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Article

Research on the Construction of Core Competence Framework for the Smart Health Care and Elderly Care Service and Management Major Driven by Digital Technology

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Abstract: The construction of the core capability system for intelligent health elderly care management services provides precise guidance for professional talent cultivation. This research was carried out through four stages of actions. In the first stage, through policy text analysis, job task analysis, and expert interviews, the intelligent elderly care service management capability items were initially generated. In the second stage, based on the Delphi expert consultation results, the final capability indicator system was modified and confirmed. In the third and fourth stages, relevant indicator data were collected through questionnaires and statistical methods, and the rationality of the indicator structure was verified using statistical quantities. The final determined core capabilities of the intelligent health elderly care service and management major include 4 first-level indicators, 12 second-level indicators, and 22 third-level indicators. Through exploratory analysis, 6 principal component factors were extracted, and confirmatory factor analysis verified that this core capability indicator system has coordination and consistency.

Keywords: Intelligent health elderly care; Professional core capability; Delphi consultation; Principal component analysis

1. Introduction

With the intensification of China's aging population, the elderly care service industry has become a highly concerned field [1-2]. How to meet the needs of the elderly and provide high-quality elderly care services is an important issue. The Smart Health Elderly Care Service and Management major has emerged as a new interdisciplinary major that responds to the national "14th Five-Year Plan" for healthy aging and the policy orientation of Guangdong Province's "Silver Age Health Care Action". It aims to cultivate high-quality talents with modern elderly care service concepts and skills who can meet the development needs of the elderly care service industry [3-6]. With the acceleration of China's aging process, as of 2022, the number of people aged 60 and above in China has reached 280 million, accounting for 19.8% of the total population. It is expected to exceed 400 million by 2035 [7-9]. At the same time, the shortage of compound talents in the smart elderly care field is as high as 2 million. This severe situation provides a broad space for the professional development.

However, the digitalization level of the Smart Health Elderly Care Service and Management major in universities is still generally low. Although it has the name of "smart", the connotation of digitalization and intelligence is insufficient, making it difficult to meet the demand for skill-based talent training in the transformation and development of the elderly care service industry under the continuous acceleration of the aging process [10]. Especially with the in-depth development of digital technologies, smart health elderly care services have more stringent requirements for information technology means, and the demand for smart health elderly care services is increasing. To provide high-quality smart health elderly care services, the core competence of the major is of vital importance [11-14]. Therefore, constructing the core competence framework of the Smart Health Elderly Care Service and Management major has become an inevitable demand for improving future elderly care services.

This paper uses policy text analysis method, job task analysis method and semi-structured interview method to identify and recognize the core competence items of the Smart Health Elderly Care Service and Management major, and preliminarily constructs the ability index structure. Inviting relevant experts, through two rounds of Delphi expert consultation actions, the final indicators are reduced and modified. Relevant survey questionnaires are designed for the ability indicators, and the data of the three-level indicators are quantified using the Likert five-level scale. Using exploratory factor analysis and confirmatory factor analysis, the usability of the characteristics of the ability indicators is verified.

2. Research Design

2.1. Overall Research Framework

This study adopts an "exploratory sequential design", with the qualitative stage serving as the preliminary step and the quantitative stage as the subsequent verification. The qualitative stage (stages one and two) is responsible for identifying, generating, and screening experts for the capability elements, forming the initial capability framework structure; the quantitative stage (stages three and four) is responsible for the statistical verification of the capability framework, conducting empirical tests on the structural rationality of the framework through exploratory factor analysis and confirmatory factor analysis.

2.2. Establishment of Multi-stage Research Approach

2.2.1. Generation of Capability Items

The objective of this stage is to systematically identify the core competency elements that professionals in the field of intelligent health care services and management may possess, and to form a comprehensive initial competency item pool. The method tools include content analysis of policy texts, workshop for job task analysis, and semi-structured expert interviews.

