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Synergistic optimization of nursing services and health management in geriatric healthcare education under the medical-care integration model

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SUMMARY: *The integration of medical care and elderly care is a new approach that combines the provision of healthcare services and elderly care services, enabling their development through integration. However, some issues have emerged during its implementation, including poor nursing services' quality and the relatively low health management standards. This paper aims at investigating how advanced algorithms, big data technology, and cloud computing can be integrated and used in nursing information platforms under the condition of healthcare and elderly care service requirements. Decision tree algorithms and association rule algorithms will be used for mining the relationship data about nursing services associated with various factors in order to establish a nursing information platform suitable for the elderly's health management needs. Based on the sample data provided by 36,981 elderly people in District A of a city, four factors affecting the required nursing time were discovered: the ability for independent living, health state, living conditions, and the residential form. With the help of the designed nursing information platform, participants obtained the result scores ranging from 76 to 88 in terms of mental, physical, and social environments.*

KEYWORDS: *nursing services; nursing information platform; decision tree; association rules; elderly health management; medical-nursing integration*

1 Introduction

According to the information provided by WHO, the phenomenon of aging has accelerated globally since the 1950s. The number of the world's population aged over 60 years is projected to grow up to 2 billion by 2050 and account for one-third of the entire population on Earth [1]. On the other hand, the physical abilities of elderly people including mobility, sensory perception, cognition, and immune system deteriorate with age. Moreover, the incidence of many chronic diseases such as diabetes (projected to affect about 180 million people by 2030) grows [2-5]. Mental health conditions caused by physical problems, social alienation, and shrinking social network are another challenge associated with aging [6]. Thus, the conventional approach to treatment of these health-related issues becomes less efficient in terms of addressing emerging challenges of the elderly population. As a result, the new integrated model was created.

This innovative model integrates medical care and elder care to provide comprehensive personalized health and aging-related services [7]. According to the key principle, namely the necessity to consider "prevention as the primary focus, supplemented by rehabilitation," this approach is aimed at improving the quality of health and life of senior citizens. This service

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includes the daily care concerning both the health and physical well-being of individuals. However, the application of medical technologies, treatment, and rehabilitation is also crucial within the framework of the proposed service [8-10]. Within the scope of the relevant policy, this innovation has shown high potential regarding improvement in the quality of life, recovery, and slowing down of the aging process [11-13].

In light of the problem of healthy aging becoming more topical in society, the implementation of health education for elderly citizens seems to be especially important. Studies suggest that rational scientific health management can prevent 40 percent of chronic diseases as well as alleviate depressive symptoms in elderly patients [14, 15]. Health education for the elderly disseminates knowledge and intervenes in behaviors through symptom explanation and health guidance, aiming to enhance the physical and mental well-being of older adults and achieve healthy longevity [16, 17]. Zhang et al. [18] investigated the demand for healthy aging care services among the elderly, including but not limited to medical care, psychological counseling, nursing, diet, and facilities. However, there remains a significant disconnect between nursing services and health management within health education for the elderly.

Second, with the development of science and technology, various technologies have been used to provide elderly health services to record the physical conditions of senior citizens. Nevertheless, information silos and deficiencies in information coordination still exist [19-21]. In other words, insufficient information coordination between elderly health record system and care service record system resulted in repeated tests of the associated items. Through survey research, Svensson [22] identified some problems such as inconsistent communication among health professionals, inadequate information sharing, different IT system application by different health organizations, and the difficulty in coordinating different health institutions. Melin Emilsson et al.[23] investigated the role of coordination difficulties between healthcare organizations and social care institutions in multidisciplinary teams that provided holistic care for the elderly with comorbidities, which were caused by professional barriers, competition, and geographical barriers.

Third, there is institutional fragmentation in elderly health services, in which medical institutions concentrate on treatments and rehabilitation, nursing institutions pay attention to health, and community services target basic care for senior citizens. According to Hansen et al.[24], due to restricted policy arrangements, hospital nurses and home nurses depended entirely on the electronic health record system for communication when the elderly transitioned from hospital to home, making face-to-face communication necessary. Lemetti et al. [25] agreed that communication and collaboration between hospital nurses and nurses working in primary care facilities should be carried out to ensure continuous elderly health services. Hu et al. [26] pointed out that there was institutional fragmentation between medical institutions and care facilities and proposed integrating geriatric medicine and care together.

Furthermore, a severe shortage of professional geriatric care personnel exists, with most providing basic care as volunteers, leading to inadequate elderly health management. According to survey data by Li et al. [27], only 53.4% of nursing assistants in relevant healthcare facilities held valid practice certificates, and over 85% of caregivers reported that video-based training alone was insufficient, indicating a need for more comprehensive training. Soares et al.'s [28] research revealed that, beyond basic care competencies, older adults highly value interactive, communicative, and emotional-social skills in healthcare professionals. This further underscores the critical importance of professional caregivers in delivering geriatric care services and health management.

Finally, as intelligent healthcare services advance, their technological limitations become increasingly apparent. The coverage of smart monitoring devices in nursing services remains insufficient to address current and future elderly health management needs. Although fall prevention and other early warning systems are under continuous development and deployment, response delays persist [29-31]. Currently, most countries face constraints in home care service development due to limitations in public healthcare systems and commercial insurance coverage. Fang et al. [32] note that the United Nations requires countries to establish healthcare systems achieving universal health coverage by 2030, promoting high-quality medical services for individuals and communities. Tipirneni et al .[33] further clarified the correlation between health insurance literacy and the likelihood of delaying or forgoing medical services due to costs, demonstrating that higher literacy levels reduce this probability. This indicates that disseminating relevant knowledge and education to older adults can enhance elderly care services and health management levels. Rudnicka et al. [34] pointed out that the WHO's Healthy Aging approach promotes healthy aging by coordinating preventive health and social health. This is achieved by providing comprehensive care human resources, promoting the global campaign against ageism, and strengthening the global network of age-friendly communities in cities. This approach embodies a multidimensional health care model integrating medical care, nursing, and social support. Therefore, synergistic optimization of care services and health management is imperative.

