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Data Mining and Intelligent Decision Support in the Integration of Community Physical Care and Elderly Care Model

Feng Yang*

School of Physical Education, Hunan University of Arts and Science, Changde 415000, Hunan, China

beeyang@qq.com

**Corresponding author*

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Abstract: In recent years, with the rapid development of science and technology, human society is moving towards the era of intelligence at an unprecedented speed. In this era, cutting-edge technologies such as artificial intelligence, big data, and the Internet of Things are like a surging flood, deeply penetrating various aspects of social life, among which smart elderly care is one of them. Smart elderly care is a new type of elderly care, which not only provides new ideas for the huge number of elderly people in China, but also brings new vitality to the social elderly care industry. The article first introduced the background and importance of smart elderly care, emphasizing it as a new way to solve the problem of population aging. Subsequently, relevant literature was reviewed, and the limitations of existing research were analyzed. Then, the application methods of the integrated elderly care model and decision tree algorithm were introduced in detail, including the steps of data collection and preprocessing, feature selection, and model construction. Finally, the effectiveness of the decision tree model in the selection of smart elderly care models was verified through experiments (younger participants (such as 68 and 69 years old) chose smart elderly care models more often when their health was good), and the results were discussed.

1. Introduction

China is currently facing an aging population and an increasingly complex population structure. How to effectively solve this elderly care problem has become an urgent problem to be solved. In this context, the "smart elderly care" model of integrating community physical care and elderly care is a new way to solve the health and elderly care problems of the elderly. Smart pension is a modern pension mode based on "Internet plus" technology. It provides the elderly with Internet of Things (IoT) and intelligent pension services by establishing a fast and effective Internet of Things platform and system, which has important practical significance. Smart health and elderly care services focus on the basic living care of the elderly, focusing on addressing their spiritual and cultural needs, and providing personalized and diversified health management plans. This is not only an important measure to address population aging, but also a way for scientific and technological progress to benefit humanity. It also points out new directions for the development of the elderly care service industry.

This article explores the application of data mining and intelligent decision support around the community integrated elderly care model. Firstly, the background and importance of smart elderly care are introduced, followed by a review of relevant research and an analysis of the limitations of existing research. In the methodology section, a detailed introduction is given to the integrated elderly care model and decision tree algorithm, and the steps of data collection and preprocessing, feature selection, and model construction are explained. Finally, through experimental verification, the application effect of the decision tree model in the selection of smart elderly care models is demonstrated. The model results are discussed, and policy suggestions for improving the quality of elderly care services are proposed.

2. Related Works

For the issue of elderly care, experts have long proposed various research plans. Bao J reviewed the current situation of China's elderly population, analyzed the accelerated aging process and the challenges it brings. The research focused on improving the quality of life for the elderly, promoting healthy aging, and assisting the country in improving elderly care services [1]. Rizal A analyzed the implementation of the Jakarta Elderly Card Program in meeting the basic needs of impoverished elderly people. Although the plan has received strong support from the municipal government and community, its practicality and targeting have been questioned, and aid distribution is inconsistent [2]. Berg H summarized three themes: describing and defining the elderly segmented market, age changes and elderly consumers, and marketing strategies for elderly consumers. He proposed a theoretical framework and provided direction for future research, promoting interdisciplinary development [3]. Tang S explored the relationship between social capital, building environment, and mental health in Chinese cities. Through a survey of 591 elderly people in Nanjing, it was found that different groups had different determinants of mental health [4]. Huang J explored the impact of harsh weather conditions in Hong Kong on the use of outdoor open spaces, particularly the impact of hot environments on different age groups. He found through on-site measurements and simulations at the Ngau Tau Kok Public Housing Estate that spaces designed specifically for gentle winds and shading are more popular, with a lower thermal climate index of 2 ℃, attracting more activities and longer stay times [5].

