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Research on Individualized Health Risk Identification and Intervention Decision Model Supported by Artificial Intelligence

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Abstract: Since the 1990s, global personalized health management has evolved rapidly, centered in the US with multi-country collaboration, transitioning from systematic care to technology integration (e.g., AI, blockchain). Challenges include inefficient data integration, imprecise population segmentation, and static risk assessment. This study proposes a "theory-method-application" framework: a credit model using reliable/integrity/ contribution behaviors enhances data quality and sharing via differentiated services; an unsupervised model combining Gol coefficient & PAM algorithm with t-SNE visualization achieves precise risk stratification (validated via Stanford data with contour/elbow metrics); XGBoost with hyperparameter tuning quantifies biopsychosocial-environmental risk impacts via feature importance and partial dependence; a 4-stage digital platform (data collection, visualization, risk assessment, intervention) supports smart contract alerts and dynamic weight management via rolling optimization. Findings show credit models boost data sustainability, segmentation models exhibit stable stratification, XGBoost outperforms benchmarks, and the platform enables real-time alerts and BMI/cardiovascular risk control. The study advances theory (incentive mechanisms, interpretable AI), practice (resource optimization, proactive care), and future directions (wearables integration, hybrid AI, policy innovation), aligning with AI-driven trends in personalized health management.

1. Introduction

The research on personalized health risk identification and intervention decision-making model supported by artificial intelligence is based on the development trend of global personalized health management. Since the 1990s, the literature in this field has shown a period of embryonic development and rapid growth, with the United States as the core and multiple developed countries collaborating. The evolution of keywords reflects the forefront trend from systematic health management to technological integration. In response to the challenges in data integration, population segmentation, risk assessment, and other aspects of existing research, this study focuses on the core issues from the perspective of multi-source health data: constructing a credit based health data sharing model [1], characterizing user credit through the three-dimensional attributes of reliable behavior, integrity behavior, and contribution behavior, and designing differentiated service strategies to improve data quality and sharing willingness; Develop a population segmentation model based on unsupervised learning, integrating Gol dissimilarity coefficient [2] and PAM algorithm, combining contour coefficient [3], elbow point method, leave out method, and t-SNE dimensionality reduction visualization to achieve quantitative stratification of health risks; Design a health risk assessment model based on supervised learning, optimize hyperparameters using XGBoost method, and quantify the marginal impact of multidimensional risk factors on health by combining feature importance ranking and partial dependency analysis; Ultimately integrating the above modules to construct a digital platform model, including four stages of health data collection, visualization, risk assessment, and personalized intervention, and exploring application scenarios such as smart contract warning and dynamic weight management. Expanding the connotation of personalized health management at the theoretical level, innovating data sharing incentive mechanisms, intelligent algorithms, and interpretable machine learning models at the methodological level, providing decision-making basis for optimizing health resource allocation and formulating precise intervention plans at the practical level, promoting the transformation of health management from disease treatment to active prevention, forming a complete research loop of theory method application, and conforming to the development trend of personalized health management driven by artificial intelligence technology.

2. Correlation theory

2.1. Definition and Characteristics Analysis of Personalized Health Management Concept

Health management [4] originated in the United States in the 1980s, driven by health insurance, aiming to reduce medical expenses by managing customers' health status. It has now developed various service forms such as HMO and PPO, covering over 125 million people. After the 1990s, countries such as the UK, Germany, and Japan successively implemented health management. For example, the UK established the National Health Service (NHS) and relied on information databases to establish a full life cycle health record for residents; Japan provides comprehensive health management services for the elderly through the Care Insurance Act.Personalized health management is an advanced form of health management that emphasizes the integration of multiple sources of health data[5] (biological, psychological, social, environmental, behavioral, etc.) and the use of artificial intelligence technology to achieve precise and intelligent services. Its connotation includes: systematic risk assessment and intervention plan formulation based on individual health status, covering the three links of data collection, risk assessment, and health intervention. It is different from the homogeneous services of traditional health management and focuses more on differentiated and diversified service models. The core features are precision (accurate service direction and scale), intelligence (big data and AI driven), behaviorism (scheme needs to be verified by practice), visualization (intuitive display of data and value) and diversification (expanding service models relying on Internet, mobile medicine and other carriers). The data sources cover biological data psychological data (stress, anxiety, etc.), social data (education, occupation, etc.), environmental data , and behavioral data (diet, exercise, sleep, etc.), with unique attributes such as big data 5Vs characteristics and complexity (polymorphism, incompleteness), privacy (requiring full process protection), sparsity (data loss or zero value phenomenon).The World Health Organization's definition of health is constantly evolving, from "physiological, psychological, social adaptation, and moral well-being" to "health management needs throughout the entire life cycle and living space", further supporting the development direction of personalized health management with "biological psychological social environmental" multidimensional integration as the core.

