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IoT-Enabled Hierarchical Architecture for Intelligent Home-Based Elderly Care: A Multi-Objective Optimization Approach

Jiaoqian Xiao*
Changzhi Medical College, Changzhi 046000, Shanxi, China
*E-mail: 15197901237@163.com

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With the acceleration of global aging process, the contradiction between the home care needs of disabled elderly and limited nursing resources is becoming increasingly prominent. To address monitoring blind spots, delayed responses, and lack of personalized services in traditional elderly care models, a smart elderly care ecosystem based on the Internet of Things is constructed. By integrating data collection, transmission, and intelligent service modules through a layered architecture design, a multi-modal sensor network is deployed to fuse physiological parameters, behavioral trajectories, and environmental data. The research involves deploying Raspberry Pi 4B edge nodes in 15 households of disabled elderly individuals, integrating wearable devices, ultra-wideband positioning tags, and environmental sensors, totaling 23-28 units per household. The sampling frequency is 1 Hz during the day and 0.017 Hz at night, with an average data volume of 12.7 GB per day. The core algorithm includes an improved LZW compression algorithm that reduces data redundancy through differential preprocessing and dynamic dictionary elimination, a dynamic priority scheduling mechanism that uses a random forest classifier to identify event urgency and predicts pre-allocated bandwidth based on LSTM behavior, and a multi-objective particle swarm optimization algorithm for balancing energy consumption and load distribution. The proposed system was deployed in home-based elderly care for disabled individuals. The results showed that the improved compression algorithm and dynamic priority scheduling mechanism reduced the compression rate by 40.09% and shortened the transmission delay of key data in network jitter scenarios by 61.3% at a sampling frequency of 6 times/min. After introducing a multi-objective optimization load balancing strategy, the day and night energy consumption were reduced by 30.8% and 27.5%, respectively. In the 12-month controlled experiment, a single-group pre-post design was adopted, with 30 participants aged 72.5±6.8 years. Based on the MIT-BIH arrhythmia database and the UR fall dataset, the training set was constructed to verify that the prediction accuracy of chronic diseases increased to 81.5% (the original baseline was 67.7%, p<0.001), the incidence of bedsores decreased by 78.9% (the original baseline was 37%), and the nursing cost decreased by 62.1% (the original baseline was 9,354 RMB/month). The study proposes a technical approach to mitigate resource mismatches in home-based elderly care services by constructing a closed-loop management system of "monitoring-warning-intervention", promoting the intelligent elderly care towards ecological and precise direction.

Povzetek: Članek predstavi večnivojsko IoT-arhitekturo za pametno domačo oskrbo starejših, ki združuje večmodalno zaznavanje, stiskanje ILZW, dinamično razvrščanje prednosti (RF+LSTM) in večciljno PSO-optimizacijo. Sistem zmanjša porabo energije ter izboljša točnost napovedi bolezni.

1 Introduction

With the intensification of global population aging, the number of disabled elderly people is also increasing year by year. This not only poses a huge challenge to the social welfare system, but also brings unprecedented pressure to the home-based elderly care model for disabled individuals. The family-based care model for disabled elderly is difficult to bear the main responsibility of home-based elderly care due to factors such as shrinking family size and changes in intergenerational relationships, while institutional elderly care faces problems such as limited resources, high costs, and shortage of manpower [1]. Therefore, exploring new elderly care models and technological solutions tailored to disabled individuals has become an urgent task. The rapid development of new quality productive forces such as information technology, Artificial Intelligence (AI), big data, and the Internet of Things (IoT) provides new opportunities for the intelligent upgrading of elderly care services for disabled populations. IoT refers to a network system that connects various physical devices, vehicles, buildings, daily necessities and other objects through the Internet to collect and exchange data [2]. As an emerging elderly care model for disabled individuals, intelligent elderly care integrates disabled elderly people, communities, medical staff, medical institutions, governments, and service agencies through modern technology to form a targeted intelligent service system. Due to the limitations of physical functions, disabled elderly people have a more urgent need for elderly care services [3]. However, there are still many shortcomings in current elderly care services in meeting the personalized needs.

