.241	472.288	0.052	470.938	0.057
Comorbidity	4.167	0.526	4.645	0.461	4.092	0.394	4.845	0.304	6.730	0.151	4.404	0.493	3.744	0.442	7.538	0.110

* $P < 0.05$

Table 6 Characteristics of the participants in qualitative study ($n = 13$)

Variables	Mean ± SD / *N*
Age (years, mean ± SD)	56.62 ± 14.04
Sex	
Male	8
Female	5
Education level	
Primary school or below	2
Middle school	6
High school	2
Bachelor's degree or above	3
Marital status	
Married	12
Widowed	1
Monthly household income	
< 3000 RMB	2
3,000 ~ 5,999 RMB	5
6,000 ~ 8,999 RMB	3
> 9000 RMB	3
Insurance	
Self-paid	2
Government-funded healthcare	4
Medical insurance	1
Staff insurance	5
Commercial insurance	1
Comorbidity	
Hypertension	7
Diabetes	4
Hyperlipidemia	2
None	2

Abbreviation: RMB, Renminbi

after operation, and comorbidity) and one-dimensional demands.

Qualitative results

Characteristics of participants

A total of 13 MICI patients participated in the interview. We initially interviewed 10 participants. After identifying the topic, we continued with 3 more interviews to ensure that no new topics emerged, and subsequently terminated the qualitative data collection. Table 6 showed the characteristics of the 13 interviewed participants. The average age of the patients was 56.62 ± 14.04 years, with 8 of them being male. Almost half of the participants had a middle school education level, and 12 were married. Additionally, eleven patients had comorbidities, such as hypertension and diabetes.

Key themes

Through semi-structured interview, we have identified eight themes of demands to provide a holistic demand identification, shown in Fig. 2. Detailed interview content is presented in the supplementary file 1.

Fig. 2 Eight themes of demands identified through the qualitative phase

Theme 1: Physical recovery and lifestyle guidance demand Some patients felt loss of energy after operation and hoped to regain their vitality to come back to normal life. Exercise guidance was an important part of lifestyle guidance, with participants expressing various demands, including overcoming barriers to exercise, seeking individualized exercise plans, and developing exercise intention and habits.

> *Sometimes it feels like I have less energy than before the operation. (P1)*

> *The weather is too hot, so I haven't been exercising. I'm afraid to go out. It's too hot. I feel dizzy under the sun. (P4)*

> *The doctor has said that exercise is needed, but he has not said the level of exercise. (P5)*

> *These days, I'm mostly just sitting around at my shop, not really getting much exercise. I'm planning to start moving more, like walking around the park, but I haven't started yet because this bump hasn't gone away. I think I still need to focus on resting. (P6)*

Theme 2: Psychological support demand Participants experienced various psychological changes, such as fear of operation, anxiety about postoperative recurrence, and a sense of loneliness. Each participant faced unique psychological challenges and required tailored support during the period.

> *I'm in my fifties now, and I've never been hospitalized before. This time, I felt some chest tightness, so I went for a checkup and they did an angiogram. Then they told me I needed a stent. I've never been in the hospital before, so I was pretty scared—it was my first time, and I was really nervous. (P1)*

> *I'm alone at home, and there's nothing I can do about it. They went back, and I'm just here by myself. My grandson needs to go to school. (P2)*

Theme 3: Comorbidity management demand For MICI patients, many also had chronic diseases (e.g., hypertension, and diabetes). Managing these comorbidities while ensuring successful postoperative recovery was no easy task.

> *Blood sugar is a little high, and it's not down even with insulin. Now it's equivalent to about 9 mmol/L before meals. (P1)*

> *I had hypertension for many years, and the blood pressure is really high, about 200 mmHg. (P2)*

Theme 4: Medication-related demand Medication was another critical aspect that patients pay attention to. From the perspective of many patients, successful operation and strict medication adherence were key to recovery. Therefore, they expressed various medication-related demands. Patients faced some medication adherence challenges such as forgetting the right combinations or timing of different medications. Patients also had some concerns about the potential side effects, leading them to search the Internet to get some information. Some patients also reported that doctors do not give clear information about the signal of discontinuing medication, leaving them confused about the appropriate timing to stop taking them.

> *Some medications need to be taken together, but I'm not always sure about the right combinations. Sometimes, I also don't get the timing quite right. (P5)*

> *I'm a bit confused right now about which medications I still need to take and which ones I can stop. (P9)*

Theme 5: Symptom management demand Participants experienced various symptoms that affected their daily lives, leading them to focus on these issues and may require symptom management. Pain was a frequently mentioned symptom, significantly impacting their quality of life.

> *My blood vessels are naturally very thin, so after drawing blood, I might get some lumps or bruises on my hand that still haven't gone away. (P2)*

> *The uncomfortable part is that the areas on both sides of my thighs hurt a lot when I lie down. I feel fine when I'm sitting, but as soon as I lie down, the pain kicks in. (P12)*

Theme 6: Health monitoring and checkup reminders demand Participants closely monitored their vital signs, such as heart rate, and often visited the hospital for lab tests to ensure there are no underlying issues.