2.2. Core Points and Trend Analysis of Global Health Management and Personalized Health Management

Health management originated in the 1980s, initially driven by health insurance to reduce medical costs, and has now developed into a diversified service form that covers a wide range of people. The current global health management is showing significant progress: the health level of residents continues to improve, the life expectancy per capita increases, the premature mortality rate of major chronic diseases decreases, and the popularization rate of health knowledge increases; The health examination industry is booming, with an increase in the number of institutions and examination participants, forming a quality control network; The scale of the health industry has expanded rapidly, covering smart health technology, Internet platform, big data services and Internet of Things technology, and the annual compound growth rate of the market size is significant; The connotation of health management has expanded from simple physical examinations to comprehensive services such as disease screening, diagnosis and treatment, chronic disease management, and health insurance, forming a multi business integration model. However, challenges still exist: the aging population is worsening, the burden of chronic diseases is increasing, and the problem of "getting old before getting rich" is prominent; High incidence of chronic diseases and a clear trend towards younger age groups; There is a shortage of professional personnel and equipment in the prevention and control of chronic diseases at the grassroots level; Insufficient effective supply of chronic disease management, lack of multidimensional data and advanced screening technologies; The homogenization of health management intervention programs makes it difficult to meet the diverse needs of the population. The effective implementation of personalized health management relies on three core key points: multi-source health management data sharing is the foundation, which requires the integration of heterogeneous data from multiple sources such as biology, psychology, society, and environment to explore value; Precise population segmentation is key, utilizing technologies such as big data, artificial intelligence, and blockchain to optimize resource allocation and enhance grassroots chronic disease management capabilities; Comprehensive health risk assessment is the core, which requires the integration of multidimensional factors, traditional disciplinary knowledge, and new generation information technology to provide intelligent risk warning to support decision-making. In terms of development trends, full lifecycle health management covers different stages of life and provides continuous services; Comprehensive health management promotes the transition from "drug therapy" to "lifestyle intervention"; Digital technology enables real-time collection of health data and monitoring and early warning of chronic diseases; Artificial intelligence, blockchain and other technologies are driving personalized health management, creating a "product+platform+service" ecosystem to meet multi-level and personalized needs.

3. Research method

3.1. Research on the Operation Mechanism and Health Risk Stratification Model of Health Data Bank (HDB)

As a health data operator, Health Data Bank (HDB) [6]focuses on storing massive amounts of multi-source health data (such as personal basic information, health status, disease history, weekly exercise duration, and other continuous variables, as well as categorical variables such as smoking). Through big data analysis, HDB mines data association patterns, generates scientific knowledge such as chronic disease triggers, and expert knowledge such as clinical experience of medical experts. Its aim is to achieve sustainable development of personalized health management services through data value appreciation. Its operating mechanism follows the model of commercial banks, setting up multiple types of accounts for individuals, small businesses, and large institutions, and proposing differentiated service strategies based on creditworthiness - by constructing a three-dimensional creditworthiness evaluation system that includes reliable behavior (AB), integrity behavior (HB), and contribution behavior (CB), linking user creditworthiness with data sharing permissions and service priorities (such as high credit users prioritizing access to value-added services such as health risk warnings and precision medical recommendations, while low credit users face service restrictions). This strategy, combined with Monte Carlo simulation to verify its effectiveness, solves the problem of the disconnect between credit rating and incentive measures in traditional incentive mechanisms.