This paper first examines the causes and current status of healthcare and elderly care service demands among the elderly, establishing the theoretical foundation for the study. Second, it clarifies the implementation pathways for advanced algorithms, big data technology, and cloud computing within the health management care information platform. This informs the design of clinical care information systems, care management information systems, and intelligent decision support systems. It further explains the operational steps of decision tree algorithms and association rules as data mining solutions for the platform. Third, it selects research subjects, statistically analyzes and codes their characteristic data to form a sample dataset. Subsequently, analyze the differences in care requirement levels and nursing time among sample subjects. Conduct quantile regression analysis on nursing time to identify influencing factors and construct a decision tree model for elderly care time. Finally, apply the designed nursing information platform in practice. Create an experimental group and a control group and analyze the pre-and post-intervention data in six physical parameters and three quality of life assessment sections, thus assessing the feasibility of the platform.

2 The Emergence of Demand for Healthcare and Elderly Care Services

2.1 Demand for Healthcare Services

There are three main kinds of diseases that affect the elderly population, namely diseases that affect people at all ages, such as a cold and diseases of common parts; diseases that affect people from middle ages to old ages, such as hypertension and bronchitis; diseases that only affect elderly people, such as senile dementia and osteoporosis. When aging starts, internal organs in the human body begin to change and deteriorate due to their decreased ability to self-repair, which affects the functioning of different organs and tissues. Consequently, there is an increased risk of diseases associated with both the second and the third category. The current status of diseases among the elderly population is investigated based on the Chinese Health Insurance Research Association database, and the analysis focuses on the top twenty diseases that account for the highest percentage of cases (Table 1).

Table 1: The distribution of diseases among the elderly

Sort	Disease	Disease system	Proportion (%)
1	High blood pressure	Circulatory	46.19
2	Heart disease/coronary heart disease	Circulatory	24.52
3	Arthritis	Motor	24.46
4	Cervical/lumbar spondylosis	Motor	24.39
5	Rheumatoid	Immune	18.11
6	Cerebrovascular disease	Nervous	14.53
7	Gastroenteritis or other digestive system diseases	Digestive	14.36
8	Diabetes	Endocrine and metabolic	13.07
9	Glaucoma with cataract	Else	11.52
10	Chronic bronchitis/other respiratory diseases	Respiratory	10.56
11	Fracture/Osteoporosis	Motor	10.31
12	Disease of prostate	Endocrine and metabolic	7.68
13	Kidney disease	Urinary	5.28
14	Hepatic disease	Digestive	4.1
15	Diseases of urinary system	Urinary	3.7
16	Nervous system disease	Nervous	3.33
17	Alzheimer's Disease	Nervous	3.16
18	Tuberculosis	Respiratory	2.78
19	Malignant tumor	Immune	2.55
20	Parkinson's disease	Nervous	2.33

Eleven elderly diseases each accounted for over 10% of cases, ranked as follows: hypertension, heart disease/coronary heart disease, arthritis, cervical/lumbar spine disorders, rheumatoid arthritis, cerebrovascular disease, gastroenteritis or other digestive system diseases, diabetes, glaucoma/cataracts, chronic bronchitis/other respiratory diseases, and fractures/ osteoporosis, accounting for 46.19%, 24.52%, 24.46%, 24.39%, 18.11%, 14.53%, 14.36%, 13.07%, 11.52%, 10.56%, and 10.31% respectively. Circulatory and musculoskeletal disorders predominate, with others distributed across the immune, nervous, digestive, endocrine, and metabolic systems. Among the 20 disease categories, nervous system disorders were the most numerous, accounting for one-fifth of cases. These included cerebrovascular disease, Alzheimer's disease, Parkinson's disease, and others. Such systemic diseases are typically challenging to treat and often require rehabilitation therapy following primary treatment. Among diseases affecting the elderly, chronic conditions like hypertension and diabetes frequently co-occur. 68.96% of seniors suffer from at least one chronic disease. Among those with chronic conditions: - 47.81% have one chronic disease - 23.26% have two chronic diseases - 29.01% have three or more chronic diseases these conditions necessitate long-term treatment and chronic disease management.

2.2 Demand for Elderly Care Services

With the decreasing functioning capacity of their bodies, the capacity of elders to survive on their own varies in levels and is, therefore, reliant on help from others. The result is that there arises a need for the provision of services aimed at taking care of the elderly people, either in terms of daily living or in medical nursing where the person cannot fully rely on himself/herself. In terms of current definitions of long-term care, it means basic support needed on a day-to-day basis, including nursing services related to health care needs. This study is based on an analysis of the combined medical and elderly care service system, and as such, the latter takes precedence care associated with health care needs. Table 2 details medical care items required by the elderly due to illness. According to the detailed medical treatment records disclosed in the CHIRA database, the nursing services utilized by the elderly due to illness include various levels of care such as special care, Level I care, Level II care, and Level III care, as well as specialized care such as pressure ulcer care, suctioning care, and tracheostomy care. Among these, Level II care accounted for the largest proportion of usage, approximately 59.82%, followed by Level I care at approximately 27.84%. The utilization rate for specialized care services was less than 5% for each category.

Table 2: The items of elderly care services and their proportions (%)

Nursing program	Proportion
Intensive care	3.68
Level I nursing	27.84
Level II nursing	59.82
Level III nursing	9.35
Cure and Nursing	1.87
West China Medical Journal	6.54
Care for tracheotomy	2.37
Protective isolation care	1.87

3 Development of a Nursing Information Platform for Elderly Health Management

Based on the analysis of healthcare service demand and elderly care service demand presented in Chapter 2, this paper integrates technologies such as the Internet of Things (IoT), data mining and machine learning algorithms, and cloud computing to establish a comprehensive elderly health management service platform in this chapter. This platform integrates health monitoring, data analysis, intelligent nursing, and resource allocation.

