SIN-CHN SCIENTIFIC PRESS PTE.LTD.

Molecular & Cellular Biomechanics 2025, 22(2), 772.
https://doi.org/10.62617/mcb772

Article

Biomechanical application research on cognitive health management in the elderly based on data analysis and intelligent coordination in the age of artificial intelligence

Dongxian Yu[1,*], Guoke Qiu[1], Ming Li[2]

[1] College of Modern Information Technology, Henan Polytechnic University, Zhengzhou 450046, China
[2] Henan Gubo Information Technology Co. Ltd., Zhengzhou 450046, China
*** Corresponding author:** Dongxian Yu, yudongxian321@163.com

CITATION

Yu D, Qiu G, Li M. Biomechanical application research on cognitive health management in the elderly based on data analysis and intelligent coordination in the age of artificial intelligence. Molecular & Cellular Biomechanics. 2025; 22(2): 772. https://doi.org/10.62617/mcb772

ARTICLE INFO

Received: 12 November 2024
Accepted: 18 November 2024
Available online: 22 January 2025

Abstract: The conventional approach to elder care is no longer able to satisfy the rising need for medical attention for the elderly due to China's aging population. The demographic trait of "getting old before getting rich" presents a challenge to the distribution of social healthcare resources, as this article first examines the current pattern of changes in the composition of the older population. The community-based "healthcare integration" paradigm of senior care services has emerged as a successful remedy in this regard. Drawing on biomechanical principles, we can envision the community healthcare system as a complex "biomechanical network". In order to categorize and predict the health data of the elderly, this study constructs a mathematical model akin to analyzing biomechanical forces and movements. By employing methods similar to optimizing structural loads, such as the CART decision tree and support vector machine (SVM) optimization, we enhance the model's precision. Just as biomechanical systems adapt to varying loads, our model adapts to handle complex health data. By building the optimal classification plane of the support vector machine and adding relaxation variables, the model application solves the classification problem of linearly indivisible data, further enhancing the model's accuracy and effectiveness, much like how a biomechanical structure self-adjusts to external pressures. In this paper, a geriatric health service platform based on information technology, including big data and the Internet of Things (IoT), is formed. The service system is a tripartite linkage disease management service model that covers the synergistic cooperation of community hospitals, third-party enterprises, and the streets where they are located. A prediction model for common cases, such heart disease, was developed by preprocessing and cleaning the data of 2311 valid samples from the China Geriatrics Center. The dataset was then characterized. The findings demonstrate the model's high operability and accuracy in predicting health and managing long-term care for older people who are mobility. In the context of an aging society, by integrating biomechanical insights into the design of this healthcare model, the research not only establishes a theoretical foundation for community health care integration but also provides valuable references for implementing digital senior care services and enhancing health management for the elderly in an aging society.

Keywords: health care integration; biomechanical; aging society; community care; SVM; CART decision tree; health prediction model; mobile elderly population

1. Introduction

Governments and scholars are becoming more concerned with how to offer convenient and high-quality senior care services to the burgeoning senior population as the issue of global aging worsens [1]. The idea of "healthcare integration" has gained popularity recently as a viable remedy, particularly in nations where the rate of aging is accelerating. It is regarded as a crucial way to reduce the burden on healthcare systems and raise the standard of elder care services. Healthcare integration greatly enhances the quality of life for the elderly by integrating medical care with everyday senior care services, allowing for a smooth transition between life care and health monitoring [2,3]. However, the current model of health-care integration still faces a number of difficulties that urgently call for more scientific and adaptable technical means to address due to the intricate interactions of factors like population aging, the rise in the number of elderly people who are on the move, and the variety of health issues among the elderly population [4].

The conventional family and institutional methods of old age care are no longer able to satisfy the demands of an aging population. Most elderly people hope to receive comprehensive medical and nursing services in the community because of the limited resources of family-based elder care, the incapacity of children to provide long-term care due to work, and the scarcity and high cost of professional elder care facilities [5]. Community-based elder care, a government-backed service model founded on family and community, is progressively becoming acknowledged and established as one of the most popular types of updated senior care. Its basic idea is that the elderly's "home is safe, community is nourishing" vision may be realized by building an old age community, providing medical care, rehabilitation, and other support systems [6].