The primary goal of the research is to address three core issues in the home-based care scenario for disabled elderly individuals: insufficient real-time monitoring, lack of dynamic response mechanisms, and resource allocation. In terms of real-time sensor monitoring, traditional single-point sensors struggle to capture the dynamic associations between physiological, behavioral, and environmental multi-modal data, leading to delayed health risk predictions. Regarding the response mechanism, existing systems lack hierarchical transmission strategies based on event urgency, resulting in excessive delays in critical tasks under high-concurrency scenarios. In terms of resource allocation, there is a mismatch between the supply of nursing resources and the personalized needs of the elderly, and service scheduling lacks support from multi-objective optimization.

A multi-mode data collection network integrating physiological monitoring, behavior tracking, and environmental perception is established to address the above issues, improving the sensitivity of abnormal sign recognition. The LZW compression algorithm and dynamic priority scheduling mechanism are optimized to reduce the transmission delay of critical data. A blockchain driven multi-agent collaboration framework and service orchestration strategy are used to optimize nursing resources.

The study employs three types of validation methods to assess target achievement. In the algorithm performance comparison experiment, on the standard dataset (MIT-BIH arrhythmia database), ILZW is compared with traditional LZW and ISRLE algorithms, with an expected compression rate of ≤15%. In high packet loss and mixed jitter scenarios, the expected data recovery rate is ≥85%. In network performance stress tests, Mininet-WiFi simulates NB-IoT bandwidth limitations, with an expected end-to-end latency for emergency events of ≤800ms. In a multi-device concurrent (20 terminals) scenario, the expected critical task failure rate is ≤1.0%. In the health management control experiment, a single-group pre-post design (N=30) is used, with an expected monthly reduction in bedsores incidence of ≥70%. From the nursing time statistics and consumable records, the expected monthly reduction in nursing costs is ≥50%.

The innovation of the research lies in designing a hierarchical architecture intelligent elderly care ecosystem based on IoT technology. By integrating physiological monitoring, behavior tracking, and environmental perception into a multi-modal sensor network, and combining the Improved Lempel-Ziv-Welch (ILZW) algorithm and intelligent hierarchical transmission mechanism, efficient data processing and transmission have been achieved. A multi-objective optimization strategy is adopted to balance energy consumption and load, ensuring the stability and efficiency of the system. The contribution of the research lies in providing a systematic solution to the resource allocation problem in home-based elderly care, and providing reference for the technological iteration and social service collaboration in the field of smart elderly care.

2 Related works

Intelligent elderly care utilizes advanced information technology and IoT technology to improve the quality of life of elderly people, help them live more independently, and provide better support for caregivers and family members. He et al. proposed an intelligent elderly care space design based on the Kano model to improve the quality of home-based elderly care. The results indicated that this design made the method more approachable and shortened the psychological distance between the elderly and the intelligent elderly care space [4]. Yin et al. developed a new intelligent elderly care service model to address the worsening population aging. The results indicated that the intelligent elderly care service model could reduce the burden of family elderly care, which was an effective way to actively respond to population aging [5]. Yang et al. designed an intelligent nursing bed based on a low-cost resource constrained micro-controller to cope with the nursing pressure brought about by the increasing global aging population. The results showed that the gesture recognition accuracy of the device was 96.65% [6]. Ghosh analyzed the current application status of AI technology in the field of addressing malnutrition in the elderly. Deploying nutrient intake monitoring systems based on AI still posed challenges due to regional differences in dietary habits and personalized hospital menus [7]. Mohan et al. reviewed the application of AI, the IoT, and sensor technology in the prevention of falls among the elderly. The results indicated that AI and IoT technology were the best solutions for preventing falls in the elderly [8].