3.1 Research on Key Technologies

3.1.1 Application of Advanced Algorithms in Nursing Information Platforms

Within the nursing information platform, the integration of advanced algorithms such as deep learning (particularly convolutional neural networks (CNN) and recurrent neural networks (RNN)) alongside neural networks (like long short-term memory (LSTM) networks) has significantly enhanced the precision and speed of health data analysis. This enables the platform to deliver more intelligent and personalized nursing services. Simultaneously, by training models on vast amounts of annotated health data, the platform can automatically detect subtle fluctuations in elderly patients' physiological indicators—such as heart rate variability and blood pressure trends—using algorithms, thereby precisely identifying changes in their health status.

3.1.2 Application of Big Data Technology in Elderly Health Management

Application in the fields of health risk assessment, disease prediction, and resource allocation in healthcare. For example, through the use of Hadoop distributed file system technologies to store health data, and by applying the Spark big data processing technology to conduct real-time analysis, the processing speed and analysis capability of elderly health data is greatly improved. In addition, through collecting various kinds of data related to the elderly, the platform forms a complete profile that includes physiological information, medical records, and lifestyle of the elderly.

3.1.3 Application of Cloud Computing Technology in Nursing Information Platforms

The application of cloud computing technology to the nursing information platform provides solid support for data storage and data processing, which allows health data to be stored by cloud storage such as Amazon S3. Cloud services such as Amazon Elastic MapReduce can also be used for large-scale data processing. Through cloud computing, the health information of elderly people can be synchronized and shared in real-time through any device, including smartphones and tablets. The cost of using the cloud computing technology will be lowered as well, allowing the platform to concentrate more on innovations, such as building better analytical software and health management software.

3.2 Design of Platform Modules

3.2.1 Clinical Nursing Information System Module

Clinical Care Information System (CCIS) is a crucial module that stores, manages, and analyzes clinical information of elderly patients. It consists of the following components: Electronic Medical Record System, Nursing Documentation System, and Medication Management System. Firstly, the Electronic Medical Record System contains all relevant patient data (such as personal information, medical history, diagnosis, and treatment). Secondly, the Nursing Documentation System tracks all care services provided to elderly patients (including monitoring of vital signs and nursing procedures). Thirdly, the medication management system creates medication schedule based on medical prescriptions and uses intelligent reminders for elderly patients' medication adherence.

3.2.2 Nursing Management Information System Module

Nursing Management Information System (NMIS) focuses on nurse resource allocation and management. It is made up of the following three systems: Nursing Human Resource Management System, Nursing Scheduling System, and Nursing Quality Monitoring System. Firstly, the Nursing Human Resource Management System provides real-time monitoring of nurses' working conditions and adjusts their number according to current needs. Secondly, the Nursing Scheduling System creates the best shift roster by allocating nurses to appropriate shifts according to their skills and abilities. Thirdly, the Nursing Quality Monitoring System analyzes nursing documentation to monitor the quality of care.

3.2.3 Intelligent Decision Support System Module

In addition, the Intelligent Decision Support System module is equipped with various technologies such as data mining, machine learning, etc., for conducting an intensive analysis of health data of older adults and giving decision support to the relevant experts. Specifically, the module is comprised of the Health Risk Assessment System, Disease Prediction System, and Resource Optimization System. Firstly, the Health Risk Assessment System makes assessment of the level of health risks according to physiological indicators and lifestyles of older adults and gives corresponding health management proposals. Secondly, the Disease Prediction System predicts possible diseases and their possibilities based on historical data.

Thirdly, the Resource Optimization System puts forward optimization plans by taking into account the distribution of medical resources and ensuring their effective use.

3.3 Data Mining Solutions

3.3.1 Decision Tree Algorithm

As one of the most widely studied topics in data mining studies, various types of decision tree algorithms have emerged. One of the earliest and most influential decisions of decision tree algorithms is ID3, which uses information gain as its splitting criteria when constructing decision trees. As a follow-up to ID3, the C4.5 decision tree algorithm was proposed. In addition to the same idea of constructing the decision tree, C4.5 introduced another splitting criteria, i.e., information gain ratio, thus solving the problem of biasing towards multivalued attributes that existed in ID3. Therefore, C4.5 is accepted as the standard solution to the problem. C5.0 is the commercial version of C4.5 and follows the same approach, but it uses novel strategies.

However, what is essential in decision tree algorithms is how to learn from training samples and build a decision tree classifier. The specific steps for inductively deriving a decision tree from training samples are described below.

Let the training sample set be denoted as T, and the class set be represented by $\{C_1, C_2, \ldots, C_k\}$. The contents within dataset T encompass three possible scenarios:

(1) Dataset T contains at least one sample where all samples belong to a single category C_j from the category set, where $1 \le j \le k$. In this case, the decision tree generated from dataset T is a leaf node with class label C_j;

(2) Dataset T contains no samples. In this case, the decision tree generated from T is also a leaf node. Its class label is not determined by T itself but can be assigned based on the frequent class in T's parent node;

(3) The dataset T has multiple samples belonging to different class labels. It is then necessary to divide the dataset T into multiple data subsets. The division is done by selecting an attribute V in the sample data by a suitable splitting criterion, where the attribute V has n different values $\{V_1, V_2, \ldots, V_n\}$, and then splitting the set T into n subsets based on the attribute V $T_1, T_2, \ldots, T_n$, where the subset T_i is a sample of the dataset T whose attribute V value is V_i.

Repeat this decision tree construction procedure for each subset T_i of the dataset T. Construct the ith branch of the decision tree using the subset of training samples T_i. Continue partitioning the set of training samples until all training sets fall into either the first or second case.

The original ID3 algorithm used information gain as a splitting criterion for selecting attribute V when partitioning the dataset T, where information gain is based on the concept of entropy in information theory. From the knowledge of information theory, it is understood that the smaller the expected information, the larger the information gain and thus the purity of each partition. Therefore, ID3 selects the attribute with large information gain for splitting each time the dataset T is split.