Research on health prediction modeling is a significant component of the healthcare integration system in this trend. Because the health circumstances of the older people who live on the go are sometimes more complicated and unstable, it is very vital to monitor their health. It has been discovered that health prediction models are useful in lowering older persons' health risks during healthcare integration services and averting unforeseen medical incidents, which lessens the strain on the healthcare system [7,8]. Because of their exceptional ability to handle complicated data, machine learning techniques like SVM and CART are frequently employed in evaluating the health condition and predicting diseases of the elderly. Community healthcare facilities can offer tailored care and intervention programs based on the health status of the elderly by using precise health prediction, greatly increasing the effectiveness and caliber of healthcare services [9,10].

There are still a lot of issues, even if previous research has achieved some strides in healthcare integrated health prediction. First, there are significant obstacles to the gathering and exchange of health data, which means that many studies only use one data source or are restricted to a small number of variables, which means that they do not accurately represent the health condition of older persons [11]. The accuracy and generalizability of prediction models are jeopardized in the case of the mobile senior population, whose health data from many locations is hard to combine in a systematic manner. Second, it is challenging to achieve real-time health risk prediction since current models are primarily based on static data and are unable to monitor dynamic changes in the health condition of the aged. Furthermore, even while models like SVM and CART have somewhat increased prediction accuracy, they still need a lot of data to function well, which makes it challenging to use limited or poor quality data.

The promotion and growth of the community-based health care integration model have also been hampered by unequal service quality and insufficient financial allocation. It is difficult to meet the various health needs of the elderly population, particularly those with chronic or multiple diseases, and the current solutions are unable to provide accurate health services. On the one hand, the infrastructure of the community healthcare integration system is not yet fully popularized, and there is a lack of professional healthcare personnel and technical support. On the other hand, the development of health prediction models does not adequately take into account the diversity of health states of the elderly. Furthermore, it is impossible to overlook data security and privacy concerns because current health data sharing practices fail to sufficiently take into account the privacy requirements of the elderly, which impedes the effective integration and use of data.

With the goal of achieving real-time assessment and early warning of the health status of the mobile elderly population based on multi-source health data and dynamic data analysis, this paper presents a novel health prediction model for healthcare-integrated community aging in order to address the aforementioned shortcomings. In terms of technical solutions and application realization, this study offers the following benefits:

This study presents the construction of a multi-level data gathering and analysis system that combines medical, activity, and life data in the community to create a comprehensive health database. This method not only successfully increases the data's richness but also makes it possible for the model to forecast health outcomes using multidimensional data, increasing the forecasts' accuracy and dependability.

Using an algorithm that combines the SVM and CART to realize the dynamic prediction, this paper integrates a real-time updating mechanism into the health prediction model with the goal of addressing the dynamic change characteristics of the elderly's health status. To guarantee the accuracy and timeliness of the prediction, the model can modify the results in real time based on changes in the elderly's physiological indicators and daily activities.

In addition to predicting the health condition of the elderly, the model put out in this research offers tailored intervention recommendations based on individual characteristics and the distribution of health risks. Healthcare providers can offer tailored care programs based on individual health problems by incorporating the prediction results into the community healthcare service process. This significantly improves the efficacy of integrated healthcare services.

2. Integration of multi-level health data and dynamic predictive modeling

Traditional single data sources and static data analysis techniques frequently struggle to handle the diversity and unpredictability of the health condition of the elderly when building health prediction models suited to community healthcare integration [12]. As a result, multilevel health data integration and dynamic prediction-based health models have steadily emerged as a research hotspot. A multi-level data integration system is presented in this chapter with the goal of combining health data from several sources and implementing machine learning algorithms to provide dynamic health prediction. This gives community elder care a technical and scientific foundation.

2.1. Design of a multi-level data integration framework

Under the community healthcare integration approach, there are many different types and sources of data. This study develops a multilevel data integration framework to efficiently combine various forms of information, including medical, activity, and life data, to create a multidimensional health dataset that better captures changes in the health condition of the elderly.

Medical data layer: Medical data comprises information about physical examinations, medical history records, and indicators of chronic disorders (e.g., blood pressure, blood glucose) in the elderly [13]. This kind of data, which has a low update frequency but excellent data quality, is primarily supplied by community health groups and routine medical examinations. A reliable reference standard for evaluating health risks has been established with the inclusion of medical data.

Activity data layer: activity data, such as steps taken, exercise duration, sleep quality, etc., show how frequently and how intensely older adults engage in their everyday activities. These data are frequently captured by wearable technology or sensors [14]. The dynamic evaluation of health status is supported in real time by these data, which are updated in real time and sensitively record even the smallest changes in the elderly's everyday lives.