Based on the analysis of policy texts, the workshop for job task analysis, and the semi-structured expert interviews, all the competency elements are produced. Through a systematic integration and refinement process, a structured initial competency item pool is ultimately formed. The integration process is divided into three steps. The first step is to remove duplicates and merge: the research team (including the researcher themselves and two project group members with backgrounds in elderly care or vocational education research) compares each ability element from all sources one by one, combines those with different expressions but the same meaning, and merges overly specific elements that should be sub-items into larger ability categories. The second step is to classify and name: referring to the general logical classification logic of the competency framework, the ability elements after the duplicate and merge process are classified and summarized to form a preliminary framework of primary dimensions (ability domains) and secondary indicators (ability categories), and names are drafted for each dimension and indicator. The third step is to standardize the item expression: following the general norms for competency item expression - "ability verb + behavior object + context/standard" - ensure the comparability of each item at the abstract level and the operability in questionnaire compilation.

2.2.2 Delphi Expert Consultation

The objective of this stage is to build upon the initial list of items generated in the first stage through multiple rounds of structured expert consultation, to screen, revise and integrate the competency items, reach expert consensus, and form a preliminary competency framework. Based on the selection of research experts by multiple stakeholders, two to three rounds of anonymous consultation are implemented. After each round, the group statistics results (median, interquartile range) are provided to the experts for them to revise their judgments in the next round.

The Delphi method mainly involves specific experts in a particular field providing their opinions on a specific issue [15]. After the researchers integrate the expert opinions and feed them back to the experts, a method is formed to reach a common understanding on this issue. Throughout this process, experts remain anonymous to each other. In this process, the invited experts should have relevant research background and experience on the consulted issue. This process usually requires at least two rounds. In the initial stage of this study, based on the coding results of text analysis, the "Core Competencies of the Smart Health Care Service and Management Specialization" was revised and improved. Subsequently, in order to collect more professional and specific opinions, an "Expert Opinion Survey Questionnaire for Core Competencies of the Smart Health Care Service and Management Specialization" was carefully compiled, and three rounds of opinions solicitation were conducted among experts with rich research experience and practical teaching experience (who are also front-line teachers). During the solicitation process, the feedback opinions of the expert teachers were fully adopted, and targeted corrections were made to the relevant indicators in the "Evaluation Index System for Core Competencies of the Smart Health Care Service and Management Specialization". The specific operation steps of the solicitation and correction process are shown in Figure 1.

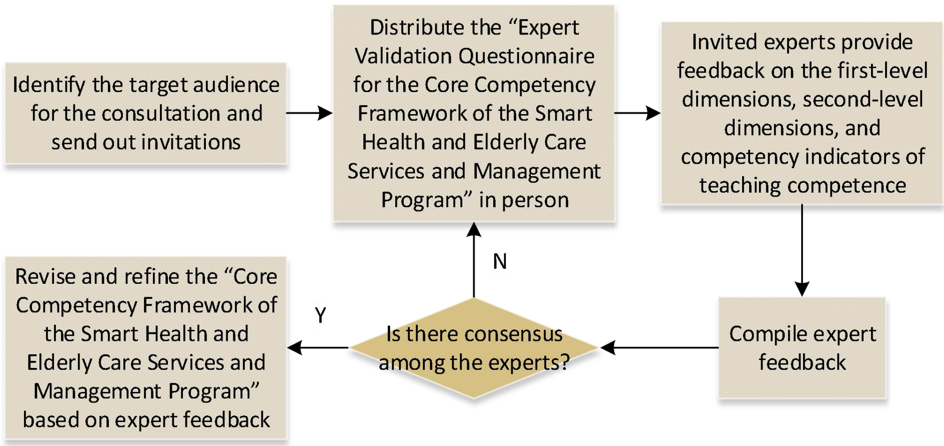

Figure 1. The implementation process of the Delphi method

2.2.3. Questionnaire Design and Data Collection

The objective of this stage is to transform the initial draft of the capability framework formed in Stage Two into a testable structured questionnaire, and conduct large-scale data collection among students and graduates majoring in Smart Health Care Services and Management. The questionnaire adopts the Likert five-point scale format, requiring respondents to rate the importance of each capability item or their own compliance level. The sample size determination follows the statistical requirements of factor analysis, with the target sample size being no less than 10 times the number of capability items.