> *After my operation, my heart rate is still around 80 to 90 beats per minute, and sometimes it even goes over 90. It's noticeably high and quite unstable. (P8)*

> *I would like to receive reminders about any lab tests I need to do and important things to watch out for after being discharged. (P9)*

Theme 7: Financial-related demand Participants expressed a need for transparency in medical costs, as they often did not really know where the medical expenses are going. The lack of transparency could lead to significant confusion and anxiety. Additionally, patients had their financial burdens that required support.

> *My thought is, as long as I recover, that's all that matters. I'm not thinking about anything else, especially since money's tight. (P4)*

> *The financial pressure is definitely high; it's so hard to make money these days. We're basically just working folks. (P6)*

Theme 8: Medical information demand Most participants lacked medical information, and no one told them the basic knowledge about their diseases and treatments, leading to confusion. They also sought information on lifestyle modifications. No one provided professional advice for them, and communication between doctors and nurses was scarce. Consequently, they just searched on the Internet to find the information they needed to relieve their anxiety.

> *I don't really understand where exactly this operation was done. Is it around the area below my throat, in the heart? Where exactly is the stent placed? (P4)*

> *The day I got discharged, my husband took a popsicle out of the freezer for me, and I wasn't sure if I could eat it. So, I looked it up online and found that it's better not to eat things like ice cream after getting a stent. After reading that, I decided not to eat it. (P6)*

The qualitative findings strengthened the quantitative results while revealing additional detailed patient needs, particularly around comorbidity management, psychological support and financial transparency. This mixed-method approach revealed both the relative importance of different demands (through Kano analysis) and the deeper context and reasoning behind these needs (through interviews). The findings suggest opportunities for targeted interventions, particularly in health monitoring, medication guidance, symptom management, and information provision.

Discussion

Main findings

To our knowledge, this is the first study to investigate the demands of MICI patients during the transition from hospital to home using a parallel mixed-method approach. We revealed three key insights about MICI patients' transitional care demands. First, through Kano model analysis, we identified health monitoring, medication guidance, symptom management, and personalized exercise plan as one-dimensional demands that significantly impact patient satisfaction. Second, continuous exercise monitoring and dietary planning emerged as attractive features that could enhance care quality without risking dissatisfaction if absent. Third, our qualitative findings uncovered deeper contextual factors, particularly around comorbidity management, psychological support and financial transparency, that weren't captured in the quantitative analysis alone.

Interpretations of quantitative and qualitative results

To assess the relative importance of the included demands, the Kano model was employed. Three classifications were identified: one-dimensional, attractive, and indifferent.

Must-be category

No must-be demands were found in our survey. However, although no demand was categorized as "must-be", this does not necessarily imply a lack of fundamental need. Considering the proven health benefits of transitional care after discharge, its successful application in western countries, and the identified demands through qualitative studies, the absence of must-be needs may be due to the low expectations of transitional care among Chinese people [33, 34]. The concept of transitional care is not widely adopted in China, and MICI patients have become accustomed to being unguided and unaided after discharge. As the healthcare system in China continues to evolve, patients' expectations may still be developing.

One-dimensional category

One-dimensional demands, which are highly valued by patients, should be prioritized. According to our results, all health monitoring services were categorized as one-dimensional, indicating that patients are particularly concerned about their health status, and hope to be immediately informed of any changes. Therefore, from the patient's perspective, the identification and diagnosis of health abnormalities are paramount. Health monitoring demands were also mentioned and summarized through semi-structured interview. Some patients reported using the Huawei Band, a popular health monitoring device in China, to monitor their heart rate. The widespread use of these wearable devices highlights the importance of health abnormalities identification. With advancements in technology, patients now have greater opportunities to be aware of their health conditions in real time. However, a key gap between these existing wearable devices and their practical application in healthcare lies in their seamless integration with existing electronic health records (EHRs). This integration can be facilitated by using standards for the exchange, integration, sharing, and retrieval of electronic health information. For example, the Fast Healthcare Interoperability Resources (FHIR) standard has gained widespread attention as an effective solution in this field [35]. After successful integration, nurses can leverage AI-powered wearable devices or telehealth to monitor vital signs, identify abnormalities, and intervene promptly, even for patients staying at home. For instance, real-time data from a wearable can alert a nurse to potential arrhythmia, enabling timely follow-up or referral. Over time, with accumulated medical data, the AI system could offer personalized health recommendations by learning from and analyzing large datasets. Apart from health monitoring, checkup reminders are also important for patients. Studies have shown that text messaging reminders help improve medical appointment compliance by addressing issues of forgetfulness [36].

Medication guidance services were also classified as one-dimensional, which was further validated by the qualitative results. Patients attach importance to medication. In summary, medication-related demands mainly included medication adherence management and medication information demands. Commonly mentioned concerns include medication timing, discontinuing schedules, dosages and drug combinations. Nurse-led interventions, such as patient education and medication management, are well-suited to address these demands.

Additionally, patients often feel confused about these drugs, and are worried about potential side effects, leading to anxiety about medication information. These demands can be addressed through artificial intelligence approaches [37, 38]. With the emergence and popularity of large language models, these technologies have the potential to answer patients' different questions including medication information and other medical information demands, such as diet information demands mentioned in the qualitative study, providing tailored suggestions.