Let $|T|$ be the number of samples in the dataset T, and $freq(C_i, T)$ be the number of samples in T belonging to C_i, the formula for the entropy of the training sample set T is shown in Equation (1):

$$Info(T) = -\sum_{i=1}^{k}\left(\left(\frac{freq(C_i,T)}{|T|}\right)\cdot\log_2\left(\frac{freq(C_i,T)}{|T|}\right)\right) \tag{1}$$

The data set T is split according to the attribute V. The expected information is calculated as in equation (2):

$$Info_V(T) = -\sum_{i=1}^{n}\left(\left(|T_i|/|T|\right)\cdot Info(T_i)\right) \tag{2}$$

The information gain is the difference between the entropy and the desired information and is calculated as in equation (3):

$$Gain(V) = Info(T) - Info_V(T) \tag{3}$$

There is a problem with ID3 using information gain as a splitting rule, which favors attributes with more values. To overcome this defect of ID3 algorithm, C4.5 algorithm is designed to use information gain rate as a splitting criterion for attributes, the information gain rate is based on the information gain with an extra parameter, and the calculation formula is similar to the definition of entropy of ID3 algorithm as in Equation (4):

$$Split\_info(V) = -\sum_{i=1}^{n}\left(\left(|T_i|/|T|\right)\cdot\log_2\left(|T_i|/|T|\right)\right) \tag{4}$$

The information gain rate is calculated as equation (5):

$$\text{Gain\_ratio(V)=Gain(V)/Split\_info(V)} \tag{5}$$

3.3.2 Association rules

In data mining research, correlation analysis is one of the most active research methods, which is often used to mine out the correlations between data items from a large amount of data. In the early days, association analysis was earlier applied to the analysis of people's shopping habits, through mining and analyzing the intrinsic connection of people's purchase of goods, to find out the association rules between different goods, and thus the pattern of customers' shopping behavior, in order to formulate a better sales strategy, and to achieve the purpose of increasing sales.

To understand the association rules, we must first understand the following concepts:

(1) Item Set: Let $I = \{i_1, i_2, \ldots, i_n\}$ denote a set composed of n distinct items, where $i_k\,(k = 1, 2, \ldots, n)$ represents the kth data item and n is the length of set I. Then set I constitutes an item set;

(2) Transaction: Let T denote a non-empty subset of data item set I, i.e., $T \subseteq I$. T constitutes a transaction, each of which contains a unique transaction ID (TID). All transactions collectively form a transaction database D;

(3) Support: Let A be a data item set. A transaction T contains A, i.e., $A \subseteq T$. Association rules are expressed as $A \Rightarrow B$, where A is the antecedent and B is the consequent. Both A and B are non-empty sets, $A \cap B$ is the empty set, and $A \subset I$ and $B \subset I$ hold. A rule $A \Rightarrow B$ holds in transaction database D if its support s is the percentage of occurrences of $A \cup B$ in all transactions in D, i.e., the probability $P(A \cup B)$. The definition of support s

is given by formula (6);

$$\text{support}(A \Rightarrow B) = P(A \cup B) = \frac{|A \cup B|}{|D|} \tag{6}$$

(4) Confidence: let c be the confidence level that the rule $A \Rightarrow B$ has in the transaction database D, where c is the percentage of the number of occurrences of $A \cup B$ in relation to the number of transactions that contain A in the transaction database D, i.e., the conditional probability $P(B | A)$, and the confidence level s is defined as in Equation (7);

$$\text{confidence}(A \Rightarrow B) = P(B | A) = \frac{|A \cup B|}{|A|} \tag{7}$$

(5) Frequent item set: set min_sup as the minimum support interval value, that is, in the application of association rules mining data items should meet the minimum support interval value, which takes the value of 0% to 100%, then the item set that meets the minimum support min_sup is known as the frequent item set;

(6) Strong association rule: set min_conf as the minimum confidence interval value, which is defined as the same as the minimum support interval value. Rules that satisfy both min_sup and min_conf are called strong association rules.

The mining process of association rules can be simply summarized into two steps. The first step is to find out all the frequent itemsets that satisfy the minimum support, and then the strong association rules are generated from the obtained frequent itemsets.

4 Nursing service optimization based on nursing information platform

In this paper, a total of 38623 elderly people over 60 years of age in street A of a city were selected as the research sample, and a comprehensive questionnaire and interview were used to collect 11 basic factor characteristics of the sample subjects. The 11 basic factors are: gender, age, residence status, spouse status, children's status, education level, type of place of residence, self-care ability, health, source of living and medical insurance. A total of 38623 questionnaires were distributed and 36981 valid questionnaires were recovered, with a validity rate of 95.75%. The questionnaire data were sorted out to form a research dataset, on which the mining of association rules of elderly care needs and the construction of system decision tree were carried out sequentially in this chapter to provide data support for the optimization of care services and application analysis of the designed care information platform.

4.1 Factors associated with demand for care

In this section, we initially selected the self-care ability of the elderly as an important factor influencing the duration of demand for care services, so as to further explore other relevant factors.

4.1.1 Sorting and Coding of Sample Data

Before mining the correlation rules between different elderly care service demand factors, it is necessary to code the basic factor data, and the basic coding rules of the data in this paper are as follows:

(1) Gender coding: G1=female, G2=male.

(2) Age coding: A1=[60,65), A2=[65,75), A3=[75,85), A4=[85,95), A5=[95,120).

(3) Residence status codes: L1=living with family, L2=living alone, L3=nursing facility.

(4) Spouse status codes: S1=Married and living with spouse, S2=Married but not living with spouse, S3=Divorced, S4=Widowed, S5=No history of marriage.

(5) Codes for children: C1=no children, C2=only child, C3=2-5 children, C4=more than 5 children.

(6) Codes for educational attainment: E1=never attended school, E2=did not graduate from elementary school, E3=elementary school, E4=junior high school, E5=high school, E6=junior college and above.

(7) Codes for type of residence: T1=main urban area, T2=urban-rural area, T3=town center area, T4=special area, T5=village.

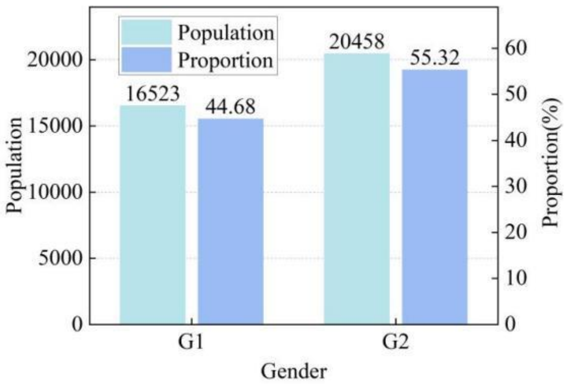
(8) Coding of self-care ability: D1=Living on one's own without difficulty, D2=Living partially on one's own and needing help, D3=Living beyond one's reach.