The initial draft of the competency framework, after being screened and revised by the Delphi expert consultation, needs to undergo structural validation based on empirical data from a large sample. The measurement tool used for quantitative data collection in this study is the self-compiled "Core Competencies Survey Questionnaire for Professional Talents in Smart Health Care Services and Management". The questionnaire was compiled based on the initial draft of the competency framework formed after the Delphi consultation, converting the three-level competency items into scoreable survey questions. The scale questions directly correspond to all the three-level competency items retained after the Delphi consultation, using the Likert five-point self-assessment format. The two ends of the five-point scale are anchored at "very unimportant" (1 point) and "very important" (5 points), as well as "Very inappropriate" (1 point) and "very conforms" (5 points).

This study adopted a combined method of stratified purposive sampling and convenience sampling. The stratification dimensions included two: the identity of the participants (students in school vs. graduates) and the region where the institutions are located (eastern, central, western). The sample of students was collected by establishing a cooperative relationship with vocational colleges offering the major of Smart Health Service and Management. The counselors or professional teachers of the cooperating colleges distributed anonymous electronic questionnaire links within the classes for collection. The sample of graduates was obtained through two channels: first, sending questionnaire invitations to the recent three graduating students through the alumni contact system of the cooperating colleges; second, conducting targeted dissemination through professional communities in the elderly care industry, the list of attendees at industry conferences, and online professional communities.

2.2.4. Data Analysis and Framework Validation

The objective of this stage is to conduct a systematic analysis of the data collected in stage three using various statistical methods to test the internal structure, reliability, and validity of the ability framework.

The core analytical techniques include: item analysis (critical ratio method and total score correlation method), exploratory factor analysis, and confirmatory factor analysis.

The item analysis of the scale is conducted using the total score correlation method, extreme group comparison method, and homogeneity test. The total score correlation method calculates the Pearson correlation coefficient between a single item and the total score; the difference value of the extreme group comparison result is called the decision value, which is obtained by the T-test of two independent samples and used to measure the discrimination of the scale items; the homogeneity test requires calculating the consistency α coefficient of each item and testing the commonality and factor loadings. Each item's Pearson correlation coefficient should be > 0.4, the decision value should be > 3, and the consistency α coefficient after deleting the item should be < the Cronbach's α coefficient of the total scale, the commonality should be > 0.2, and the factor loadings should be > 0.45. Otherwise, the item should be deleted or modified.

The reliability of the scale is tested using Cronbach's α coefficient, split-half reliability, and test-retest reliability. A Cronbach's α coefficient > 0.7, split-half reliability > 0.7, and test-retest reliability > 0.6 indicate that the reliability test has passed.

Exploratory factor analysis is performed using SPSS 27.0 software. The KMO value is used to determine whether the scale data is suitable for factor analysis. Principal component analysis and variance maximization orthogonal rotation methods are used to extract common factors [16]. The rationality of the scale item setting and dimension division is judged based on the cumulative variance contribution rate of the common factors, the factor loading situation, etc. The cumulative variance contribution rate of the common factors should be > 60%, and the loading of an item on a certain common factor should be > 0.5 as the criterion for item attribution to that common factor. If the loading of an item on each common factor is < 0.5, there is double loading (an item has loading > 0.5 on two or more common factors) or only one item in a certain common factor, then the item should be deleted or revised. If an item is deleted or revised, exploratory factor analysis should be performed again.

Confirmatory Factor Analysis (CFA) was conducted using Amos 26.0 software. The fit, convergent validity, and discriminant validity based on the factor scales obtained from exploratory factor analysis were calculated. The fit was judged based on indicators such as $\left(\chi^2 / df\right)$, root mean square error of approximation (RMR), root mean square error of approximation (RMSEA), incremental fit index (IFI), non-normed fit index (TLI), and comparative fit index (CFI). The fitting situations of different factor combination models were compared using the multi-factor method to test the discriminant validity. If the model based on the factor scales had a higher fit than other models and $P < 0.05$, it indicated that the scale had good discriminant validity.