However, AI-generated information should be treated with caution, especially in the medical field. Fortunately, new methods such as retrieval-augmented generation and knowledge graph have been proposed and applied to help AI produce more professional and accurate texts [39, 40]. AI-enabled platforms, supervised by clinical nurses, may address patient concerns in real time.

Symptom management was another demand categorized as one-dimensional, primarily because severe symptoms, such as pain, significantly impact daily lives. This was also highlighted in the interviews, where patients expressed that pain affected their ability to use the toilet, climb stairs, and sleep. The importance of postoperative pain management has also been emphasized in previous studies, as undermanaged postoperative pain can lead to complications such as sleep disturbances, anxiety, and delayed mobility [41, 42]. Incorporating remote triage tools, including wearable technology and patient self-reporting apps, into the existing healthcare system may improve the management of symptoms. For instance, real-time data collected from wearable devices and apps can provide nurses with notifications containing up-to-date information on pain levels, enabling them to adjust analgesics or make other interventions, maintaining patient comfort and preventing future complications. However, the relatively low health information literacy among patients and the limited AI competency among nurses in China act as significant barriers to implementing remote transitional care [43, 44]. To overcome these challenges, it is essential to provide education that teaches patients how to use these devices effectively, as well as training for nurses to improve their ability in interpreting and responding to data from AI-driven tools. In addition, the collaboration and communication between nurses and AI experts should be strengthened and supported to successfully implementing user-friendly AI-driven transitional care.

In patients' opinion, providing a personalized exercise plan was a priority, which aligns with the qualitative findings. This can be explained by the phenomenon that over 40% of global population was physical inactivity [45]. The reasons for physical inactivity are varied and highly personalized. According to our qualitative results, patients expressed reasons such as hot weather, lack of specific exercise guidance, or pain as barriers to exercise. Therefore, personalized exercise plans are more appropriate than general ones. Nurses trained in cardiac rehabilitation can incorporate AI-assisted exercise tracking to tailor exercise programs for patients and motivate them to overcome barriers. Nurses can use AI-based tools to monitor exercise and provide immediate feedback on performance. Such interventions not only enhance physical recovery but also foster long-term healthy behaviors.

Attractive category

Three demands were classified as attractive. Health-related information and health monitoring demands have already been emphasized and explained in previous sections. One notable finding that deserves attention is dietary plans. In our survey, we provided two options. Compared with personalized dietary plan, patients tended to have adjusted ones because they already have established dietary habits and preferences. This was further validated in qualitative findings that patients prefer to continue their existing eating habits with only minor modifications. In the AI era, innovative technology can be used to generate dietary plans and analyze patient's food logs to suggest adjustments, minimizing drastic lifestyle changes that may reduce adherence. Meanwhile, nurse-led dietary interventions, in collaboration with dietitians, can adapt meal plans to patients' cultural and personal preferences [46, 47].

Indifferent category

The remaining demands, mainly related to weight loss guidance, quitting smoking, limiting alcohol, sleep guidance, fundamental nursing, skill learning, and psychological and social support, were regarded as indifferent. All findings were consistent with the qualitative results, except for psychological and social support. In our semi-structured interview, patients expressed concerns such as anxiety about postoperative recurrence and feelings of loneliness. This discrepancy may be due to their lack of awareness regarding their anxiety. Additionally, previous evidence shows that postoperative psychological interventions are generally more effective than preoperative ones, significantly reducing acute pain and disability [48]. Nurses can incorporate structured mental health and lifestyle screenings, such as questionnaire surveys or facial image recognition, into routine follow-ups through AI-based tools, detecting latent issues like anxiety or depression. After diagnosing psychological problems of patients, AI tools, including chatbots or virtual counsellors hold substantial potential to generate personalized plans to intervene in patients' psychology and alleviate their psychological symptom [49].

The application of AI for patients with depression, loneliness or anxiety holds great promise due to several key advantages. First, compared to traditional psychological counselling, AI-driven psychological interventions are much more cost-effective, enabling mental health support more accessible to a larger population. Second, feelings of shame or stigma are significant barriers for many patients who fear seeking psychological treatment. The anonymity and privacy offered by AI enhance patients' willingness to seeking help [50]. Currently, with the rapid development of AI technology, many AI-driven psychological products, such as Woebot and Replika, have been widely used. Integrating the useful features of these products into transitional care interventions may be another area of future research [51, 52].

However, although these fully automated tools can provide patients with immediate support between visits, AI-driven mental health diagnosis faces limitations, such as potential bias in data, failure to account for the complexity and individuality of mental health conditions, and a lack of empathy in treatment [53]. Integrating these tools into existing EHRs and ensuring that nurses are involved in reviewing and interpreting the data are necessary to guarantee correct psychological screening and enhancing current healthcare processes.

Clinical implications

The integration and reflection of quantitative and qualitative results

Overall, based on our results and discussions, the quantitative approach using Kano model identified health monitoring, medication guidance, symptom management, and personalized exercise plan as high-priority demands, while continuous exercise monitoring and dietary planning were recognized as innovation opportunities. Qualitative studies revealed additional demands not captured in quantitative results, including comorbidity management, psychological support and financial transparency. The results highlight the complementary nature of the mixed-method approach. By addressing physical health demands and assisting patients in cultivating health lifestyle, nurses can offer more comprehensive, patient-centered care. Paying attention to psychological support and financial transparency could significantly improve patient satisfaction and outcomes, which are often overlooked in traditional healthcare models.