(9) Codes for health status: H1=excellent, H2=very good, H3=good, H4=fair, H5=bad.

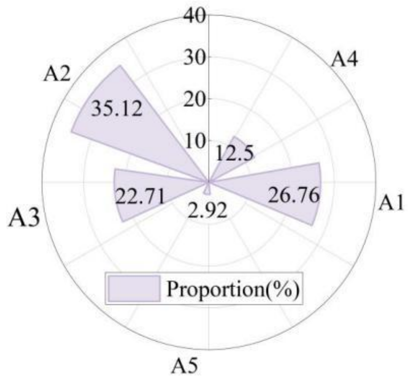
(10) Codes for sources of livelihood: I1=pension, I2=own labor or work, I3=child support, I4=other relatives, I5=local government or community, I6=spouse's income, I7=no source of livelihood.

(11) Health insurance codes: M1=with health insurance, M2=no health insurance.

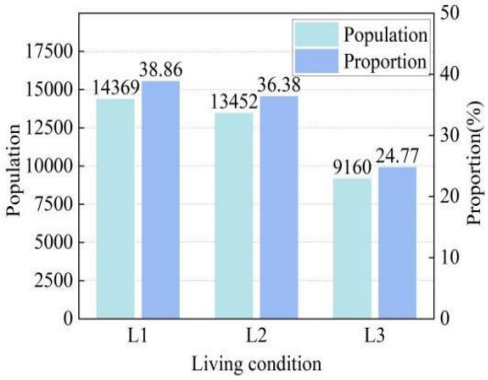
Data from 36,981 questionnaires were entered into the designed information platform, and the combing of the data for the 11 factors is shown in Figure 1(a)-(k). Sample subjects were slightly more male older adults at 55.32%, with the highest number (35.12%) in the [65,75) age group. 38.86% of the elderly currently live with their families, 48.39% are married and live with their spouses, and 42.32% have 2-5 children. The education level of the sample was mainly concentrated in the pre- and post-primary level, with a combined percentage of 71.04%. The place of residence of the sample was mainly villages (29.42%), and 30.91% of the sample were able to take care of part of their own lives, but needed assistance. As many as 37.44% of the sample were in average health, 26.34% of the elderly obtained their livelihood through their own labor and work, and only 26.04% of the elderly had health insurance.