3. Research Results

3.1. Creation of Initial Capability Items

The research obtained the core competence node system of the Smart Health Care and Service Management major from the core literacy perspective by decoding the textual materials. Based on the principle of indicator construction, the evaluation index system was initially selected, with each index element as shown in Table 1. Through the integration processing of policy text analysis, job task analysis workshops, and semi-structured interviews, a system structure consisting of 4 first-level indicators, 12 second-level indicators, and 25 third-level indicators was constructed.

Table 1. The elements of each indicator in the initial evaluation index system

Primary indicator	Secondary indicator	Tertiary indicator
Digital technology application ability A1	Smart Device Operation & Maintenance B1	Operation of Common Smart Elderly Devices C1
		Daily Maintenance & Fault Handling C2
	Smart Platform & Data Analytics B2	System Ops & Record Management C3
		Service Data Analysis & Application C4
	Tech Awareness & Scenario Application B3	AI & IoT Scenario Recognition C5
		Age-Friendly Smart Environment Renovation C6
Professional care and service capability A2	Comprehensive Elderly Assessment B4	ADL & Cognitive Function Assessment C7
		Mental Status & Social Participation Assessment C8
	Health Care & Rehabilitation Training B5	Chronic Disease Care & Disability/Dementia Support C9
		Daily Living & Cognitive Rehab Guidance C10
	Psychological Support & Communication B6	Psychological Issue Identification & Counseling C11
		Age-Friendly Communication & Trust Building C12
Smart operation and management ability A3	Institutional Operations Management B7	Daily Ops & Personnel Management C13
		Quality Monitoring & Risk Prevention C14
	Case & Community Management B8	Medical-Nursing Case Management & Care Planning C15
		Community Home-Based Smart Health Care Management C16
		Resource Coordination & Referral Across Settings C17
	Innovation & Integration B9	Interdisciplinary Knowledge Integration C18
		Innovative Service Design for Multiple Scenarios C19
Ethics, law and humanistic literacy A4	Regulations & Data Ethics B10	Compliance with Policies, Regulations & Standards C20
		Health Data Privacy & Ethics Compliance C21
	Humanistic Care & Professionalism B11	Practice of Elderly Respect, Care & Protection C22
		Effective Communication & Team Collaboration C23
	Sustainable Development Capacity B12	Lifelong Learning & Self-Improvement Awareness C24
		Career Development Planning & Adaptability C25

3.2. Delphi Expert Consultation Results

3.2.1. Expert Information and Feature Evaluation

The value judgment on indicator selection and the expertise of the experts will influence the final establishment of the core capability system. Therefore, the selected experts should be deeply rooted in the practice of intelligent health care services and management, have a thorough understanding of the development of the discipline of intelligent health care services and management, and be able to propose profound insights on the research topic from practical experience at a high level. In the end, a total of 28 authoritative experts were included in the study. The specific information of the experts is shown in Table 2. Among them, there were 10 male experts and 18 female experts, with a ratio of approximately 5:9. The average age was relatively high, with 32.14% of them being over 52 years old. The experts' professional titles were relatively high, with 82.14% having senior professional titles.

Table 2. Delphi Expert Information

Project	Category	Count	Percentage (%)
Gender	Male	10	35.71
	Female	18	64.29
Age	42~48	4	14.29
	48~52	15	53.57
	>52	9	32.14
Educational qualifications	Undergraduate	7	25.00
	Master	9	32.14
	Doctor	12	42.86
Title	Assistant level	5	17.86
	Senior level	23	82.14
Years of service	10~17	5	17.86
	18~25	7	25.00
	26~33	12	42.86
	>33	4	14.29

The enthusiasm of experts reflects the degree of their support for the research, and is usually measured by the questionnaire response rate or the rate of opinion submission as reference indicators. Among them, the questionnaire response rate refers to the proportion of valid returned questionnaires among the total distributed questionnaires. Generally speaking, a questionnaire response rate of more than 75% indicates good enthusiasm. In this study, the questionnaire response rates for both rounds were 100%, indicating high support from the experts for the research. The expert authority coefficient is a criterion for evaluating the level of expert authority in the research topic. It is usually composed of the basis for experts' answers to questions and the experts' familiarity with the questions. According to the generally accepted standards in the academic community, it is generally considered that the expert authority coefficient should be greater than 0.72. Based on the assigned scores according to the basis for answers and the degree of familiarity, the expert authority calculations for the two rounds of questionnaires were 0.88 and 0.92 respectively, indicating high authority of the consulting experts.