Life Data Layer: Life data includes social activities and mental health evaluations of community-dwelling older persons. These are gathered by community workers using psychological testing instruments or daily interviews, and they typically show the mental health and life satisfaction of older adults. The foundation for tailored treatments to address the emotional and psychological requirements of senior citizens may be found in this data layer. Therefore, Equation (1) can be used to define the Gini index:

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

2.2. Developing and using a dynamic health prediction model

Support vector machines (SVM) and categorical regression trees (CART) were used in this study to build a health model with dynamic prediction capabilities. The model is capable of producing health risk prediction results based on real-time updated data by combining and evaluating multi-source data from several data layers [15]. In particular, CART uses its sensitivity to data features to increase the accuracy of identifying abnormal health states, which are defined in Equation (2), whereas SVM deals with the nonlinear features of the data to improve the classification ability of the prediction model for various health states.

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

Equation (3) illustrates the construction of the classification condition for the ith observation of the community health care integration model.

$$\left.\begin{matrix} W^T x_i + b \geq d & y_i = +1 \\ W^T x_i + b \leq -d & y_i = -1 \end{matrix}\right\} \Leftrightarrow y_i(W^T x_i + b) - d \geq 0 \tag{3}$$

The simplified interval Equation (4) is used to fit the health care integration model.

$$y_i(W^T x_i + b) \geq 1 \tag{4}$$

$$\begin{cases} min\, \tau\,(W) = min\frac{1}{2}\|W\|^2 = min\frac{1}{2}W^T W \\ \text{st.} \quad y_i(b + W^T x_i) - 1 \geq 0, i = 1,2, \cdots m \end{cases} \tag{5}$$

$$L(W, b, \lambda) = \frac{1}{2}\|W\|^2 - \sum_{i=1}^{m} \lambda_i\,(y_i(b + W^T x_i) - 1) \tag{6}$$

The simplified hyperplane of the mathematical model of health care integration for the senior mobile population in the community can then be obtained using the optimal classification function, as shown in **Figure 1**. Vectors A, B, and C are the support vectors that meet the equal sign condition since they are parallel to the ideal hyperplane.

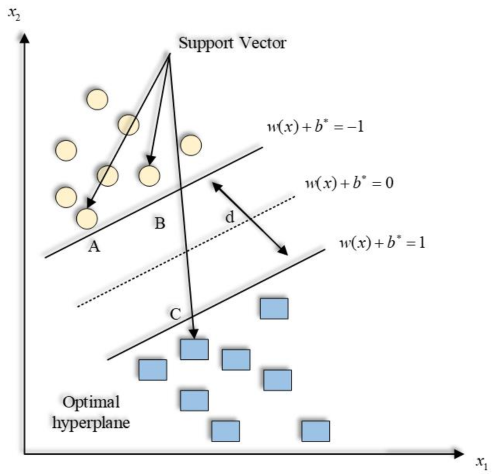

Figure 1. health care integration mathematical model.

The hyperplane $w\phi(x) + b = 0$ after mapping ϕ transformation, and the introduction of the relaxation variables ε_i inequality is shown in Equation (7):

$$\left.\begin{matrix} wx_i + b \geq 1 - \varepsilon_i & \text{for} & y_i = +1 \\ wx_i + b \leq -1 + \varepsilon_i & \text{for} & y_i = -1 \end{matrix}\right\} \Leftrightarrow y_i(wx_i + b) + \varepsilon_i \geq 1 \tag{7}$$

3. Methods

3.1. Model build and run

The secret to increasing the efficacy of health management services is the creation of intervention methods tailored to each person's needs, guided by the findings of health risk assessments. Different interventions are appropriate for different risk levels, with the goal of enhancing older individuals' quality of life and lowering health risks through individualized services. Health education and lifestyle management are primarily employed for low-risk older persons in good health. We assist senior citizens in forming healthy habits and maintaining a healthy lifestyle by delivering them individualized food and exercise recommendations as well as frequent health reminder texts. However, consistent health monitoring and self-evaluation can also assist older adults understand their own health and raise their level of health management awareness, as demonstrated in **Figure 2**.