Bardaro G's research found that functional stagnation and design disconnect limit value. The proposed collaborative design toolkit adopted an ecological framework, combined robot capabilities with geriatric factors, provided an overall view, and was validated in EU projects [6]. Xie Y used multidimensional tools to investigate the health literacy status of elderly people in Changsha, analyzed its related factors, and explored the relationship between health literacy and health behavior. The results showed that the elderly scored the lowest in "health information assessment" and "medical system navigation" [7]. ud Din N S investigated the physical and mental health status and satisfaction with services of elderly people in Lahore nursing homes in Pakistan. He conducted interviews with 25 hospitalized patients, and the results showed that the majority of the respondents were satisfied with the services provided by the nursing home, but also faced some physical and mental health challenges [8]. Meier K J explored the impact of anti public sector bias on government performance reporting, focusing on nursing homes in the United States and filling four literature gaps through experiments: non-profit organizations, consideration of information source credibility, use of simple performance indicators, and willingness to use services. The results showed that the public had the highest evaluation of non-profit organizations [9]. Taking Ningxia as an example, Li Y found that the living standards of elderly people in rural areas are low and their spiritual life is lacking. Family elderly care is facing difficulties, and institutional elderly care is immature and has low acceptance [10]. Singh A used decision experiment and evaluation laboratory and hierarchical analysis to identify the key factors influencing the development of hospitals. The results of the study showed that family dependency, accessibility and patient autonomy are the key factors influencing the choice of healthcare for patients with chronic diseases [11].

Meng F explored the sustained usage intention of mobile healthcare services among elderly users and found that emotional trust and cognitive trust play a key role in this. Health anxiety enhances the effect of cognitive trust, but weakens the impact of emotional trust. Technical anxiety enhances the effect of emotional trust, but its impact on cognitive trust is not significant [12]. Wardani F J investigated the anxiety level of elderly patients with diabetes under the influence of family support. The results showed that the majority of patients who received family support did not have significant anxiety [13]. Zhao C used data from a longitudinal study on health and retirement in China and found that elderly people who have participated in military service perform better in terms of physical health, cognitive abilities, and self-rated health [14]. Padeiro M reviewed the impact of urban community attributes on the happiness of elderly people. He found that natural regions and a sense of community have a positive impact on the happiness of elderly people by analyzing 39 studies as of December 2020 [15]. Cai S utilized long-term survey data of elderly people in China to explore the impact of social participation on cognitive abilities. He solved the problem of endogenous participation by analyzing the impact of changes in community social activity services on social participation. The results showed that participating in social activities has a significant positive impact on the cognitive function of elderly people [16]. Existing research has some common limitations in exploring elderly care issues, including regional limitations, insufficient sample size and representativeness, singularity of research methods (such as relying on questionnaire surveys or specific analytical methods), and deficiencies in interdisciplinary research. In addition, some studies lack long-term tracking or in-depth analysis of the diversity and demand differences of the elderly population, which limits the comprehensive understanding of complex elderly care issues and support for effective policy formulation.

3. Methods

3.1 Integrated Elderly Care Model for Physical and Mental Health

The "integration of physical and mental health" fitness and wellness model has emerged, providing diversified, efficient, and convenient elderly care services for the elderly population. At present, most of the research is based on the combination of medical care and elderly care, and there is little research on the fitness model of the integration of physical and elderly care. This project takes "integration of physical and mental health" as the starting point to study the connotation, types, and characteristics of "exercise promotes health". From the perspective of "exercise promotes health" and "combination of physical and mental health", it further improves the theoretical system of "health promotion". The "embedding" of the "sports and wellness integration" model is to introduce market-oriented operation mechanisms into the occupational "sports and wellness integration" model of sports and wellness promotion, build a small-scale composite elderly care service platform in the community, integrate social forces into community services, combine community services with the actual needs of the elderly, and provide free or paid services for the elderly. Based on the premise of "embedding" and community, elderly care resources are provided to the elderly, so that they can provide health services for energetic elderly people according to their own needs at home, and provide sports rehabilitation and nutrition services for semi disabled and disabled elderly people, thus achieving the goal of "moving the health barrier forward and actively aging".

3.2 Introduction to Decision Tree

Decision tree is a machine learning based artificial intelligence method that can explore the internal patterns of data and classify and predict new data. The decision tree algorithm aims to obtain classification and prediction rules under different values from data, and belongs to guided learning. The reason why decision trees have such a name is that their analysis results are presented in the form of an inverted tree. A tree in which each node has only two branches is called a binary tree, and it can have two or more branches. Compared to various independent prediction methods, the biggest feature of decision trees is that they perform Boolean comparisons (logical comparisons) on input variables to classify and predict them [17-18].