With the development of cloud computing, big data, and AI technologies, the application scenarios of the IoT are constantly expanding. Li et al. discussed the current application status and development prospects of IoT technology in the field of mental health services. The results indicated that IoT technology could improve the quality of life of patients with mental disorders, but it also faced challenges on patient privacy and security [9]. Ni et al. proposed an intelligent monitoring system based on the Medical IoT to improve the medical monitoring efficiency of elderly patients and patients with chronic diseases. Real-time data such as location, weight of infusion urine bags and heart rate were collected through low-cost sensors and transmitted to the cloud server via wireless network. Medical staff could check the patient's status with the help of mobile applications, reducing human resource consumption and improving the flexibility of diagnosis and treatment [10]. SanchezIborra et al. proposed a hierarchical integration TinyML solution to achieve intelligent perception in the distributed IoT.

Heterogeneous terminal decision-making was integrated through a two-layer edge computing architecture and applied to intelligent agriculture scenarios. This method reduced the frequency of wireless transmission while lowering energy consumption and response delay, and enhanced data privacy protection, providing an efficient solution for edge intelligence in resource-constrained environments [11]. Almasoudi et al. evaluated IoT information security in the health care for people with disabilities from strategy, technology, organization, personnel, and environment to identify assets, threats, and protective measures, combining the confidentiality, integrity, and availability assessment and safety performance. Case studies showed that this method could be flexibly updated, revealing the correlations between various elements and providing an extensible evaluation framework for medical IoT security research [12]. Wang et al. proposed a solution based on the IoT and edge computing technology to improve the information processing efficiency of the expressway intelligent transportation system. The results indicated that this approach outperformed traditional intelligent transportation systems in monitoring response speed, congestion rate, and accident rate prediction [13]. The comparison of relevant studies is shown in Table 1.

Table 1: Comparison analysis of relevant studies

Author (Year)	Method/Technology	Dataset/Application Scenario	Accuracy/Performance	Latency	Energy Consumption	Limitations
He et al. (2023) [4]	Kano model-based smart elderly care space design	Simulation environment (no specific dataset)	Psychological distance reduced by 38%	Not mentioned	Not mentioned	No validation of real-user scenario adaptability
Yin et al. (2023) [5]	Novel intelligent elderly care service model	Community pilot (N=200)	Family burden reduced by 52%	Not mentioned	Not mentioned	Lacks dynamic resource scheduling
Yang et al. (2024) [6]	Low-cost microcontroller-based smart nursing bed	Lab gesture dataset (N=50)	Gesture recognition accuracy 96.65%	≤200 ms	0.8 W	Lacks real-time health monitoring
Ghosh (2024) [7]	AI-based nutrition monitoring system review	Multi-regional hospital menu data (N=300)	Personalized menu matching rate 68%	Not mentioned	Not mentioned	Limited generalization due to dietary habits
Mohan et al. (2024) [8]	AIoT-enabled fall prevention review	Public fall dataset (URFD)	Average recall rate 89.7%	Not mentioned	Not mentioned	Lacks dynamic priority scheduling
Li et al. (2024) [9]	IoT-based mental health services	Mental disorder patients (N=120)	Quality of life improved by 23%	Not mentioned	High device dependency	Weak privacy protection mechanisms
Ni et al. (2023) [10]	Medical IoT smart monitoring system	Hospital infusion monitoring (N=80)	Infusion anomaly detection rate 94%	120 ms	2.1 W	Limited to clinical settings, not adaptable to home environments
SanchezIborra (2023) [11]	Hierarchical TinyML edge intelligence solution	Smart agriculture dataset (N=1500)	Energy consumption reduced by 40%	≤500 ms	0.5 W	Untested in complex home network jitter scenarios
Almasoudi (2023) [12]	Healthcare IoT security assessment framework	Disabled care case studies (N=45)	Security compliance score 92%	Not mentioned	Not mentioned	Unquantified data misuse risks
Wang and Shang (2024) [13]	Edge computing-based traffic monitoring	Highway monitoring data (10 km)	Response latency reduced by 45%	85 ms	12.3 W	Not optimized for resource-constrained home elderly care scenarios
Proposed Approach (2025)	Multimodal IoT ecosystem	Real home scenarios (N=30)	Chronic disease prediction accuracy 81.5%	235 ms	Daytime/Nighttime energy consumption ↓30.8%/27.5%	Needs enhanced privacy protection techniques