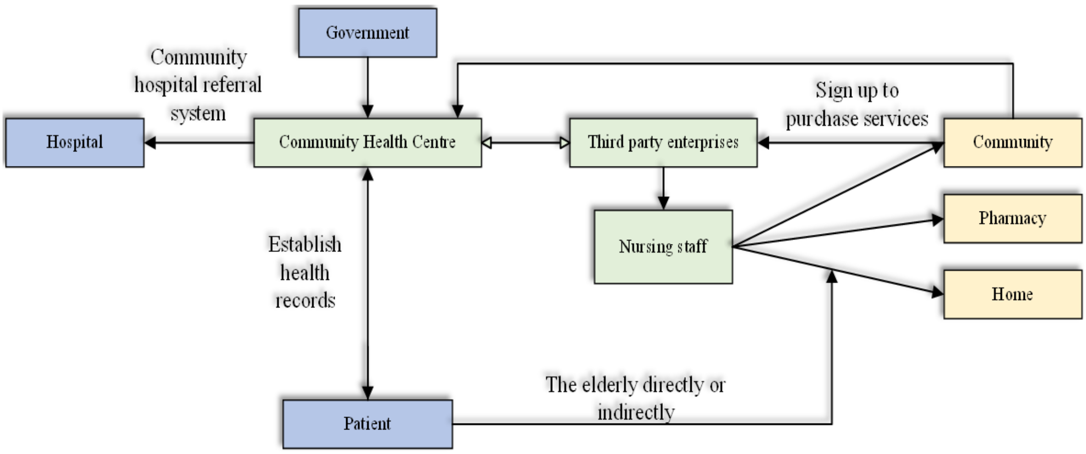

Figure 2. Model of community health care.

Under this paradigm, the community hospital is in charge of diagnosing and communicating with local elderly patients, providing medication and monitoring their status, and conducting related health education. Following a community contract, the third-party company invests medical consultations, dispensing medication, and helping with daily care, as shown in **Figure 3.** The third-party company also establishes connections with the community pharmacy. Despite being two distinct organizations, the community hospital and the third-party corporation are integrated to connect the health information of the elderly.

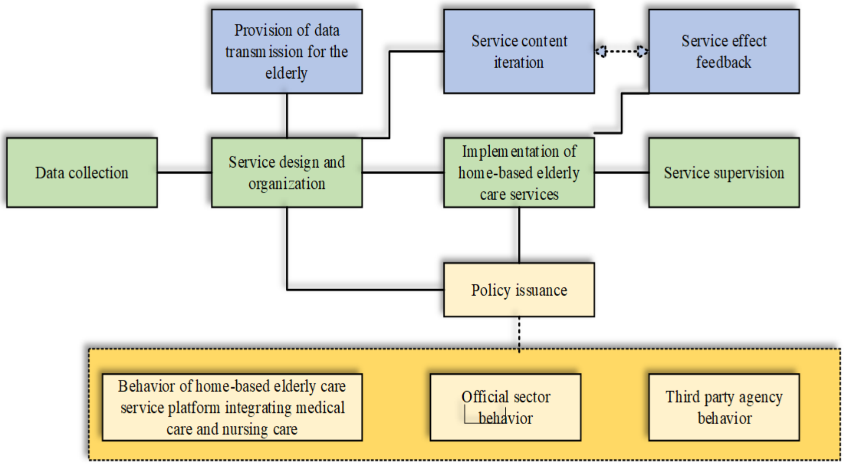

Figure 3. Cooperation model.

3.2. Data set fetching and analysis

This study refined the data from the China Geriatrics Center and produced 2311 valid sample data, in this research, we use these data as samples to develop and train a predictive model of common heart disease cases among middle-aged and older individuals in the floating population. The general populace, including the elderly in the neighborhood, is not excluded by this paradigm. The original dataset has inconsistent data formats, erroneous data values, and blank values. As a result, data conversion, data interpolation, and null value removal are all used in this paper. **Table 1** displays the section data that was intercepted following preprocessing.

Table 1. Health care integration dataset.

Age	Gender	Types of chest pain	Resting blood pressure	Plasma steroid content	Fasting blood glucose	ECG	Maximum heart rate	ST decrease caused by movement	Slope of ECG ST at maximum exercise	Slope of ST	Number of main blood vessels measured by fluorescent staining	THAL value	Sickness
60	1	3	130	315	0	2	108	0	2.2	2	3	3	1
61	1	1	114	558	0	2	154	0	1.5	2	1	6	1
63	1	2	118	255	0	0	123	1	0.5	1	2	7	0
64	0	2	135	252	0	0	122	1	1.2	2	1	6	1
65	1	2	124	267	1	2	142	1	1.2	3	2	4	0
66	1	2	135	298	0	2	103	0	1.5	3	1	5	0
67	1	4	140	223	0	0	158	1	2.3	2	1	3	1
68	0	3	135	260	0	1	145	1	2.5	2	0	1	1
69	0	2	113	240	0	1	144	1	3.2	2	1	6	0
70	1	3	147	251	1	2	122	1	3.1	1	0	5	0

4. Results

4.1. Model reliability and validity analysis

Table 2. Comparison table of operating parameters of data sets.