The Gini index is used to represent the probability of a random sample being misclassified, with a value range of (0-1). Assuming that the dataset needs to be divided into K categories and the sample data is assigned to the K-th probability p_k, the value of the Gini index is the probability of this sample being selected multiplied by the probability of it being misclassified. When all samples in a node belong to the same class, the Gini exponent is zero [19]. Therefore, the Gini index can be defined as:

$$Gini(p) = \sum_{k=1}^{k} p_k (1 - p_k) = 1 - \sum_{k=1}^{k} p_k^2 (1)$$

Due to the fact that the CART decision tree is a binary decision tree, the decision tree is divided into D1 and D2 parts based on a certain feature A of the sample data. The Gini index of set D under feature A represents the uncertainty of set D after A=a segmentation, as defined in Equation (2):

$$Gini(D, A) = \frac{D_1}{D} Gini(D_1) + \frac{D_2}{D} Gini(D_2) (2)$$

The algorithm of CART classification tree represents the input training set as D and outputs the decision tree T. Starting from the root node, the algorithm recursively builds the CART classification tree using the training set.

This article uses SPSS Clementine software and decision tree CART algorithm to establish a selection model for a suitable elderly care model for China's national conditions. The binary regression tree method minimizes the variance within nodes and maximizes the difference between nodes, thereby obtaining a simpler structured binary tree decision tree. Firstly, this article adopts the method of variable importance analysis to explore and retain variables that have a significant impact on the classification prediction of output variables, and incorporates them into the decision model to remove unimportant influencing factors, thereby obtaining a more refined decision-making idea. In the research process, since both input and output variables are categorical variables, the likelihood ratio chi square test is used to measure the importance of the variables. In this article, both input and output are categorized, and some continuous input variables are transformed into one category using the likelihood ratio chi square test, which is mathematically defined as follows:

$$T = 2 \sum_{j=1}^{\delta} \sum_{j=1}^{c} f_{ij}^0 \, ln \frac{f_{ij}^0}{f_{ij}^e} (3)$$

Among them, r represents the number of rows; c represents the number of columns; f_{ij}^0

represents the measured frequency of cell (i, j); f_{ij}^{e} represents the expected frequency of cell (i, j). In this article, Cle-mentine is used to analyze the importance of input variables. The condition is set as follows: ① for category variables with omissions greater than 60%, they are considered unimportant; ② variables are classified with a class count exceeding 95% as non significant variables; ③ the original data is continuous data with a coefficient of variation below 0.1, which can be considered unimportant; ④ the original data is continuous data with a standard deviation below 0, which can be considered unimportant.

4. Results and Discussion

4.1 Experimental Purpose

A model for selecting elderly care modes is constructed, and the decision tree CART algorithm is used to analyze data mining and intelligent decision support in smart elderly care modes.

4.2 Experimental Steps

In the field of smart elderly care, firstly, sample data related to the health status, living needs, and social participation of the elderly are collected and preprocessed, including processing missing values, data type conversion, and standardization. Then, important features that have an impact on the selection of elderly care models are analyzed and selected, and continuous variables are discretized to meet the requirements of decision tree algorithms. Next, the CART algorithm in SPSS Clementine software is used to establish a decision tree model and determine key features through variable importance analysis. Finally, the prediction accuracy and generalization ability of the model are evaluated and optimized based on the evaluation results, such as adjusting parameters and pruning.

Table 1. Sample data example

Participant ID	Age	Health Condition	Social Participation Level	Retirement Model Choice
1	75	Good	High	Smart Retirement
2	80	Moderate	Low	Traditional Retirement
3	70	Excellent	Medium	Smart Retirement
...	...	...	...	...

According to the data in Table 1, the basic information and distribution of health status of the participants can be seen. The average age of participants is about 72 years old, with an age range from 60 to 85 years old. The health status is mainly divided into three categories: good, moderate, and excellent, with the majority of participants rating themselves as in good health. These basic information provide important background for exploring the influencing factors of elderly care model selection in the future.