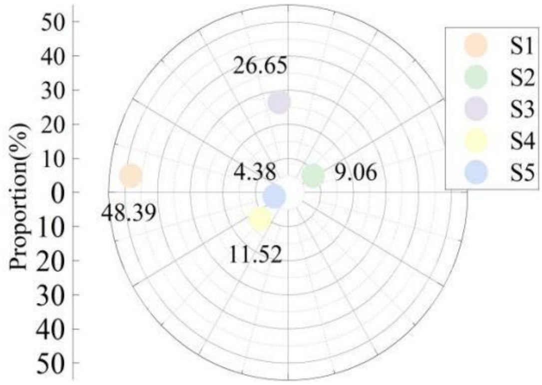
(a) Gender



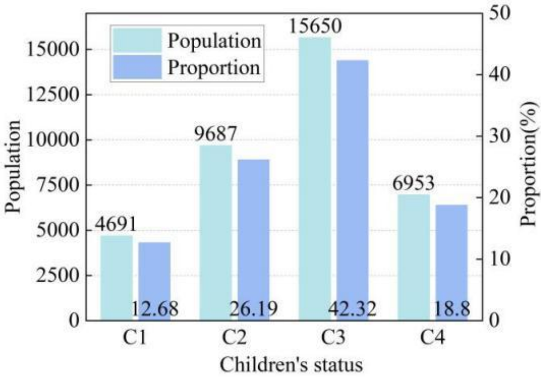
(b) Age



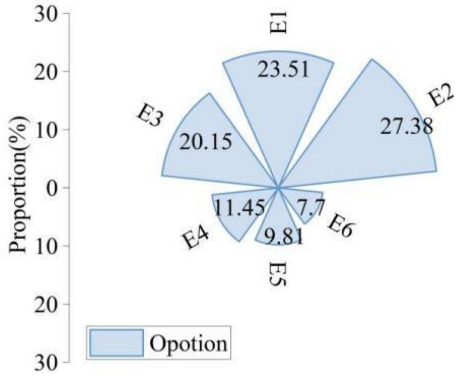
(c) Living condition



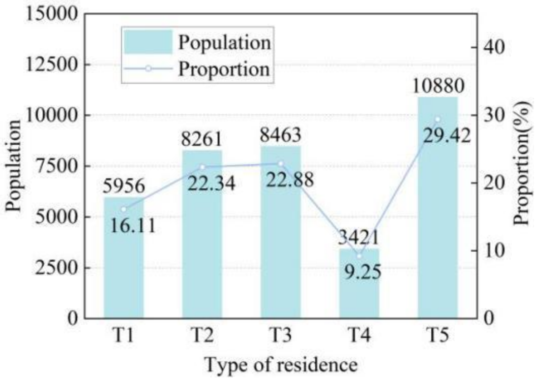
(d) Spouse status



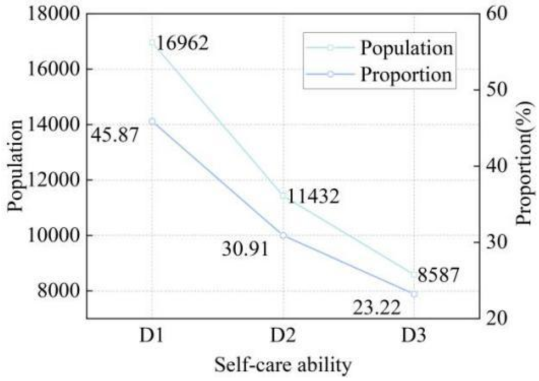
(e) Children's status



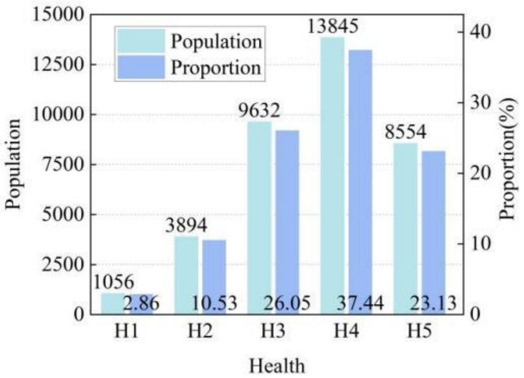
(f) Education



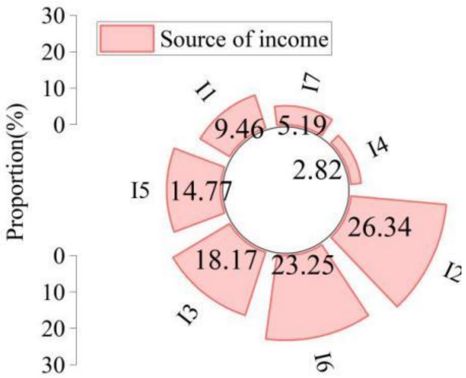
(g) Type of residence



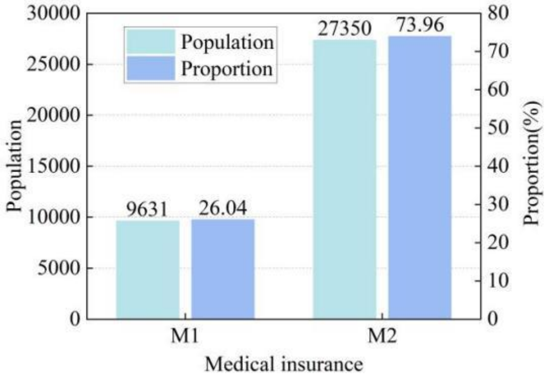
(h) Self-care ability



(i) Health



(j) Source of income



(k) Medical insurance

Figure 1: Statistics on the basic situation of the research sample

4.1.2 Mining association rules

Based on the survey statistics from the previous subsection, the current self-care abilities of the research sample are as follows: (D1) Independent in daily living, no difficulties (45.87%), (D2) Partially self-sufficient, requiring assistance (30.91%), and (D3) Unable to care for oneself (23.22%). By inputting minimum support and minimum confidence thresholds into the care management information system module of the designed platform, association rules were mined. Taking the first two categories as examples, the mining results and analysis are as follows:

(1) Fully self-sufficient, no difficulties

This category represents the largest proportion of elderly data, totaling 16,962 records. To avoid excessive frequent sets, the minimum support threshold was set at 0.15 and confidence at 0.85. The intermediate results for mining information related to "(D1) Independent in daily living, no difficulties" are shown in Table 3. Elderly individuals in this category who live with family members are capable of self-care and are typically accompanied by a spouse. Elderly individuals supported by their children are more inclined toward family-based care. The greater the number of children, the more likely the elderly are to choose to live with family members for their care.

Table 3: Living with Family Part Mining Intermediate Results

Antecedent	Consequent	Sustain degree	Confidence coefficient
[T1,H3]	D1	0.05	0.92
[S1, H3]	D1	0.07	0.99
[G2, S1, H3, I3]	D1	0.06	0.96
[A2, H3, G2]	D1	0.05	0.92
[S1, H2, I3]	D1	0.08	0.94

(2) Partially self-sufficient in daily living, requiring assistance

Set the minimum scale threshold to 0.02 and the confidence level to 0.05. Intermediate results and analysis of information mining for elderly individuals categorized as "(D2) Partially self-sufficient in daily living, requiring assistance" are presented in Table 4. Most individuals in this category have 2–5 children, rely on their children for support, reside with their children in urban centers or urban-rural fringe areas, have generally good health, and possess relatively comprehensive medical insurance coverage.

Table 4: Old Man Living Alone Part Mining Intermediate Results

Antecedent	Consequent	Sustain degree	Confidence coefficient
[C3, H4, S4,L1]	D2	0.04	0.14
[S1, H3,M1,L1]	D2	0.03	0.08
[C2, H3, T5]	D2	0.04	0.13
[A3, H4, G2, I3]	D2	0.02	0.35
[C3, T2,I1,M1]	D2	0.02	0.09
[H4, I3,L1]	D2	0.03	0.27

4.2 Nursing Time Decision Tree Model

The duration of nursing care directly reflects the level of care service needs for individual elderly individuals. This section explores the relevant factors influencing nursing time and constructs a decision tree model for determining nursing time.

4.2.1 Care Need Level and Nursing Time

As is seen from the previous section, 54.13% of the sample population consisting of 20,019 elderly cannot take proper care of themselves. Out of this number, 11,432 elderly individuals need some help to carry out their everyday tasks, whereas 8,587 elderly individuals have to be totally dependent on others regarding self-care. The self-care capability of the elderly varies with their care requirements, which range from level zero to level five in increasing order of care requirements.

This sub-section presents comparison between the nursing time needed by individuals having various care requirement levels as illustrated in Table 5. It can be observed that the differences in nursing time between levels 0–1, 0–2, 0–3, 1–3, and 3–4 did not reach statistical significance ($P > 0.05$). However, differences in nursing time between all other care requirement levels exhibited varying degrees of statistical significance ($P < 0.05$).