Project	Elderly living in Elderly Care Department (n = 214)		Elderly at home (n = 244)		x^2	P
	Number of cases (n)	%	Number of cases (n)	%		
Age						
60–65	17	7.8	22	11.6	7.43	0.15
66–70	36	15.2	42	18.1		
71–75	35	14.2	44	19.6		
76–80	35	15.8	37	13.2		
≥80	91	46.8	81	38.2		
Gender						
Male	72	34.5	104	42.3	3.15	0.08
Female sex	161	65.2	148	52.8		

According to the data set module analysis, the parameters were run 218 and 250 times in the two surveys, respectively, and 214 and 244 valid parameters were recovered for each, with a parameter efficiency of 98.17% and 97.60%. The general information on the aged in both categories is included in **Table 2**.

As a result, **Table 3** displays the findings of the integrated numerical model of community medical care for the old floating population.

Table 3. Results of the numerical model of community health care integration.

			Elderly living in Elderly Care Department (*n* = 214)		
Project	Number of cases	%	Score	*F/T* value	*P* value
Age				4.182	0.003
60–65	16	7.28	3.62 ± 0.22		
66–70	32	15.52	3.51 ± 0.32		
71–75	34	14.52	3.54 ± 0.31		
76–80	34	15.98	3.58 ± 0.28		
≥80	99	46.58	3.75 ± 0.25		
Primary school	105	49.56	4.11 ± 0.46		
Junior high school or technical school	66	30.25	4.11 ± 0.55		
High school or technical secondary school	15	6.55	4.5 ± 0.62		
Junior college	5	1.88	3.56 ± 0.22		
Bachelor degree or above	3	1.56	4.25 ± 0.25		

Table 4. Decision tree curve.

Inspection results	**The measure of area**	**Standard error**	**Progressive Sig**	**Progressive 95% confidence interval**	
				lower limit	**Upper limit**
CART Decision Tree	0.865	0.012	0.001	0.956	0.989

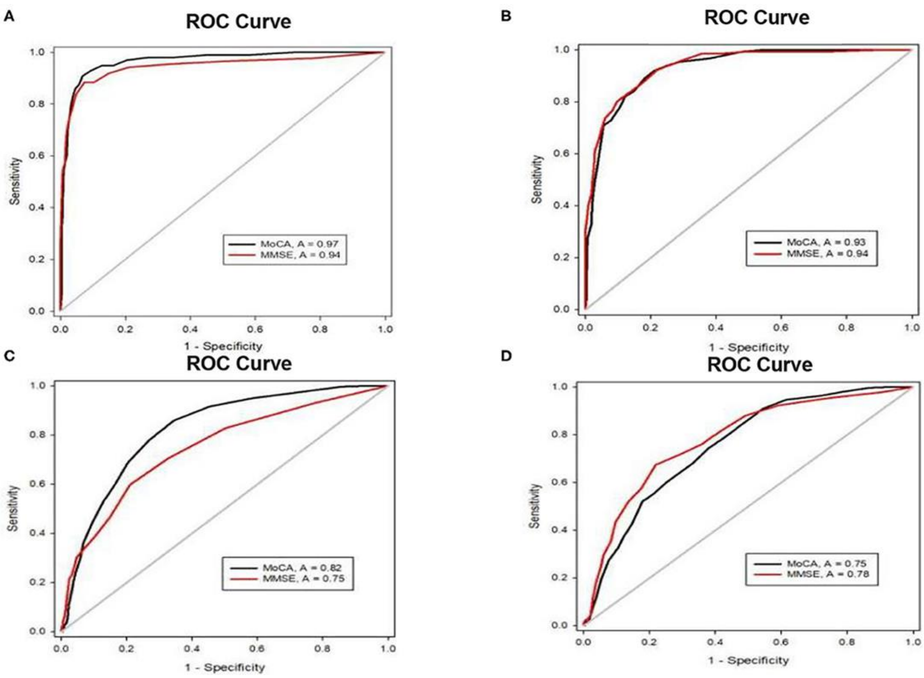

Figure 4. Community health care integration for elderly mobile population. **(a)** Age; **(b)** Gender; **(c)** Male; **(d)** Female.

Based on this, the ROC curve is created by comparing the actual results with the predicted disease results of the CART decision tree model. The ROC curve's area is then calculated using the formula for determining the ROC curve's AUC value in Chapter 2, which is displayed in **Table 4**. The ROC curve is displayed in **Figure 4**.