The specific formula for calculating the three-dimensional attributes of creditworthiness is: reliable behavior (AB) value

$$\mathrm{AB_i} = \frac{\mathrm{S_i^+}}{\mathrm{S_i^+} + \mathrm{S_i^-}} \times \left(1 - \frac{\mathrm{N_i^-}}{\mathrm{T_i}}\right) \text{ (Formula 1)}$$

Among them, $\mathrm{S_i^+}$ represents the amount of data uploaded by user i that meets the needs of other users, $\mathrm{S_i^-}$ represents the amount of data that cannot meet the needs, $\mathrm{N_i^-}$ represents the number of suspicious services (feedback inconsistent with data authenticity), and Ti represents the total number of services; Integrity behavior (HB) value

$$\mathrm{HB_i} = 1 - \frac{\mathrm{N_i^-}}{\mathrm{N_i}} \text{ (Formula 2)}$$

where $\mathrm{N_i}$ is the total number of feedback and $\mathrm{N_i^-}$ is the number of suspicious feedback (contrary to $\mathrm{AB_i}$ value); Contribution Behavior (CB) Value

$$\mathrm{CB_i} = \mathrm{w_1} \cdot \mathrm{Available_i} + \mathrm{w_2} \cdot \mathrm{lnvolvement_i} \text{ (Formula 3)}$$

among them

$$\mathrm{Available_i} = \min\left(\frac{\text{Response times}}{\text{Average response times}}, 1\right) \text{ (Formula 4)}$$

$$\mathrm{lnvolvement_i} = \min\left(\frac{\text{Upload data volume}}{\text{Download data volume}}, 1\right) \text{ (Formula 5)}$$

, $\mathrm{w_1} + \mathrm{w_2} = 1$The weight coefficient can be adjusted.In the scenario of health data sharing, the risk grading objective function can be optimized as the objective function= α · empirical risk+ β · structural risk+ γ · credit risk, where α, β, and γ are risk weight coefficients (α + β + γ =1), and credit risk is a joint risk term calculated based on the ABi, HBi, and CBi values of user i.

Aiming at the mixed type characteristics of multi-source health data, a PAM clustering algorithm based on Gaul dissimilarity coefficient is constructed to achieve health risk quantification stratification. This algorithm is compatible with multiple types of variables such as binary, ordinal, and interval scale, and determines the optimal number of clusters through the average contour coefficient method (evaluating cohesion and separation, with a value range of [-1,1], significant sample classification when approaching 1) and elbow point rule (identifying elbows through the curve of error square sum SSE with the number of clusters k). Compared with k-means, it is more robust to outliers; At the same time, t-SNE dimensionality reduction technology is used to achieve high-dimensional data visualization. The Gaussian kernel function preserves the local and global structure of the data, and maps the high-dimensional space to 2-3 dimensions to visually present the clustering results. Through the three module process of "health indicator construction - model establishment - risk quantification and stratification", the model adapts to the multi-dimensional health management data of biology, psychology, society and environment, promotes the transformation of health resource allocation from "disease treatment" to "active prevention", and has the advantages of simple and efficient algorithm and visible and interpretable results.

3.2. Construction and optimization of integrated learning health risk assessment model based on XGBoost

This article constructs an ensemble learning health risk assessment model based on XGBoost, which comprehensively incorporates multidimensional health factors such as personal physiological characteristics, lifestyle, and psychological status. Through gradient boosting mechanism and regularization optimization objective function, multiple decision tree based learners are integrated in series to improve prediction performance and generalization ability. The model fitting adopts a 5-fold cross validation and step-by-step hyperparameter grid search strategy, optimizing conventional parameters (such as the number of base learners n_estimators), base learner parameters (such as learning rate eta, maximum tree depth max_depth, minimum splitting loss gamma, subsample proportion), and learning task parameters (such as logistic regression loss function and AUC evaluation criteria), balancing training errors and generalization errors, and avoiding overfitting. Regarding the interpretability of the model, the marginal impact of key health risk factors (such as exercise duration, smoking status, etc.) on health risks is quantitatively analyzed through feature importance measurement (weight counts feature usage frequency, gain statistics information gain, cover statistics leaf node sample coverage) and partial dependency graph visualization, enhancing the practical application value of the model. The advantages of this model lie in the high predictive ability of ensemble learning, the generalization guarantee of cross validation, the overfitting control of regularization terms, and the introduction of explanatory tools, which promote the transformation of health management from "disease treatment" to "active prevention" and provide scientific basis for personalized health management.