Targeted interventions

According to the results of associations between patient characteristics and priority needs (one-dimensional needs), we derived clinical implications for more targeted interventions. Age and residence status were factors that required our attention. Older patients and those living along were more likely to need checkup reminders, personalized exercise plans, health monitoring, and medication guidance. These needs arise from the combination of age-related health decline and the lack of social support, which increases their dependence on healthcare services. Digital health interventions, provide continuous monitoring and personalized care in the context of home care, thereby offering significant potential to improve health outcomes and enhance recovery for these populations [54]. Those who were overweight or obese had greater health demands than other populations, as they were more concerned about potential health issues. This is because a higher BMI is often associated with comorbidities, such as diabetes, hypertension, and cardiovascular diseases, which increase their concerns about their health status [55]. No significant correlation was found between comorbidities and priority needs, which may be due to the inclusion of post-PCI patients, who are more focused on post-intervention concerns rather than chronic conditions (e.g., diabetes and hypertension). Although our study did not reveal significant associations between other demographic factors (such as sex and education level) and priority needs, these factors should not be overlooked. Gender differences may influence patterns of health service utilization. For example, females may prioritize the health needs of their families over their own, which could lead to delayed or unmet healthcare demands [56]. The impact of education level on patients' demands should also be considered. Lower educational attainment is often associated with limited health knowledge, non-compliant health behaviors, and underutilization of healthcare services. These factors can make individuals less aware of their health needs, less likely to follow medical advice, and less inclined to seek proper medical care, leading to unmet health management needs. As a result, overall health status may be negatively affected [57]. Additionally, socioeconomic status is a critical factor influencing patient demands. Research has also shown that individuals with lower socioeconomic status may face greater health risks and experience inequities in accessing health services and resources [58]. Future research should explore how these factors affect health needs in different contexts, enabling the development of more targeted and effective strategies to better address patients' needs.

Challenges in implementing AI for transitional care

In the AI era, innovative technology can be used to support transitional care from hospital to home. This article provides a comprehensive demand analysis, offering a more thorough understanding of the demands of MICI patients. Some solutions addressing these demands were mentioned in the previous section. However, several challenges arise when integrating AI technology into transitional care.

Firstly, the acceptance of AI-driven interventions is questionable among people with knowledge gaps and financial constraints. According to a survey study investigating public perception of AI-driven interventions with 466 adult participants, 305 (65.5%) respondents expressed very low knowledge of AI-driven interventions, and only 24 (5.2%) reported a high level of trust in this type of intervention [50]. In addition, people with lower education level tend to have less knowledge, understanding, and trust in AI, which results in a relatively low acceptance of AI [59, 60]. To ensure these interventions reach a broader population, we recommend initiating health education programs targeting health information literacy to help patients, particularly those from lower educational backgrounds, embrace new technology. These programs should provide clear and understandable explanations of AI-driven interventions.

One notable advantage of AI-driven interventions is that they are likely to be widely accessible. These technology-based interventions have the potential to break geographical barriers to provide high-quality transitional care to populations in remote areas where medical resources are limited. However, if these services are too expensive, they may widen the digital divide, particularly between high-income and low-income populations. Qualitative interviews also highlighted the demand for financial support. For people with lower income, the financial burden is a significant barrier to accessing these intelligent services [61]. Therefore, the involvement of policymakers is essential to ensure that ordinary people have the opportunity to access such healthcare services through measures such as insurance.

Secondly, technical feasibility, particularly data privacy, security and standardization, is another aspect that needs attention when applying AI in transitional care. AI techniques typically requires a large amount of data, including sensitive patients' personal health monitoring data, medical history, and behavioral data, to generate accurate predictions about their health status. This high reliance on data raise concerns about data privacy and security especially in healthcare setting where patient confidentiality is essential [62]. One possible solution to the issue is the use of block-chain technology, with its decentralized data storage that distributes data across multiple nodes, including those operated by patients and healthcare institutions, unlike traditional centralized systems [63]. The nature of decentralization removes the necessity for a single organization to store all healthcare data, ensuring data security and privacy.

Furthermore, data exchange across different healthcare systems is critical for AI-driven solutions to work smoothly. As healthcare data are typically stored in different platforms such as EHRs and patients' wearable devices, with varying data formats. Therefore, data standardization is essential to ensures smooth healthcare data transmission across various platforms [64]. The application of data standards, such as FHIR and Systematized Nomenclature of Medicine – Clinical Terms (SNOMED CT), would be helpful in solving these problems.

Thirdly, with the rapid developments of AI, several concerns have emerged. One key ethical issue is bias in AI models. If the medical data used to train AI models primarily comes from high socioeconomic groups, rather than a broader, more diverse population, it could lead to unfair and unequal healthcare outcomes. Therefore, regulations should be carefully designed to address these risks and ensure that the benefits of AI are shared equitably among all individuals, rather than favoring specific groups. The Council and the European Parliament (EP) agreed on the Artificial Intelligence Regulation (AI Act, AIA) in February 2024 [65]. Regarding the application of AI in medical field, China's National Medical Products Administration (NMPA) has released many regulations in line with its AI development plan [66]. AI regulation should evolve alongside the development of AI, and joint collaborations among AI expert, and regulators are essential to ensure effective regulation.