3.2.2. Delphi Consulting Implementation

The scores given by experts for each level of indicators are shown in Tables 3 to 5. They respectively present the scores of the first-level, second-level and third-level indicators. According to the indicator selection criteria, the mean values of the four first-level indicators range from 4.608 to 4.912, and the coefficient of variation ranges from 0.056 to 0.128. All of these meet the inclusion criteria for indicators, indicating that experts have a high level of recognition for the first-level indicators. The mean values of the 12 second-level indicators range from 4.022 to 4.632, and the coefficient of variation ranges from 0.051 to 0.202. All the second-level indicators meet the inclusion criteria. The mean values of the 25 third-level indicators range from 3.874 to 4.676, and the coefficient of variation ranges from 0.094 to 0.439. Some of the indicators have a mean value lower than 4 points, which requires modification of the third-level indicators. At the same time, the range of the coefficient of variation for the third-level indicators is larger compared to the first-level and second-level indicators, suggesting that there are certain differences in expert opinions and the degree of coordination needs to be improved.

Based on the first round of Delphi expert consultation, the scores of indicators C6, C15 and C23 in the third level were all less than 4 points. Therefore, these three indicators - the application of adaptive elderly-friendly smart environment, medical care case management and care plan formulation, and effective communication and expression and team collaboration - were deleted.

Table 3. Score of the primary indicator

Indicators	Mean	SD	CV
A1	4.904	0.109	0.080
A2	4.912	0.111	0.056
A3	4.634	0.29	0.128
A4	4.608	0.152	0.140

Table 4. Secondary indicator score

Indicators	Mean	SD	CV
B1	4.302	0.198	0.081
B2	4.533	0.250	0.085
B3	4.192	0.131	0.122
B4	4.408	0.350	0.099
B5	4.222	0.253	0.122
B6	4.237	0.162	0.134
B7	4.438	0.147	0.202
B8	4.157	0.309	0.139
B9	4.254	0.234	0.152
B10	4.022	0.147	0.051
B11	4.607	0.235	0.195
B12	4.632	0.266	0.13

Table 5. Score of the third-level indicators

Indicators	Mean	SD	CV
C1	4.511	0.097	0.321
C2	4.186	0.226	0.437
C3	4.318	0.109	0.094
C4	4.396	0.302	0.098
C5	4.652	0.255	0.333
C6	3.874	0.133	0.219
C7	4.571	0.206	0.439
C8	4.593	0.104	0.322
C9	4.265	0.105	0.183
C10	4.324	0.312	0.395
C11	4.149	0.322	0.301
C12	4.512	0.32	0.31
C13	4.412	0.337	0.224
C14	4.077	0.263	0.386
C15	3.935	0.318	0.325
C16	4.041	0.193	0.294
C17	4.676	0.077	0.098
C18	4.098	0.109	0.290
C19	4.345	0.134	0.327
C20	4.261	0.207	0.146
C21	4.299	0.309	0.106
C22	4.463	0.327	0.126
C23	3.907	0.311	0.394
C24	4.295	0.215	0.218
C25	4.344	0.247	0.311

After the modification of the indicator system following the first round of Delphi expert consultation, the second round of Delphi consultation was conducted. From the results of the second round of expert consultation, the scores and coefficient of variation of all levels of indicators met the standard requirements, so no further deletion or modification of the indicators was necessary.

Ultimately, this paper determined that the core competence indicator system of the Smart Health Care Service and Management major consists of 4 first-level indicators, 12 second-level indicators, and 22 third-level indicators.