3.3. XGBoost Heart Disease Risk Prediction Model Driven by Multi Source Health Data

This section uses data from the Stanford University Heart Disease Risk Survey project as the source, and completes preprocessing through data cleaning, standardization, and feature screening to construct a health dataset data stream that includes 13 indicators such as physiological characteristics, exercise and sleep, dietary structure, psychological status, and family history. As shown in Figure 1

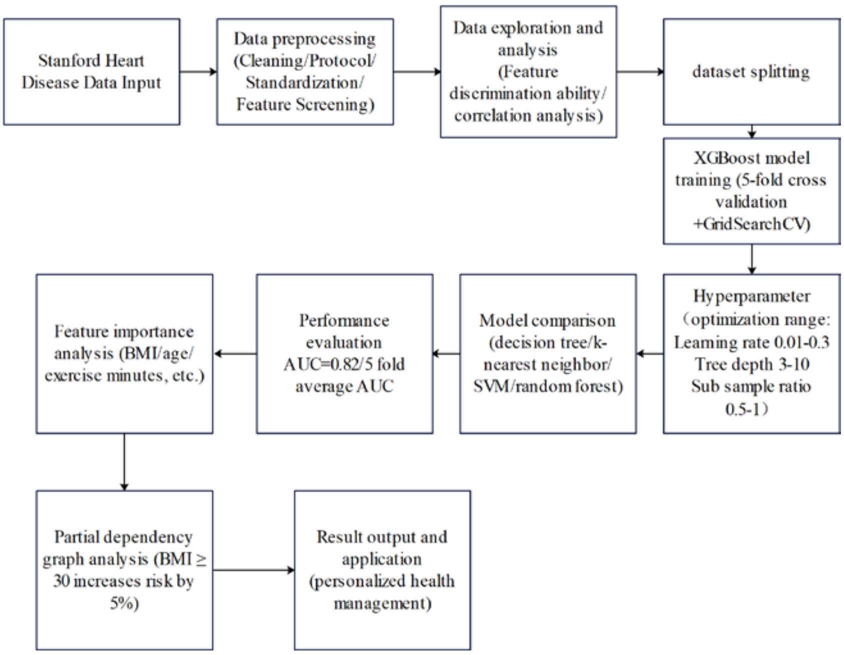

Figure 1 XGBoost Heart Disease Risk Prediction Model Driven by Data Stream

Exploratory data analysis shows that different features have differentiated abilities to distinguish the risk of heart disease, such as the number of minutes of vigorous exercise per week, life satisfaction, etc; The correlation between features is weak (maximum Pearson coefficient [7] 0.5), and there is no significant multicollinearity problem. The model fitting adopts a 70%/30% training test set partitioning, and uses 5-fold cross validation and GridSearchCV step-by-step optimization of XGBoost hyperparameters (such as learning rate, tree depth, subsample proportion, etc.), and compares their performance with typical machine learning methods such as decision trees, k-nearest neighbors, naive Bayes, support vector machines, and random forests. As shown in Table 1,

Table 1 Comparative Study on XGBoost Training Set Performance

Model	Accuracy	Weighted Average Precision	Weighted Average Recall	Weighted Average F1-Score	AUC
Decision Tree	0.91	0.91	0.90	0.86	0.88
k-Nearest Neighbors	0.86	0.90	0.87	0.87	0.90
Naive Bayes	0.86	0.86	0.86	0.86	0.84
Support Vector Machine	0.89	0.80	0.90	0.85	0.84
Random Forest	0.96	0.85	0.89	0.86	0.98
XGBoost	0.95	0.85	0.89	0.86	0.97

On the training set, the fitting performance of Random Forest (AUC=0.98) and XGBoost (AUC=0.97) is significantly better than other models; On the test set, the AUC value of XGBoost reached 0.82, the highest among the six methods, and the average AUC of 5-fold cross validation was about 0.82, verifying the robustness of the model. The analysis of feature importance shows that, BMI、 Age, moderate exercise minutes per week, vigorous exercise minutes per week, and life satisfaction are the top five characteristics that affect the risk of heart disease; Partial dependency graphs further quantify the marginal impact of key features, such as a 5% increase in heart disease risk when BMI $\geqslant$ 30, a 5% decrease in risk within 30 minutes of vigorous exercise per week, and a decrease in risk when life satisfaction $\geqslant$ 6. This empirical study validates the effectiveness of the XGBoost model on multi-source health data, and enhances the interpretability of the model through feature importance ranking and marginal impact analysis, providing a scientific basis for personalized health management.