Table 5: Comparison of care time for different levels of care needs

Comparison of care needs levels	Test statistics	Standard test statistics	Significant
0 vs 1	-21.211	-0.033	1.000
0 vs 2	-56.403	-0.775	1.000
0 vs 3	-137.029	-2.242	0.087
0 vs 4	-196.211	-3.415	0.000
0 vs 5	-281.68	-5.021	<0.001
1 vs 2	-20.403	-0.24	1.000
1 vs 3	-101.029	2.929	0.205
1 vs 4	-160.211	-3.346	0.001
1 vs 5	275.258	-5.254	0.000
2 vs 3	-65.837	-2.62	0.032
2 vs 4	-125.019	-5.749	<0.001
2 vs 5	-210.488	-9.826	<0.001
3 vs 4	-44.393	-2.39	0.057
3 vs 5	-129.862	-6.769	0.000
4 vs 5	-70.68	-5.183	0.000

4.2.2 Quantile Regression Analysis of Elderly Care Time

Based on the preceding discussion and practical circumstances, this study employs elderly care time as the dependent variable and preliminarily selects (T) residence type, (L) living conditions, (D) self-care ability, (H) health status, and (M) medical insurance as independent variables for quantile regression analysis (see Table 6). Among these, (D) self-care ability and (H) health status exhibit statistical significance (*P*<0.01) across all quartiles from the low (10%) to high (90%) quartiles of direct care time for the elderly. Their standardized regression coefficients increase from 5.332 to 26.137, and 0.232 to 4.403, respectively, with their impact intensity increasing as the quantile rose. (L) Living arrangements showed statistical significance across all quantiles (20%–80%) for direct care time (*P*<0.01), with the standardized regression coefficient increasing from 4.972 to 13.332. (T) Type of residence only influenced direct care time at the lower deciles (10%-40%) (*P*<0.01). (M) Health insurance had no effect on care time across all deciles.

Table 6: Quantile regression analysis of nursing duration

Quantile	Nodal increment	T	L	D	H	M
q10	-10.378*	8.798***	-0.468	5.332**	0.232*	4.242
q20	-10.882**	3.225***	4.972**	8.748***	0.631*	3.389
q30	-12.518***	2.328**	10.373***	9.315***	0.832*	2.597
q40	-13.919***	3.739*	11.794***	10.634***	2.224**	4.509
q50	-15.801**	5.059	12.096***	11.986***	2.608**	7.279
q60	-19.163	10.132	11.515***	14.714***	3.104**	7.771
q70	-12.864	6.527	13.332***	19.037***	3.113**	6.785
q80	-11.887	8.702	9.259***	24.484***	3.143**	5.094
q90	-1.589	5.967	5.683	26.137***	4.403***	7.251

*:*P*<0.05,**:*P*<0.05,***:*P*<0.05

4.2.3 Decision Tree Model for Elderly Care Timing

This section constructs a nursing time decision tree variable with nursing time as the dependent variable and self-care ability, health status, and living conditions as explanatory variables. Ultimately, three predictor variables—(F1) eating, (F2) vision and hearing, and (F3) toileting, facial/oral care, and body hygiene—are incorporated into six groups (see Figure 2). The scores for all three predictor variables are uniformly set to 10 points across different nodes.

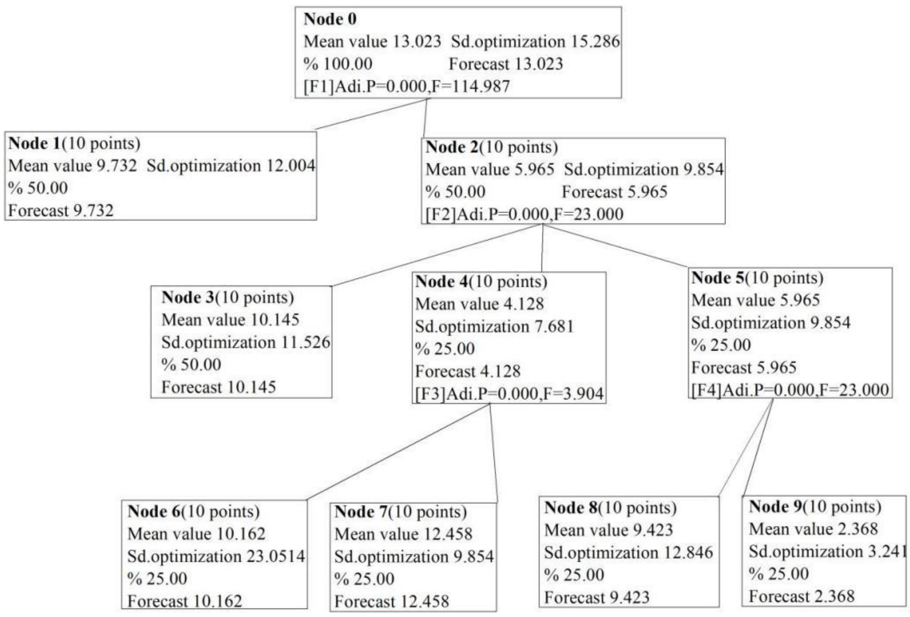


Figure 2: Decision tree model for elderly care time

Based on the decision tree model in Figure 2, the six groups of nursing time are summarized in Table 7. The nursing time for the six groups is as follows: 41.61 (22.63, 69.87) min/d, 30.35 (13.51, 54.82) min/d, 21.97 (8.41, 32.18) min/d, 20.33 (6.29, 34.67) min/d, 29.95 (12.36, 47.58) min/d, and 21.15 (10.89, 39.66) min/day. Nonparametric testing of the six nursing time groups yielded H = 204.681, P < 0.001, indicating significant intergroup differences. The model's R^2 = 0.4523, indicating that the model explains 45.23% of the variance in nursing time for the elderly.