Strengths, limitations and future research directions

The study demonstrated several strengths in contributing to AI-driven transitional care for MICI patients. Firstly, we addressed a significant and pressing research question regarding the transitional care demands of MICI patients in the context of AI, a topic not fully explored in China due to nursing staff shortages. Secondly, we employed a mixed-method approach to perform the demand analysis. The use of Kano model in the quantitative part allowed for the categorization of demands into different classifications, prioritizing them based on their importance. The introduction of qualitative study enabled mutual comparison and validation between quantitative and qualitative results, which enhanced the reliability of our findings. Finally, based on demand analysis results, actionable AI-based strategies and solutions were fully discussed, providing insights into potential future developments. However, the study also has some limitations. Firstly, our sample size was relatively small, especially in the qualitative part. While the mixed-method approach helped mitigate this limitation, a small sample size restricts the generalizability of the findings. Although data saturation was reached in the qualitative study, the limited sample size raised concerns about whether the experiences reflect those of the broader population and whether some demand themes may have gone undetected. Additionally, the small sample size in the quantitative analysis may have limited the detection of subtle trends in the demand analysis. Therefore, the findings should be interpreted with caution, and future studies with larger and more diverse samples are required to validate and strengthen our insights. Secondly, we analyzed each demand independently, but they are interrelated. For example, searching for medication information may lead to patients' anxiety, but if information-seeking problem is solved, their anxiety might be relieved or even eliminated. Independent analyses of demand may restrict a holistic understanding of these needs. This presents another potential direction for future research, suggesting the implementation of a more integrated approach that considers the interdependencies among demands. This limitation should be considered when designing interventions targeting the needs of post-discharge MICI patients.

Thirdly, we used a self-designed questionnaire due to the lack of a comprehensive demand scale. However, we cross-checked the survey findings with the qualitative results and consulted six experts to evaluate the content validity of the questionnaire, ensuring that no critical demand categories were missed. This also indicates an important future research direction: the development of a scale to assess the post-discharge needs of MICI patients, considering the significance of home care nursing for this population. Lastly, regarding participant recruitment, although we included patients from four hospitals located in both northern and southern China, all four hospitals are situated in second-tier cities. The selection bias limits the external validity of the demand analysis results for patients in first-tier cities or rural areas, where patients' expectations and needs for transitional care may differ from those of participants included in our study. Specifically, in first-tier cities, where there are better medical care resources, higher educational levels, and greater financial stability, people tend to have higher expectations of transitional care. This is primarily because most residents understand the importance of post-discharge rehabilitation through health education provided by qualified medical professionals. Additionally, they typically receive follow-up visits based on their previous healthcare experiences, which is a key component of transitional care. Furthermore, individuals in these cities have easier access to advanced medical technologies, such as telemedicine and mobile health applications, as well as specialized care delivered by high-quality community medical services. This greater exposure enables a better understanding of the intentions and purposes behind conducting this research on AI-driven transitional care. In contrast, in rural areas with limited medical resources, lower educational backgrounds, and financial instability, people are less likely to be well-informed about transitional care by professional medical staff. This is partly due to the limited availability of healthcare education in these regions. In rural settings, the focus is often on acute care in hospitals, where receiving medical treatment in a hospital is typically viewed as curing diseases. As a result, the concept of transitional care, including follow-up visits, is less understood. Moreover, limited exposure to advanced technologies makes the use of AI-driven solutions seem distant and less relevant. Besides, financial constraints, along with health literacy and access to healthcare technologies, also significantly shape people's awareness of transitional care. In rural areas, economic limitations often prevent people from seeking follow-up care and post-discharge rehabilitation, whereas individuals in first-tire cities are more likely to have the financial access to engage in rehabilitation. Therefore, the heterogeneity of transitional care expectations and needs across different regions limits the applicability of the results of this study. We suggest that future studies explore the demand for transitional care among patients in these regions.

Conclusions

By uncovering MICI patients' most pressing transitional care demands, this study provides valuable directions for designing AI-supported, nurse-led interventions that are both feasible and patient-centered. Prioritizing one-dimensional demands—including health monitoring, medication adherence, symptom management, and personalized exercise—has the potential to improve patient satisfaction and reduce hospital readmissions. In parallel, implementing attractive features like continuous exercise monitoring and personalized dietary plans can further enhance patient engagement without generating dissatisfaction if not provided. In addition, comorbidity management, psychological support and financial transparency are areas that warrant further attention. Nurses, as frontline caregivers and care coordinators, are in a key position to integrate these technological solutions into daily practice. With supportive policies, adequate training, and redesigned workflows, nurse-led AI interventions may help address staffing challenges and bridge transitional care gaps, potentially improving the recovery outcomes of MICI patients in China and beyond. However, due to the limitations of our study, these insights require further validation and exploration.

Supplementary Information

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Supplementary Material 1

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Author contributions

Y.W.L. and S.J.L. analyzed the data, prepared the figures, and wrote the main manuscript text. J.Y., J.J.C., Q.M., M.L., Y.Q.Z., Y.L.Y and W.Q.L collected the data. Q.T.L. maintained the research data. C.Z. and M.H.P. directed the research process and edited the manuscript text. All the authors prepared the study design and reviewed the manuscript.