4. Results and discussion

4.1. Core mechanism of blockchain digital health platform

The digital health platform follows the core idea of "countless carriers", which means that the platform does not own the data ownership, but only has the right to use and operate it under authorization, helping data owners achieve value generation and realization. In terms of health management data storage, blockchain distributed storage supports synchronization and verification of content change validity among nodes, achieves access control and privacy protection through asymmetric encryption, and can build different architectures such as public chains, private chains, and consortium chains according to individual and group health service models, adapting to different privacy level requirements - public chains support arbitrary user queries and transaction confirmations, suitable for personal data service scenarios; Private chains restrict write permissions to specific institutions, while read permissions can be flexibly restricted, making them suitable for medical knowledge accumulation and cost control in medical or research institutions. To incentivize users to share health data, a consensus mechanism based on Proof of Health Data Asset Value (PoDAV) is designed: the value of health data assets is measured by reliability (reflecting data quality and demand matching) and liquidity (reflecting transaction frequency and scale). The PageRank algorithm[8] is used to rank users and select the top N as validators. After paying a deposit, a pseudo-random number is used to select new block initiators; The consensus process consists of two rounds of voting, both using Byzantine fault-tolerant methods - in the first round of preparation stage, validators cast preparation votes, and if more than 2/3 of the valid votes are cast, the process enters the second round of confirmation stage. Each round of voting validators can receive a reward of 1.5x tokens; Successfully adding a compliant new block will reward 1x tokens, while voting failure will result in a loss of 0.5x tokens. This mechanism promotes the circulation and value appreciation of health data assets through token incentives and punishments, and drives the transformation of health management from traditional models to data ownership, assetization, and personalized services.

4.2. Model experiment

The health management platform takes data value generation as its core, integrates human-machine intelligence, relies on data resources, technology, and organizational elements, and achieves quantitative and qualitative evolution through "data knowledge" correlation. It includes three major paths: long-term data accumulation to form a knowledge system, cross dimensional data collaboration to enhance full cycle management, and human-machine intelligent interaction to optimize diagnostic capabilities. The four stage model involves collecting panoramic data from multiple channels and securely storing and preprocessing it; Visualize and describe health information; Intelligent risk assessment (combining unsupervised/supervised learning); Personalized intervention (including two major scenarios of abnormal warning automatic notification and regional group health monitoring).Application scenario two (as shown in Figure 2) is weight dynamic management based on personal health data: the platform constructs a dynamic model that includes historical weight, dietary habits, exercise habits, and other factors based on medical knowledge. Through utility function minimization and double-layer optimization methods, the exercise guidance plan is updated daily and the exercise goals are adaptively adjusted to form a "prediction optimization solution" closed-loop control mechanism. For example, the correlation between BMI and cardiovascular disease is used to achieve precise weight regulation.

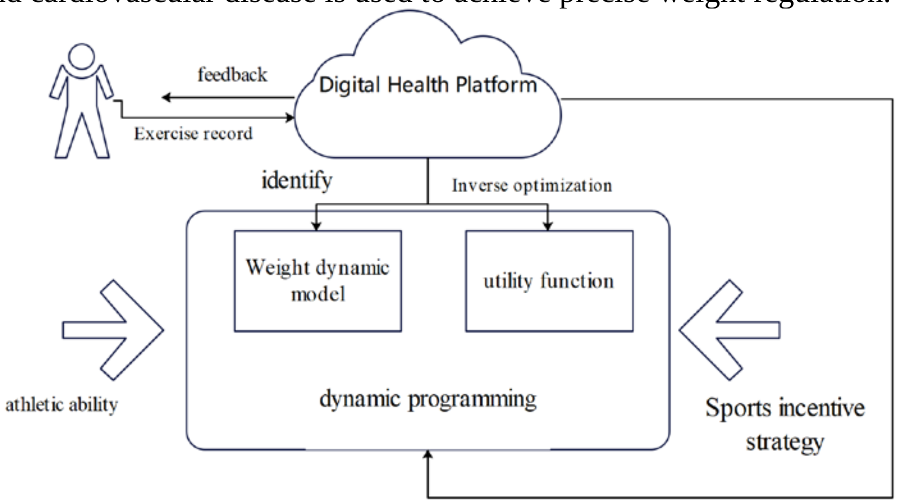

Figure 2 Application flowchart of dynamic programming in motion incentive strategy