3.3. Results of Exploratory Factor Analysis

Import the collected data from the questionnaire into the software. Select "Analysis - Dimension Reduction - Factor Analysis" from the menu bar, and then select the remaining 22 variables and import them into the "Variables" box. After checking the options for obtaining the analysis process and results, click "OK" to run the program. The following output results can be obtained. The KMO and Bartlett test results are shown in Table 6. It can be seen that the KMO measure value is 0.922, with a significance of 0.000, indicating that there is a strong correlation among the variables in the questionnaire structure, and the analyzed model has good reliability.

Table 6. The results of KMO and Bartlett's tests

The Kaiser-Meyer-Olkin measure of sampling adequacy		0.922
	Approximate Chi-square	23784.221
Bartlett's test for sphericity	df	2214
	Sig.	0.000

Based on the modified ability indicators, the total variance of the indicator explanations is shown in Table 7. The variance proportion of the first principal component extracted is 36.024%, and the cumulative variance proportion of the first 6 principal components reaches 71.164%, which exceeds 70%. Therefore, the first 6 principal components can be used to describe the dimensions of the core abilities of students majoring in Smart Health Care Services and Management.

Table 7. Total variance of indicator explanation

Component	Initial eigenvalue			Extract sum of squares and loadings		
	Total	**Var %**	**Acc %**	**Total**	**Var %**	**Acc %**
C1	32.655	36.024	36.024	32.655	36.024	36.024
C2	12.057	13.301	49.325	12.057	13.301	49.325
C3	7.975	8.798	58.123	7.975	8.798	58.123
C4	4.943	5.453	63.576	4.943	5.453	63.576
C5	3.935	4.341	67.917	3.935	4.341	67.917
C7	2.943	3.247	71.164	2.943	3.247	71.164
C8	2.533	2.794	73.958			
C9	2.427	2.677	76.635			
C10	2.328	2.568	79.203			
C11	2.324	2.564	81.767			
C12	2.314	2.553	84.32			
C13	2.142	2.363	86.683			
C14	2.137	2.357	89.04			
C16	1.482	1.635	90.675			
C17	1.182	1.304	91.979			
C18	1.472	1.624	93.603			
C19	1.453	1.603	95.206			
C20	1.39	1.533	96.739			
C21	1.055	1.164	97.903			
C22	0.792	0.874	98.777			
C24	0.683	0.753	99.53			
C25	0.426	0.47	100			

The load matrix of the six main component factors is shown in Table 8. The meanings of the questions under each of the six factors are relatively concentrated. Based on the specific content of the items, attempts have been made to name the factors.

Factor 1 includes the abilities related to the operation of common smart elderly care equipment, daily maintenance and fault handling of the equipment, operation and record-keeping of the elderly care management system, service data analysis and application, and identification of AI and IoT technology scenarios. It is named "Intelligent Technology Integration Application Ability for Elderly Care".

Factor 2 includes the abilities related to self-care and cognitive function assessment, mental state and social participation assessment, chronic disease management and care for the disabled and demented elderly, and guidance for daily life and cognitive rehabilitation training. It is named "Comprehensive Assessment and Health Care Ability for the Elderly".

Factor 3 includes abilities related to the identification and counseling of common psychological problems, communication skills for adapting to an aging environment and building trust, and daily operation and personnel management of elderly care institutions. It is named "Frontline Service and Basic Management Ability".

Factor 4 includes abilities related to quality control and risk prevention, community and home-based smart health care service management, resource coordination and referral among medical, community, and institutions, and cross-disciplinary knowledge integration and application. These are all related to the professional establishment and subsequent construction, and it is named "System Collaboration and Quality Control Management Ability".

Factor 5 includes the innovation design of multiple scenarios for service solutions, compliance with elderly care policies, regulations, and industry standards. It is named "Innovation, Compliance, and Service Design Ability".

Factor 6 includes the protection of health data privacy and ethical compliance, the practice of "respecting the elderly, respecting the elderly, caring for the elderly, assisting the elderly, and protecting the elderly", lifelong learning and self-improvement awareness, career planning and adaptability. It is named "Ethical Humanities and Sustainable Development Ability".