In summary, most existing studies (such as smart nursing beds and fall prevention systems) focus on optimizing a single function, lacking dynamic hierarchical response mechanisms for emergencies (such as abnormal heart rates and falls). This results in significant delays in critical tasks during high-concurrency scenarios, making it difficult to meet the real-time requirements of home environments. Moreover, current technologies (such as edge computing for traffic monitoring and agricultural IoT solutions) are often designed for industrial or urban settings, which do not suit the frequent network jitter and strong device heterogeneity of home environments, making it challenging to balance energy consumption and stability. The research on msental health monitoring and nutritional management relies heavily on manually annotated data, lacking a closed-loop feedback mechanism that can dynamically capture real-time changes in disabled elderly individuals. These limitations make it difficult for existing technologies to achieve an ecological closed-loop management system of "monitoring-warning-intervention." To address the insufficient dynamic response capability in existing technologies, this study combines Random Forest (RF) classification with Long-Term Short-Term Memory (LSTM) networks for contextual reasoning, enabling preemptive transmission of urgent tasks and reducing key data transmission latency in bandwidth-constrained scenarios. Additionally, to tackle the challenge of network heterogeneity in home environments, a multi-objective optimization load balancing strategy is designed, using Particle Swarm Optimization (PSO) to dynamically coordinate service quality, energy consumption, and load balancing, thereby reducing equipment energy consumption over time. A blockchain-driven ecological closed-loop architecture is constructed, incentivizing collaboration among hospitals, pharmaceutical companies, and other stakeholders through quantified data contribution, and forming a "risk-sharing-data-sharing-benefit-repayment" model.

3 Methods and materials

3.1 Architecture design of intelligent elderly care system based on IoT

When building an IoT-based home care ecosystem for disabled elderly, the research first focuses on the design and technical implementation of the system architecture to ensure efficient operation and meet the diverse needs. The research adopts a modular and layered design approach, dividing the system into three main modules: data acquisition layer, data transmission layer, and intelligent service layer. Through IoT technology, the collaborative work among these modules is achieved, providing real-time and reliable home-based elderly care support for the elderly [14]. The architecture of the home intelligent elderly care IoT system for disabled elderly is shown in Figure 1.