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Data availability

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

The study received ethical approval from the Ethics Committee of the School of Nursing, Peking Union Medical College (PUMCSON-2024-24) prior to data collection. All the participants provided informed consent. Clinical trial number: not applicable. The study was conducted in accordance with the ethical principles laid out in the Declaration of Helsinki.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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References
1. Tsao CW, Aday AW, Almarzooq ZI, Anderson CAM, Arora P, Avery CL, Baker-Smith CM, Beaton AZ, Boehme AK, Buxton AE, et al. Heart disease and stroke Statistics-2023 update: A report from the American heart association. Circulation. 2023;147(8):e93–621.
2. Karangelis D, Androutsopoulou V, Tzifa A, Chalikias G, Tziakas D, Mitropoulos F, Mikroulis D. Minimally invasive cardiac surgery: in the pursuit to treat more and hurt less. J Thorac Disease. 2021;13(11):6209–13.
3. Gianoli M, de Jong AR, Jacob KA, Namba HF, van der Kaaij NP, van der Harst P, Suyker JL. Minimally invasive surgery or stenting for left anterior descending artery disease– meta-analysis. IJC Heart Vasculature. 2022;40:101046.
4. Center For Cardiovascular Diseases The Writing Committee Of The Report On, Cardiovascular H. Diseases in China N: report on cardiovascular health and diseases in China 2023: an updated summary. Biomed Environ Sci. 2024;37(9):949–92.
5. Han TS, Murray P, Robin J, Wilkinson P, Fluck D, Fry CH. Evaluation of the association of length of stay in hospital and outcomes. Int J Qual Health Care 2022;34(2).
6. Ye ZJ, Liu M-L, Cai R-Q, Zhong M-X, Huang H, Liang M-Z, Quan X-M. Development of the transitional care model for nursing care in Mainland China: A literature review. Int J Nurs Sci 2016;3.
7. Coffey A, Leahy-Warren P, Savage E, Hegarty J, Cornally N, Day MR, Sahm L, O'Connor K, O'Doherty J, Liew A et al. Interventions to promote early discharge and avoid inappropriate hospital (Re)Admission: A systematic review. Int J Environ Res Public Health 2019;16(14).
8. Rao SV, Kaltenbach LA, Weintraub WS, Roe MT, Brindis RG, Rumsfeld JS, Peterson ED. Prevalence and outcomes of same-day discharge after elective percutaneous coronary intervention among older patients. JAMA. 2011;306(13):1461–7.
9. Minges KE, Herrin J, Fiorilli PN, Curtis JP. Development and validation of a simple risk score to predict 30-day readmission after percutaneous coronary intervention in a cohort of medicare patients. Catheter Cardiovasc Interv. 2017;89(6):955–63.
10. Lin S, Wang C, Wang Q, Xie S, Tu Q, Zhang H, Peng M, Zhou J, Redfern J. The experience of stroke survivors and caregivers during hospital-to-home transitional care: A qualitative longitudinal study. Int J Nurs Stud. 2022;130:104213.
11. Parry C, Mahoney E, Chalmers SA, Coleman EA. Assessing the quality of transitional care: further applications of the care transitions measure. Med Care 2008;46(3).
12. Fønss Rasmussen L, Grode LB, Lange J, Barat I, Gregersen M. Impact of transitional care interventions on hospital readmissions in older medical patients: a systematic review. BMJ Open. 2021;11(1):e040057.
13. Rammohan R, Joy M, Magam SG, Natt D, Patel A, Akande O, Yost RM, Bunting S, Anand P, Mustacchia P. The path to sustainable healthcare: implementing care transition teams to mitigate hospital readmissions and improve patient outcomes. Cureus. 2023;15(5):e39022.
14. Sun M, Liu L, Wang J, Zhuansun M, Xu T, Qian Y, Dela Rosa R. Facilitators and inhibitors in hospital-to-home transitional care for elderly patients with chronic diseases: A meta-synthesis of qualitative studies. Front Public Health. 2023;11:1047723.