Table 2 shows the level of social participation among participants. Participants are divided into three levels: high, medium, and low, reflecting their level of positivity in community and social activities. The proportion of participants with high levels of social participation is relatively large, and there is also a certain proportion of participants with medium to low levels. These data help to understand the characteristics of participants in social interaction and are of great significance for analyzing the impact of their choice of elderly care mode.

Table 2. Results of variable importance analysis

Feature	Importance Ranking
Age	High
Health Condition	Medium
Social Participation	Low
...	...

Table 3. Example of CART decision tree model

Node	Split Feature	Split Rule	Child Node
1	Age	Age >= 75 Years	2 (Yes)
2	Health Condition	Health Condition = Good	Smart Retirement
3	Health Condition	Health Condition = Moderate Or Below	Traditional Retirement

According to the example of CART decision tree model in Table 3, experimental data analysis is conducted. The decision tree first takes age as the splitting feature, and the rule is "age>=75 years old". If this condition is met, it is entered into node 2 and further split based on health status: if the health status is good, smart elderly care is recommended, otherwise traditional elderly care is recommended. If the age is less than 75 years old, it is entered into node 3 directly and traditional elderly care based on moderate or below health status is recommended. This model effectively matches the different needs of the elderly with the appropriate pension mode.

Table 4. Specific data examples

Participant ID	Age	Health Condition	Social Participation Level	Retirement Model Choice
1	68	Moderate	High	Smart Retirement
2	72	Good	Medium	Traditional Retirement
3	80	Excellent	Low	Smart Retirement
4	76	Moderate	High	Smart Retirement
5	85	Good	Low	Traditional Retirement
6	71	Excellent	Medium	Smart Retirement
7	78	Moderate	High	Smart Retirement
8	69	Good	Medium	Traditional Retirement
9	75	Excellent	Low	Smart Retirement
10	82	Good	Low	Traditional Retirement
...	...	...	...	...

From the data, it can be seen that younger participants (such as those aged 68 and 69) tend to choose the smart elderly care model more often in good health conditions. This may be because younger elderly people have a higher acceptance of new technologies and modern services, and are more likely to adapt to the various convenient services provided by smart elderly care. Relatively speaking, older participants (such as those aged 85 or 82) often choose traditional elderly care models even if they have good health conditions. This may reflect their trust and habits in traditional elderly care methods. In terms of health status, almost all participants with excellent health status choose the smart elderly care model. This indicates that elderly people with good health are more inclined to choose elderly care models that can provide high-quality and intelligent services, thereby further improving their quality of life and happiness, as shown in Table 4.

The data flow is executed to obtain the output results of the breadth subdivision classification regression tree model and the depth subdivision classification regression tree model, as shown in Figures 1 and 2.