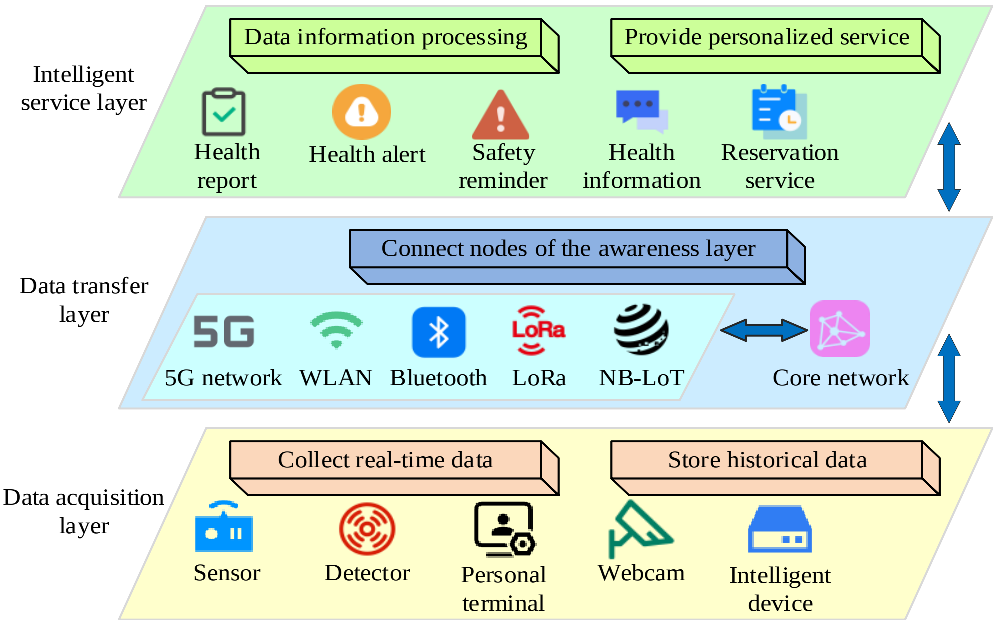


Figure 1: Architecture of intelligent home care IoT system for disabled elderly

In Figure 1, the data acquisition layer focuses on the deployment and optimization of sensor networks. By configuring multiple intelligent sensors, various physical data in the environment of disabled elderly people can be collected. Intelligent sensors include physiological parameter monitoring devices, such as wearable heart rate and blood oxygen monitors. Environmental sensing devices include smoke and gas leak sensors, behavior tracking devices such as infrared motion sensors and pressure pads [15]. In the data acquisition layer, physiological monitoring employs Photoplethysmography technology due to its non-invasive and low-power characteristics, ensuring long-term wear comfort. Environmental sensing uses a combination of electrochemical sensors and Micro-Electro-Mechanical Systems, reducing bandwidth usage and supporting local calibration. Behavioral tracking utilizes ultra-wideband technology, leveraging its high-precision positioning at the 10 cm level and strong penetration capabilities to adapt to complex home environments. To improve the pertinence of data collection and reduce resource waste, a data collection strategy based on spatial partitioning is designed, which divides the home environment into sub areas with clear functions. This strategy optimizes sensor deployment based on the characteristics and needs of activity areas such as bedrooms, living rooms, kitchens, bathrooms, and corridors. The activity trajectory and lifestyle habits are analyzed to identify regional functions. Floor plan and ultra wideband indoor positioning technology are used to divide boundaries and evaluate priority based on the needs of the elderly [16]. Through continuous 30-day behavioral monitoring of 12 disabled elderly individuals, their daily activity range is mainly concentrated within a 0.5-1.5 m space. A grid that is too small can lead to high sensor density, while a grid that is too large can reduce the accuracy of fall detection. The study compares different grid densities through pre-experiments. When the grid size is reduced to 0.5 m×0.5 m, the positioning accuracy is improved to 0.12 m, but the number of devices increased by 120%, and the average daily energy consumption is 68%. When the grid expands to 2 m×2 m, the number of devices decreases by 55%, but the missed critical event rate increases to 15%. A 1 m×1 m grid achieves the optimal balance between positioning accuracy and sensor deployment cost. Therefore, the sensors are arranged in a 1 m×1 m grid pattern. Sensor positions are determined based on activity frequency and demand weights. During the day, elderly people are more active, moving an average of 12 times per hour, while at night, their activity frequency drops to 1.5 times per hour. Through simulation experiments comparing data integrity and energy consumption under different sampling frequencies, 1 Hz daytime sampling can cover 95% of critical events (such as abnormal heart rates), while nighttime sampling once per minute only misses 2% of low-risk events. Additionally, maintaining 1 Hz sampling at night increases the device's daily energy consumption by 81%, but the detection rate of critical events improves by only 0.8%. If the daytime sampling frequency is reduced to 0.5 Hz, the error rate in reconstructing activity trajectories rises from 7.2% to 19.5%. Therefore, the device performs high-frequency sampling at 1 time/s during the day and low-frequency sampling at 1 time/min at night to reduce redundancy in data collection and energy consumption of the device.