Table 8. The load matrix of the main component factors

Component	Factor					
	1	2	3	4	5	6
C1	0.843					
C2	0.868					
C3	0.818					
C4	0.837					
C5	0.744					
C7		0.843				
C8		0.663				
C9		0.833				
C10		0.826				
C11			0.886			
C12			0.78			
C13			0.869			
C14				0.844		
C16				0.899		
C17				0.78		
C18				0.839		
C19					0.649	
C20					0.646	
C21						0.674
C22						0.653
C24						0.744
C25						0.804

3.4. Results of Confirmatory Factor Analysis

Confirmatory factor analysis is a research method that explores whether the latent variables and observed variables conform to the predetermined structural relationship based on prior information. It examines whether different items and the overall model reach the expected level. If the results are relatively poor, it indicates that there are pre-established problems in model construction, and the previous steps need to be reviewed and optimized. The evaluation indicators for model adaptation, such as Table 9, are as follows. These indicators correspond to three levels: at the absolute fit index level, the Chi-square degrees of freedom ratio (CMIN/DF) should be less than 3. The result of this model is 2.325, which meets the requirements, indicating that the model fits relatively well. The root mean square error of approximation (RMSEA), root mean square error of residuals (RMR), and standardized root mean square error (SRMR) should be respectively less than 0.05, 0.05, and 0.08. The results of this model are 0.057, 0.038, and 0.042, all meeting the expected requirements. The goodness-of-fit index (GFI) requires its minimum value to be greater than 0.8. The result of this model is 0.882, which is relatively ideal. From the perspective of relative fit indices, the incremental fit index (IFI), non-standardized fit index (TLI), and comparative fit index (GFI) all require their values to be greater than 0.9. The results of this study model are 0.934, 0.927, and 0.945, all meeting the model requirements. From the perspective of parsimonious fit indices, the parsimonious baseline fit index (PNFI) and parsimonious fit index (PGFI) should be greater than 0.5. The results of this model are 0.776 and 0.742, both within the reference standard range.

Table 9. Model Adaptation Index Evaluation Metrics

Evaluation Metrics	Reference Range	Result	Fitting status
Absolute Fit Index			
CMIN/DF	Good<3,Reasonable<5	2.325	Ideal
RMSEA	Good<0.05,Reasonable<0.08	0.057	Ideal
RMR	Good<0.05,Reasonable<0.08	0.038	Ideal
SRMR	Good<0.05,Reasonable<0.08	0.042	Ideal
GFI	Reasonable>0.80,Good>0.85	0.882	Ideal
Relative Fit Index			
IFI	>0.90	0.934	Ideal
TLI	>0.90	0.927	Ideal
CFI	>0.90	0.945	Ideal
Simplicity fitting index			
PNFI	>0.50	0.776	Ideal
PGFI	>0.50	0.742	Ideal

Based on the above analysis, it can be concluded that the confirmatory factor analysis model constructed in this study is overall free from directional and structural errors. Both the item factor loadings and the overall fit of the model meet or are close to meeting the requirements of relevant indicators.

4. Conclusion

This research focuses on the core competence system of the Smart Health Care Service and Management major. In the qualitative stage, the structure distribution of the competence indicators was established by integrating the analysis of data texts and expert interviews. In the quantitative stage, the score of the measurement indicators was determined using the Likert five-level scale. Through exploratory factors, confirmatory factors, fit degree and adaptation index and other characteristic indicators, the competence indicators were verified. After the Delphi expert consultation, the research determined a professional core system of 12 secondary indicators and 22 tertiary indicators. Through exploratory analysis, six main component factors of smart elderly care digital technology integration application ability, comprehensive assessment and health care ability for the elderly, front-line service and basic management ability, system collaboration and quality control management ability, system collaboration and quality control management ability, and ethics, humanities and sustainable development ability were extracted. Based on the calculation results of exploratory factor analysis and confirmatory factor analysis, the applicability of the competence structure model was quantitatively verified.

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