Table 7: The results of the nursing time decision tree model

Node	Proportion (%)	Direct care time[(min/d),M(P_{25},P_{75})]
1	50.00	41.61(22.63,69.87)
3	50.00	30.35(13.51,54.82)
6	25.00	21.97(8.41,32.18)
7	25.00	20.33(6.29,34.67)
8	25.00	29.95(12.36,47.58)
9	25.00	21.15(10.89,39.66)

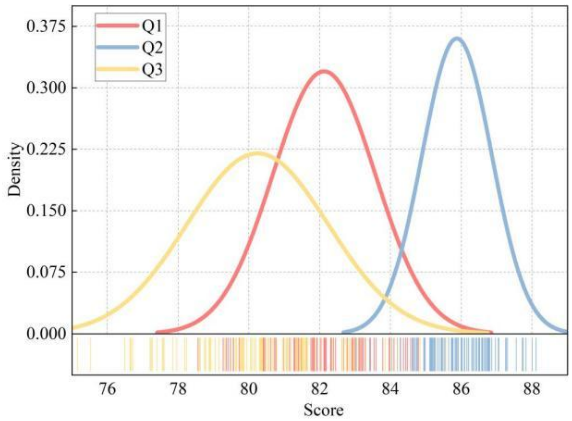
4.3 Application and Analysis of the Nursing Information Platform

From a total of 20,019 elderly individuals classified as either (D2) partially self-sufficient requiring assistance or (D3) completely dependent, 200 seniors with similar conditions were selected as subjects for this section's experiment through conditional screening and willingness inquiries. One hundred participants formed the experimental group, receiving care under the nursing model developed in this study. The remaining 100 participants constituted the control group, receiving conventional care. Both groups received care for three months. Changes in six indicators—Body Mass Index (BMI), Waist-to-Hip Ratio (WHR), Systolic Blood Pressure (SBP), Diastolic Blood Pressure (DBP), Fasting Blood Glucose (FBG), and Postprandial 2-Hour Blood Glucose (PBG)—were observed and statistically analyzed before and after the intervention. Table 8 presents the pre- and post-intervention comparisons of these six indicators between the experimental and control groups. Before the intervention was conducted, there was no statistical difference between the two groups in terms of BMI, WHR, SBP, DBP, FBG, PBG, WHR, SBP, DBP, and FBG values (P>0.05). Three months after nursing, all six indicator values of the experimental group were statistically significantly lower compared with the control group (P<0.05). This primary test proves that there is indeed an optimization effect achieved through the cooperation between nursing and the information system.

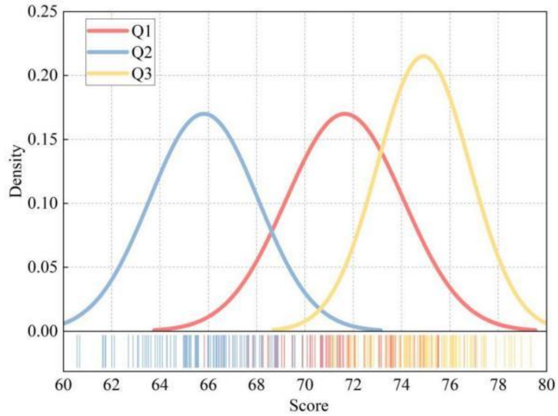
Table 8: Changes in inter-group indicators before and after nursing

group		Experimental group	Control group	t	P
BMI	Before	27.02±0.69	26.98±0.63	0.457	0.541
	After	23.89±0.28	26.04±0.37	13.945	0.00
WHR	Before	0.91±0.05	0.90±0.05	1.026	0.379
	After	0.78±0.01	0.85±0.02	17.023	0.000
SBP	Before	163.47±7.01	162.87±6.59	0.298	0.859
	After	140.12±3.11	149.23±2.61	10.792	0.00
DBP	Before	117.03±4.15	116.97±3.62	0.369	0.652
	After	89.76±2.97	102.85±2.74	16.314	0.000
FBG	Before	7.69±1.32	7.94±1.31	1.146	0.195
	After	6.03±1.09	6.93±1.29	3.001	0.002
PBG	Before	9.89±1.86	9.84±1.49	0.267	0.806
	After	6.17±0.77	8.26±0.97	10.741	0.000

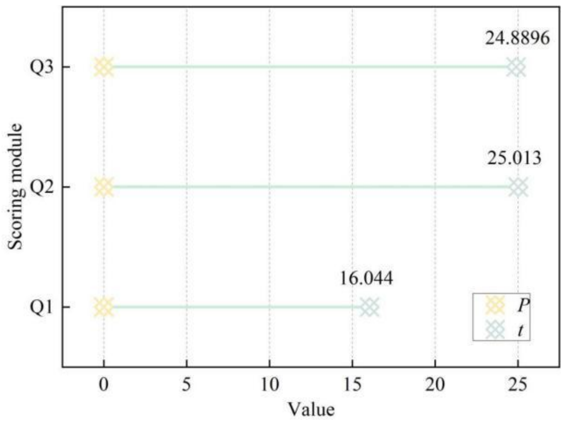
The questionnaire was designed with three evaluation modules: (Q1) Mental Health, (Q2) Physical Health, and (Q3) Social Environment, to assess participants' quality of life after the experiment. Each evaluation module will be graded on a scale of 0 to 100, where high scores represent higher satisfaction with nursing care and better quality of life of the elderly individuals. The post-experiment quality of life scores of the experimental group can be observed in Figure 3(a), whereas the post-experiment quality of life scores of the control group are illustrated in Figure 3(b). T-values and P-values representing the statistical difference in the scores of both groups in each evaluation module are indicated in Figure 3(c). In general, the post-experiment scores of the experimental group participants in all three quality of life modules were between 76 and 88 points, with negligible variance and a mean value of 80 to 86 points. Therefore, the quality of life status of experimental group participants was positive. However, the post-experiment scores of the control group participants varied between 60 and 80 points, with a considerable variance and an average score between 65 and 75 points. Thus, the quality of nursing services provided by healthcare providers in this group was heterogeneous and not satisfactory for patients. There was a statistically significant difference in the scores of the experimental and control groups for all three evaluation modules (P=0.000).



(a) Experimental group



(b) Control group



(c) *t* value and *P* value

Figure 3: Comparison of changes in the Quality of life scoring module

5 Conclusion

In this study, an elderly health management nursing information platform was developed based on three main modules of clinical nursing information, nursing management information, and intelligent decision support by using advanced algorithmic methods, big data technology, and cloud computing. The decision tree algorithm and the association rule algorithm are used in this platform to determine the main variables that have effects on elderly care services requirements, resulting in a decision tree model being built up for elderly care service schedule. This design can be considered as a solid foundation of elderly health management and nursing service coordination. In addition, experimental application results show that there exist notable differences between the proposed care strategy and traditional care strategy in terms of various physical indexes and quality-of-life assessment modules.

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