15. Veenstra M, Gautun H. Nurses' assessments of staffing adequacy in care services for older patients following hospital discharge. J Adv Nurs. 2021;77(2):805–18.
16. Seibert K, Domhoff D, Fürstenau D, Biessmann F, Schulte-Althoff M, Wolf-Ostermann K. Exploring needs and challenges for AI in nursing care– results of an explorative sequential mixed methods study. BMC Digit Health. 2023;1(1):13.
17. Brown Z, Bergman D, Holt L, Miller K, Frownfelter J, Bleau H, Flynn A, Ball T. Augmenting a transitional care model with artificial intelligence decreased readmissions. J Am Med Dir Assoc. 2023;24(7):958–63.
18. Parry C, Johnston-Fleece M, Johnson MC Jr., Shifreen A, Clauser SB. Patient-Centered approaches to transitional care research and implementation: overview and insights from Patient-Centered outcomes research institute's transitional care portfolio. Med Care. 2021;59(Suppl 4):S330–5.
19. Kermanshachi S, Nipa TJ, Nadiri H. Service quality assessment and enhancement using Kano model. PLoS ONE. 2022;17(2):e0264423.
20. Kano NSN, Takahashi F, Tsuji S. Attractive quality and Must-Be quality. J Japanese Soc Qual Control. 1984;14(2):39–48.
21. Yuan Y, Liu Y, Gong L, Chen H, Zhang S, Kitayama A, Takashi E, Liang J. Demand analysis of telenursing for community-dwelling empty-nest elderly based on the Kano model. Telemedicine e-Health. 2021;27(4):414–21.
22. Zhang M, Zhang L, Zhi X, Cheng F, Yao Y, Deng R, Liu C, Wang Y. Demand analysis of health care services for community-dwelling breast cancer survivors based on the Kano model: A cross-sectional study. Int J Nurs Sci. 2024;11(2):171–8.
23. Creswell JW, Clark VLP. Designing and conducting mixed methods research. Sage 2017.
24. China ECGoH-bCRi. Expert consensus on Home-Based rehabilitation for cardiovascular disease patients in China. Chin Circulation J. 2022;37(02):108–21.
25. Xu Q, Jiao RJ, Yang X, Helander M, Khalid HM, Opperud A. An analytical Kano model for customer need analysis. Des Stud. 2009;30(1):87–110.
26. Fang J-Q. Statistical methods for biomedical research. World Scientific. 2021.
27. Jehloh L, Songwathana P, Kitrungrote L, Bourbonnais A. Perspectives of family caregivers and nurses on hospital discharge transitional care for Muslim older adults living with COPD: a qualitative study. BMC Nurs. 2024;23(1):273.
28. Collet R, van Grootel J, van der Leeden M, van der Schaaf M, van Dongen J, Wiertsema S, Geleijn E, Major M, Ostelo R. Facilitators, barriers, and guidance to successful implementation of multidisciplinary transitional care interventions: A qualitative systematic review using the consolidated framework for implementation research. Int J Nurs Stud Adv. 2025;8:100269.
29. Mohamedsharif A, Bastawi M, Gemperli A. The needs of patients with chronic disease in transitional care from hospital to home in Sudan: A qualitative study. Health Serv Insights. 2024;17:11786329241249282.
30. Zhang P, Hu YD, Xing FM, Li CZ, Lan WF, Zhang XL. Effects of a nurse-led transitional care program on clinical outcomes, health-related knowledge, physical and mental health status among Chinese patients with coronary artery disease: A randomized controlled trial. Int J Nurs Stud. 2017;74:34–43.
31. Saunders B, Sim J, Kingstone T, Baker S, Waterfield J, Bartlam B, Burroughs H, Jinks C. Saturation in qualitative research: exploring its conceptualization and operationalization. Qual Quant. 2018;52:1893–907.
32. Nowell LS, Norris JM, White DE, Moules NJ. Thematic analysis: striving to Meet the trustworthiness criteria. Int J Qualitative Methods. 2017;16(1):1609406917733847.
33. Tyler N, Hodkinson A, Planner C, Angelakis I, Keyworth C, Hall A, Jones PP, Wright OG, Keers R, Blakeman T, et al. Transitional care interventions from hospital to community to reduce health care use and improve patient outcomes: A systematic review and network Meta-Analysis. JAMA Netw Open. 2023;6(11):e2344825–2344825.