4.3. Effect analysis

The World Health Organization's Global Strategy for Digital Health (2020-2025) emphasizes that data-driven treatment decisions, digital therapies, and people-centered care can improve health outcomes and promote the realization of the vision of universal health. As a fundamental strategic resource, the effective utilization of health data requires breakthroughs in challenges such as data fusion and sharing, privacy and security balance. In international practice, the United States has clarified the principle of user information control and "least necessary" disclosure through the Health Insurance Portability and Accountability Act (HIPAA), established a targeted, query, and patient intervention model for electronic health information exchange (HIE), and opened a multi institution database based on healthdata.gov; The Care.data project was launched in the UK to integrate general practice and hospital records. However, it was terminated due to privacy disputes and instead strengthened regulation through the Data Protection Act 2018; Germany promotes the electronic health card system through the Electronic Health Act, and combines artificial intelligence strategies to promote smart healthcare; The EU regulates the consent and accountability mechanism of data subjects through the General Data Protection Regulation (GDPR) and establishes data protection officers to supervise the processing of sensitive data; Canada promotes cross provincial sharing of electronic health record systems through the Personal Information Protection and Electronic Documents Act and Infoway organization; Japan amends the Personal Information Protection Law to include medical data in sensitive information management and implements the principle of "informed choice to withdraw"; South Korea has established a national health data management system that covers health information for over 130 million people. Currently, the development of personalized health management data worldwide is facing common problems: the definition of the connotation and protection period of personal health data is vague, and special laws, regulations, and regulatory coordination mechanisms need to be improved; The mechanism for cross institutional data sharing is not sound, and there is a natural conflict between privacy protection and data utilization; The centralized platform has incomplete coverage and uneven data quality, and the lack of unified format standards hinders exchange; The technical support for data collection, storage, and sharing is insufficient, and the integration of technologies such as federated learning and privacy computing with the healthcare field needs to be deepened.Strategic advancement requires multidimensional collaboration: improving specialized laws and regulations, refining the scope of privacy protection and the rights and obligations of each link in data circulation, and constructing a full lifecycle privacy protection model; Develop unified data standards, promote differentiated configuration of health data classification and open authorization agreements, and regularly update platform data to eliminate low-quality datasets; Establish an open sharing platform, encourage diversified data integration, connect medical and insurance data, innovate management strategies and interdisciplinary review mechanisms; Strengthen international cooperation, cultivate a digital ecosystem for health management, integrate social, family, and personal systems, activate the value of data resources, improve institutional systems and talent cultivation, integrate into the global health innovation network, promote technology open source and knowledge sharing, and ultimately achieve the maximization of health data value and the upgrading of personalized health management services.

5. Conclusion

The research on personalized health risk identification and intervention decision-making models supported by artificial intelligence focuses on the deep mining and intelligent application of health and medical big data, exploring personalized health management paths driven by multi-source health data through the introduction of machine learning, blockchain and other technologies. A credit based health data sharing model was developed, which characterizes user credit from three dimensions: reliable behavior, integrity behavior, and contribution behavior. Differentiated service strategies were designed to enhance data sharing willingness and value, and numerical experiments were conducted to verify its effectiveness in promoting sustainable data appreciation in health data banks. At the level of risk identification, an intelligent population segmentation model is constructed by integrating unsupervised learning PAM algorithm and Gaul dissimilarity coefficient. Combined with contour coefficient, elbow point method, leave out method, and t-SNE dimensionality reduction visualization, precise stratification of high, medium, and low-risk populations is achieved; Using supervised learning XGBoost method to construct a health risk assessment model, optimizing hyperparameters through cross validation, combining feature importance ranking and partial dependency analysis, quantifying the marginal impact of multidimensional risk factors (biological, psychological, social, environmental) on health, and empirically testing the effectiveness of the model with Stanford data. In terms of intervention decision-making, we explore the use of blockchain based distributed ledgers [9]and asymmetric encryption technology to enhance the security of digital health platforms. We design a consensus mechanism for the value of health data assets, construct a four stage management model that includes data collection, visualization, risk assessment, and personalized intervention, and develop application scenarios such as smart contract warning[10]and dynamic weight management. The study also proposed strategic suggestions such as improving data laws and regulations, promoting unified standards, establishing open sharing platforms, and strengthening international cooperation. At the same time, it pointed out that in the future, it is necessary to integrate real-time monitoring data from wearable devices, explore heterogeneous health data fusion methods, develop hybrid intelligent technologies to integrate expert cognition, and pay attention to multi-party collaborative management and supporting policy and institutional innovation, in order to promote the transformation of personalized health management from data-driven to intelligent, and ultimately achieve comprehensive improvement in health level and quality of life.

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