The AUC value of the ROC curve reaching 0.964, which is near to 1, the model's significance level having a *P* value less than 0.05, its KMO value of 0.93, the Bartlett's spherical test reaching a significant level, and the lack of multiple loading all demonstrate that the model classification effect is more satisfactory and statistically significant. Each entry's loading values on the relevant parameters range from 0.478 to 0.897. **Figure 5** and **Table 5** present these results.

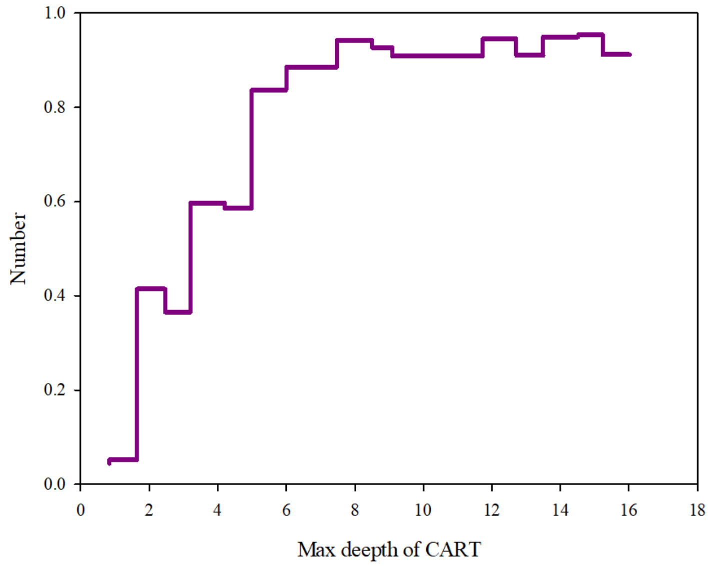

Figure 5. Optimization results.

Table 5. Analysis of predicted load values.

Actual classification	**1-Training set prediction classification**		**Total**	**2-Test Set Prediction Classification**		**Total**
	Not sick	Be ill		Not sick	be ill	
Not sick	315	9	309	186	8	170
Be ill	14	294	205	9	151	179
Total	384	219	684	154	155	239

Furthermore, the training set to test set division ratio in the optimization-seeking algorithm test is 7:3, and **Figure 5** illustrates the max_depth learning curve, for instance. The model performs best when max_depth equals 10, and testscore varies as max_depth increases. The model performs best when the max_depth parameter is 10 because it currently exhibits the overfitting phenomena, which lowers both classification accuracy and compute efficiency. Based on this, we set maxdepth = 10 and get min_samples_leaf = 1 and min_samples_split = 3 to be ideal. first looking through the grid and then cross-checking each of the other two parameters.

4.2. Empirical analysis

According to the statistical findings, the chosen dataset, which was processed by the community health care integration system platform for the elderly mobile population, comprised 500 patients aged 60–65 and 120 patients aged 65 and older, respectively, making up 43.17% and 8.99% of the entire sample. There were 70 female samples and 324 male individuals in the illness data (target ≥ 1). **Figure 6** illustrates this. The horizontal coordinates show the patients' age, the vertical coordinates show the number of sick, and different colors indicate whether or not a person is sick. It is clear that the number of people without heart disease declines with age, the number of sick people exhibits a negligible upward trend, and the number of people without heart disease.

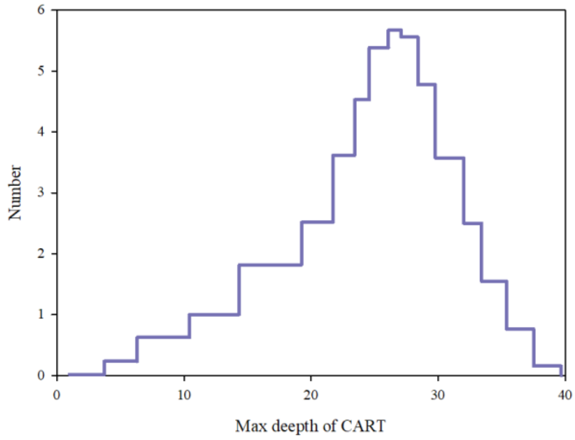

Figure 6. The distribution of community health care.

Additionally, the statistical graph of the disease probability by age was created in this paper using the case data, and as **Figure 7** illustrates, the likelihood of heart disease did not increase with age. All things considered, the incidence of heart disease is more impacted by a number of physical markers that alter with age rather than being only linearly correlated with age. Since it is evident that a number of intricate factors can contribute to heart attacks, we will examine and filter 13 types of influencing indicators in this research.