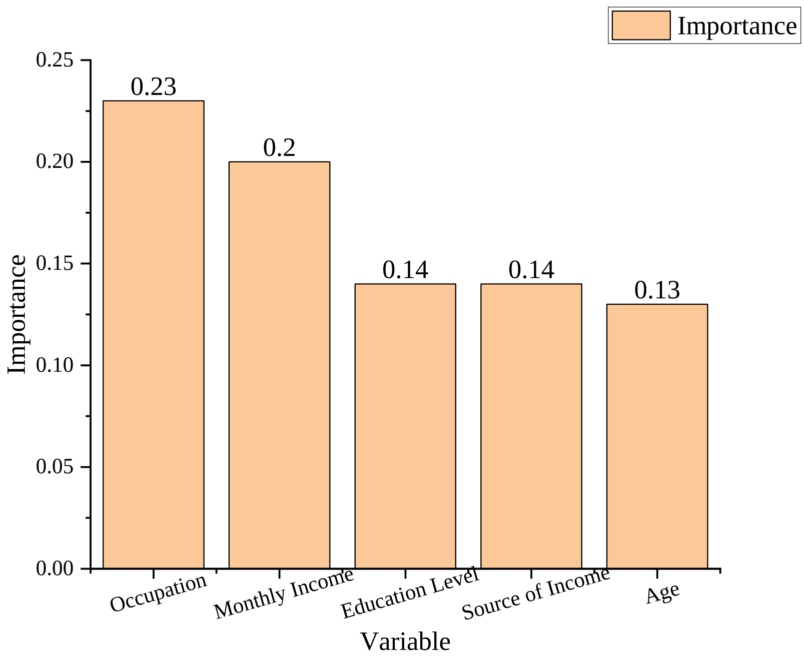

Figure 1. Importance of breadth subdivision variables

According to the data in Figure 1, it can be seen that occupation and monthly average income are the two factors that have the greatest impact on the satisfaction of elderly care in rural areas, accounting for weights of 0.23 and 0.20, respectively. This result indicates that occupation and monthly average income, as representatives of economic and social status, have a significant impact on elderly satisfaction.

According to the data in Figure 2, the impact of the subsistence allowance system on the satisfaction of elderly care in rural areas is most significant, with an importance of up to 0.80, far exceeding other variables. Through this analysis, it can be seen that improving the satisfaction of elderly care in rural areas should focus on strengthening the coverage and implementation of the subsistence allowance system to ensure that the elderly can enjoy sufficient social security.

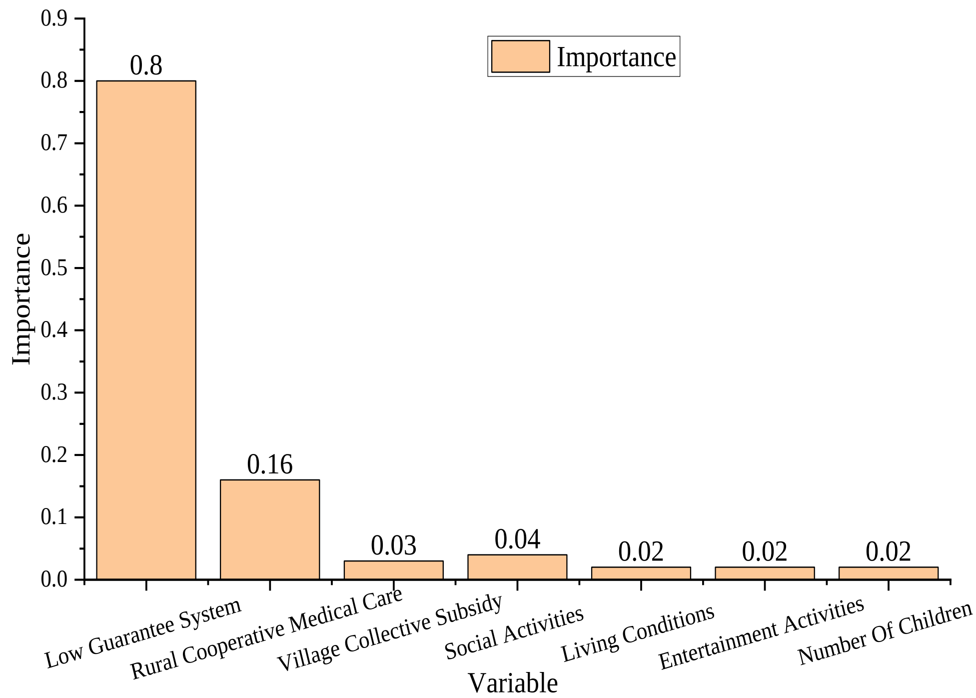

Figure 2. Importance of deep subdivision variables

5. Conclusions

Under the background of "Internet plus" era, smart health elderly care services are facing unprecedented development opportunities. The development of smart health and elderly care services not only requires government guidance and support, but also requires the joint participation and efforts of all sectors of society. By implementing strategies such as mutual assistance in elderly care, optimizing home and community elderly care services, strengthening the construction of elderly care talent teams, and promoting the development of smart health care industry clusters, Shanwei City has achieved smart health. This article studied data mining and intelligent decision support in the integrated elderly care model of community physical care. By using the decision tree CART algorithm, a suitable elderly care model selection model for China's national conditions was established. The research results indicate that age, health status, and level of social participation are important characteristics that affect the choice of elderly care models among the elderly. By analyzing the importance of variables and establishing a decision tree model, it is possible to effectively classify elderly people and recommend suitable elderly care methods for those with different needs.

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