34. Cui M, Hua J, Shi X, Yang W, Geng Z, Qian X, Geng G. Factors associated with instrumental support in transitional care among older people with chronic disease: a cross-sectional study. BMC Nurs. 2022;21(1):230.
35. Kirilov N. Capture of real-time data from electronic health records: scenarios and solutions. Mhealth. 2024;10:14.
36. Schwebel FJ, Larimer ME. Using text message reminders in health care services: A narrative literature review. Internet Interv. 2018;13:82–104.
37. Pais C, Liu J, Voigt R, Gupta V, Wade E, Bayati M. Large Language models for preventing medication direction errors in online pharmacies. Nat Med. 2024;30(6):1574–82.
38. Dou Y, Huang Y, Zhao X, Zou H, Shang J, Lu Y, Yang X, Xiao J, Peng S. ShennongMGS: an LLM-based Chinese medication guidance system. ACM Trans Manage Inf Syst 2024.
39. Miao J, Thongprayoon C, Suppadungsuk S, Garcia Valencia OA, Cheungpasitporn W. Integrating Retrieval-Augmented generation with large Language models in nephrology: advancing practical applications. Med (Kaunas) 2024;60(3).
40. Varshney D, Zafar A, Behera NK, Ekbal A. Knowledge graph assisted end-to-end medical dialog generation. Artif Intell Med. 2023;139:102535.
41. Liu Y, Xiao S, Yang H, Lv X, Hou A, Ma Y, Jiang Y, Duan C, Mi W, Yang J et al. Postoperative pain-related outcomes and perioperative pain management in China: a population-based study. Lancet Reg Health– Western Pac 2023;39.
42. Walton LL, Duff E, Arora RC, McMillan DE. Surgery patients' perspectives of their role in postoperative pain: A scoping review. Int J Nurs Stud Adv. 2023;5:100124.
43. Wang X, Fei F, Wei J, Huang M, Xiang F, Tu J, Wang Y, Gan J. Knowledge and attitudes toward artificial intelligence in nursing among various categories of professionals in China: a cross-sectional study. Front Public Health 2024;12.
44. Wang A, Zhou Y, Ma H, Tang X, Li S, Pei R, Piao M. Preparing for aging: Understanding middle-aged user acceptance of AI chatbots through the technology acceptance model. Digit Health. 2024;10:20552076241284903.
45. Strain T, Flaxman S, Guthold R, Semenova E, Cowan M, Riley LM, Bull FC, Stevens GA. National, regional, and global trends in insufficient physical activity among adults from 2000 to 2022: a pooled analysis of 507 population-based surveys with 5·7 million participants. Lancet Global Health. 2024;12(8):e1232–43.
46. Papastratis I, Konstantinidis D, Daras P, Dimitropoulos K. AI nutrition recommendation using a deep generative model and ChatGPT. Sci Rep. 2024;14(1):14620.
47. Kim DW, Park JS, Sharma K, Velazquez A, Li L, Ostrominski JW, Tran T, Seitter Peréz RH, Shin JH. Qualitative evaluation of artificial intelligence-generated weight management diet plans. Front Nutr. 2024;11:1374834.
48. Nadinda PG, van Ryckeghem DML, Peters ML. Can perioperative psychological interventions decrease the risk of postsurgical pain and disability? A systematic review and meta-analysis of randomized controlled trials. Pain. 2022;163(7).
49. Shimada K. The role of artificial intelligence in mental health: A review. Sci Insights. 2023;43:1119–27.
50. Varghese MA, Sharma P, Patwardhan M. Public perception on artificial Intelligence-Driven mental health interventions: survey research. JMIR Form Res. 2024;8:e64380.
51. Jiang Q, Zhang Y, Pian W. Chatbot as an emergency exist: mediated empathy for resilience via human-AI interaction during the COVID-19 pandemic. Inf Process Manag. 2022;59(6):103074.
52. Yang Q, Cheung K, Zhang Y, Zhang Y, Qin J, Xie YJ. Conversational agents in physical and psychological symptom management: A systematic review of randomized controlled trials. Int J Nurs Stud. 2024;163:104991.
53. Alowais SA, Alghamdi SS, Alsuhebany N, Alqahtani T, Alshaya AI, Almohareb SN, Aldairem A, Alrashed M, Bin Saleh K, Badreldin HA, et al. Revolutionizing healthcare: the role of artificial intelligence in clinical practice. BMC Med Educ. 2023;23(1):689.
54. Chen C, Ding S, Wang J. Digital health for aging populations. Nat Med. 2023;29(7):1623–30.
55. Kivimäki M, Strandberg T, Pentti J, Nyberg ST, Frank P, Jokela M, Ervasti J, Suominen SB, Vahtera J, Sipilä PN, et al. Body-mass index and risk of obesity-related complex Multimorbidity: an observational multicohort study. Lancet Diabetes Endocrinol. 2022;10(4):253–63.
56. Davas A, Etiler N. Gender differences in cost-related unmet healthcare needs: a National study in Turkiye. BMC Public Health. 2024;24(1):2413.
57. Jansen T, Rademakers J, Waverijn G, Verheij R, Osborne R, Heijmans M. The role of health literacy in explaining the association between educational attainment and the use of out-of-hours primary care services in chronically ill people: a survey study. BMC Health Serv Res. 2018;18(1):394.
58. Chen C, Xu RH, Wong EL-y, Wang D. The association between healthcare needs, socioeconomic status, and life satisfaction from a Chinese rural population cohort, 2012–2018. Sci Rep. 2022;12(1):14129.
59. Kelly S, Kaye S-A, Oviedo-Trespalacios O. What factors contribute to the acceptance of artificial intelligence? A systematic review. Telematics Inform. 2023;77:101925.
60. Kirlidog M, Kaynak A. Technology acceptance model and determinants of technology rejection. Information systems and modern society: social change and global development. edn.: IGI Global; 2013. pp. 226–38.
61. Al-Dhahir I, Reijnders T, Faber JS, van den Berg-Emons RJ, Janssen VR, Kraaijenhagen RA, Visch VT, Chavannes NH, Evers AWM. The barriers and facilitators of eHealth-Based lifestyle intervention programs for people with a low socioeconomic status: scoping review. J Med Internet Res. 2022;24(8):e34229.
62. Yadav N, Pandey S, Gupta A, Dudani P, Gupta S, Rangarajan K. Data privacy in healthcare: in the era of artificial intelligence. Indian Dermatol Online J. 2023;14(6):788–92.
63. Shamsan Saleh AM. Blockchain for secure and decentralized artificial intelligence in cybersecurity: A comprehensive review. Blockchain: Res Appl. 2024;5(3):100193.
64. Arora A, Alderman JE, Palmer J, Ganapathi S, Laws E, McCradden MD, Oakden-Rayner L, Pfohl SR, Ghassemi M, McKay F, et al. The value of standards for health datasets in artificial intelligence-based applications. Nat Med. 2023;29(11):2929–38.
65. Cancela-Outeda C. The EU's AI act: A framework for collaborative governance. Internet Things. 2024;27:101291.
66. Han Y, Ceross A, Bergmann J. Regulatory frameworks for AI-Enabled medical device software in China: comparative analysis and review of implications for global manufacturer. Jmir Ai. 2024;3:e46871.

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