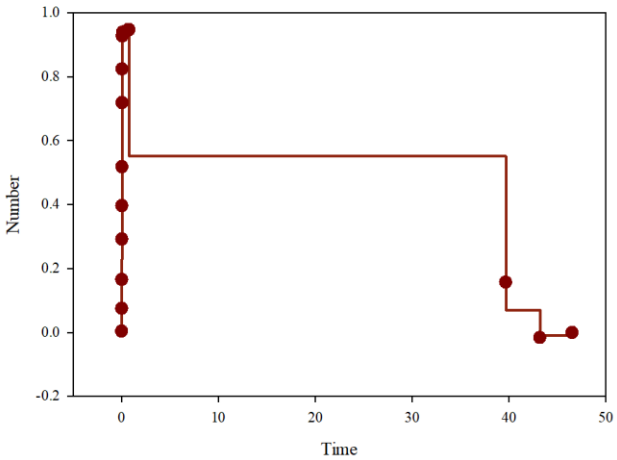

Figure 7. Predicted medical resource occupancy results.

5. Conclusion

In order to address the current needs of health management for the elderly in the community health care integration model, a multi-level health risk assessment and personalized intervention strategy based on a dynamic health prediction model is proposed in this study. This approach offers an inventive solution for the management of elderly health. The following are this paper's primary findings and contributions:

In order to analyze and evaluate the health risks of older adults in real time, this study first builds a dynamic health prediction model with multi-source data integration. This model systematically integrates information from various dimensions, including lifestyle, activity, and chronic disease management data. The accuracy and adaptability of this model are significantly better than those of conventional single data source or static assessment methods. The model's ability to constantly update health data in real-time enables it to promptly detect even the smallest changes in the health state of the elderly, offering a solid foundation for individualized actions that follow.

Second, in order to classify health risks into low, medium, and high levels, this article developed a multilayer health risk assessment method. The study creates tailored intervention plans for varying risk levels using this grading system, ranging from focused supervision to daily health monitoring, with far greater flexibility and accuracy of interventions. In the low-risk stage, the elderly are helped to maintain their health through lifestyle management and health education; in the medium-risk stage, health hazards are promptly controlled through increased monitoring frequency and early intervention; and for high-risk individuals, rigorous health monitoring and individualized care services are offered. In addition to satisfying the requirements of elderly individuals with varying health conditions, the system efficiently maximizes the distribution of resources for health management.

Third, this study used a dynamic feedback mechanism to further improve the intervention effects' flexibility and sustainability. It contributes to ensuring the efficacy and scientificity of health management interventions by tracking changes in their effects and promptly modifying tactics. A trustworthy assessment framework for future research is provided by the intervention effect assessment system in this study, which specifically quantifies the intervention effect through the dimensions of user feedback, changes in the number of health warnings, and comparative analysis of health indicators. The outcomes of the experiment demonstrate the importance of the dynamic feedback mechanism in enhancing the effectiveness of interventions and the quality of health management.

Additionally, this study confirms the viability and efficacy of the health risk assessment and intervention method based on the dynamic health prediction model through case studies and empirical analyses of experimental outcomes. According to the experimental results, the implementation of appropriate interventions significantly improves the health status and quality of life of older adults with varying levels of health risk. This includes a significant improvement in the stability of low-risk older adults in maintaining their health, a reduction in the health hazards of medium-risk older adults, and a significant reduction in the number of health risk warnings of high-risk older adults. The model's practical application effect attests to the research method's broad applicability and popularity in the community health care integration model.

Author contributions: Conceptualization, DY and GQ; methodology, GQ; software, DY; validation, DY, GQ and ML; formal analysis, GQ; investigation, GQ; resources, DY; data curation, DY; writing—original draft preparation, ML; writing—review and editing, DY; visualization, ML; supervision, GQ; project administration, ML; funding acquisition, GQ. All authors have read and agreed to the published version of the manuscript.

Funding: This work was sponsored in part by 1) Science and Technology Research Project of Henan Province, China Project name: Research on the Application of Virtual Reality 'Technology in Cognitive Health Management of the Elderly. Project Number: 232102310506. 2) Science and Technology Research Project of Henan Province, China Project name: Research on Key Technologies of Digital Human Based on Al Large Model. Project Number.242102210114. 3) Education Science Planning Project of Henan Province, China Project name: Research on Resource Construction of Virtual Simulation Base in Vocational Colleges Based on Metaverse and Knowledge Graph. Project Number: 2024YB0500. 4) Research and Practice Project on Higher Education Teaching Reform in Henan Province, China Project name: Exploration and Practice of traditional Culture Empowering Talent Cultivation in Vocational and Technical Colleges from the Perspective of Informatization. Project Number:2024SJGLX0746. 5) Research and Practice Project on Vocational Education Teaching Reform in Henan Province, China Project name: Research and Practice on the Construction of Virtual Simulation Bases in Vocational Schools ([2023] 03049).

Ethical approval: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Institutional Review Board of Henan Polytechnic University (protocol code: HPU202403126653021H and 2024,03,12 approval).

Conflict of interest: The authors declare no conflict of interest.

References

1. Abir SMAA, Islam SN, Anwar A, et al. Building Resilience against COVID-19 Pandemic Using Artificial Intelligence, Machine Learning, and IoT: A Survey of Recent Progress. IoT. 2020; 1(2): 506-528. doi: 10.3390/iot1020028
2. Górriz JM, Ramírez J, Ortíz A, et al. Artificial intelligence within the interplay between natural and artificial computation: Advances in data science, trends and applications. Neurocomputing. 2020; 410: 237-270. doi: 10.1016/j.neucom.2020.05.078
3. Afzal MK, Zikria YB, Mumtaz S, et al. Unlocking 5G Spectrum Potential for Intelligent IoT: Opportunities, Challenges, and Solutions. IEEE Communications Magazine. 2018; 56(10): 92-93. doi: 10.1109/mcom.2018.8493125
4. Guo Z, Yu K, Kumar N, et al. Deep-Distributed-Learning-Based POI Recommendation Under Mobile-Edge Networks. IEEE Internet of Things Journal. 2023; 10(1): 303-317. doi: 10.1109/jiot.2022.3202628
5. Liao H, Zhou Z, Liu N, et al. Cloud-Edge-Device Collaborative Reliable and Communication-Efficient Digital Twin for Low-Carbon Electrical Equipment Management. IEEE Transactions on Industrial Informatics. 2023; 19(2): 1715-1724. doi: 10.1109/tii.2022.3194840

6. Pan J, Ye N, Yu H, et al. AI-Driven Blind Signature Classification for IoT Connectivity: A Deep Learning Approach. IEEE Transactions on Wireless Communications. 2022; 21(8): 6033-6047. doi: 10.1109/twc.2022.3145399
7. Zhang G. Enhancing English Pronunciation Assessment in Computer-Assisted Language Learning for College Students. Journal of Combinatorial Mathematics and Combinatorial Computing. 2024; 120(1): 275-283. doi: 10.61091/jcmcc120-24
8. Gao Y, Wang B, Xu P. Big Data Analysis Based on the Evaluation of College Students' Civic Web. Journal of Combinatorial Mathematics and Combinatorial Computing. 2024; 120(1): 265-274. doi: 10.61091/jcmcc120-23
9. Azzi S, Gagnon S, Ramirez A, et al. Healthcare Applications of Artificial Intelligence and Analytics: A Review and Proposed Framework. Applied Sciences. 2020; 10(18): 6553. doi: 10.3390/app10186553
10. Holroyd C. Technological innovation and building a 'super smart' society: Japan's vision of society 5.0. Journal of Asian Public Policy. 2020; 15(1): 18-31. doi: 10.1080/17516234.2020.1749340
11. Pramanik MI, Lau RYK, Demirkan H, et al. Smart health: Big data enabled health paradigm within smart cities. Expert Systems with Applications. 2017; 87: 370-383. doi: 10.1016/j.eswa.2017.06.027
12. Syed L, Jabeen S, S. M, Alsaeedi A. Smart healthcare framework for ambient assisted living using IoMT and big data analytics techniques. Future Generation Computer Systems. 2019; 101: 136-151. doi: 10.1016/j.future.2019.06.004
13. Radwan A, Huq KMS, Mumtaz S, et al. Low-Cost On-Demand C-RAN Based Mobile Small-Cells. IEEE Access. 2016; 4: 2331-2339. doi: 10.1109/access.2016.2563518
14. Zhou S, Ni Z, Ogihara A, et al. Behavioral Patterns of Supply and Demand Sides of Health Services for the Elderly in Sustainable Digital Transformation: A Mixed Methods Study. International Journal of Environmental Research and Public Health. 2022; 19(13): 8221. doi: 10.3390/ijerph19138221
15. Roberts H, Cowls J, Morley J, et al. The Chinese approach to artificial intelligence: an analysis of policy, ethics, and regulation. AI & SOCIETY. 2020; 36(1): 59-77. doi: 10.1007/s00146-020-00992-2