To ensure the fast and secure transmission of multi-source data, this study constructs a data transmission layer through a hybrid network architecture, utilizing various network communication methods such as narrowband IoT and wireless LAN to adapt to communication needs in different scenarios. The maximum data throughput supported by the system is 10 Mbps, and each edge node can access 30 terminal devices simultaneously. 20% of the reserved bandwidth is reserved for dynamic load balancing to cope with peak traffic. At the protocol level, NB-IoT is based on the 3 GPP Release 13 standard, supporting a single-link transmission rate of 62.5 kbps for uplink and 26.15 kbps for the downlink. WLAN uses the IEEE 802.11 n protocol, with a theoretical bandwidth of 150 Mbps and an actual coverage radius of 50 m (indoor). The NB-IoT base station supports up to 50,000 device connections per cell (in compliance with 3 GPP TS 36.211 specifications), while the LoRa gateway operates at a bandwidth of 125 kHz, with the transmission rate ranging from 0.3 kbps to 50 kbps (LoRaWAN TS001-1.0.4), covering a radius of 1.5 km (urban environment). The system coordinates multiple protocols through an adaptive channel allocation mechanism (TDMA + CSMA/CA) to ensure the success rate of critical data transmission.

The intelligent service layer aims to adapt to the aging as its core goal, reducing operational complexity through multi-modal hardware interaction design, ensuring that disabled elderly people can intuitively and conveniently use system functions, while providing various services such as health alerts, safety warnings, appointment arrangements, health status reports, and medical consultations. In the intelligent service layer, edge computing nodes handle real-time tasks locally, reducing cloud transmission pressure. The cloud platform uses AWS IoT Core, leveraging its encryption and device shadow functions to ensure data security and offline caching. Human-computer interaction employs an offline voice engine and thin-film piezoresistive sensors to balance internet availability with durability for frequent use.

In the process of data transmission, data compression technology is introduced to optimize bandwidth utilization. Small fluctuations in physiological parameters can indicate early symptoms of atrial fibrillation or precursors to respiratory failure. Using lossy compression may lead to distortion of characteristic waveforms, posing a risk of false-negative diagnoses. Additionally, according to ISO 27799: 2016 Health Information Security Management Standard Clause 8.3, raw physiological data must be maintained at the bit level for audit trail purposes. Lossy compression results in irreversible data loss. Regarding the physiological data of disabled elderly individuals, the IZWL algorithm is used for lossless compression [17]. The algorithm flow is shown in Figure 2.

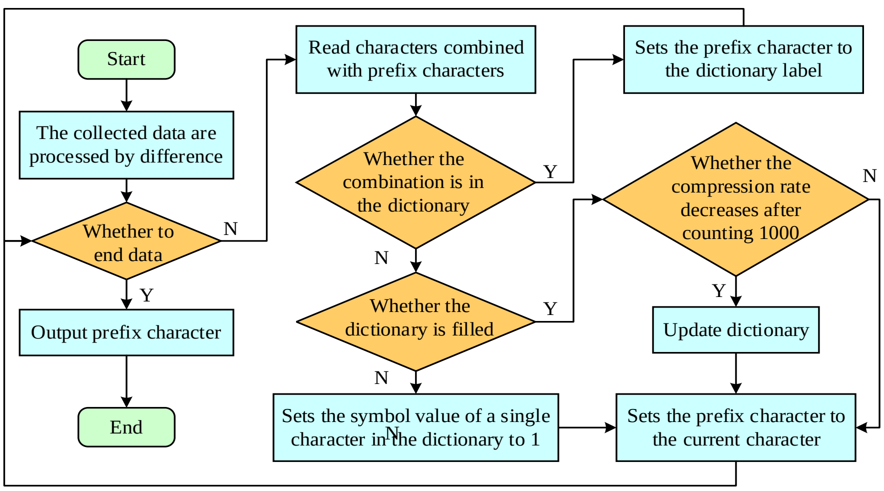


Figure 2: Improved LZW flow

As shown in Figure 2, in the ILZW algorithm, the data collected by the sensors is first preprocessed for differences, and the data repetition rate is improved by calculating the differences between adjacent data. Then, a dictionary with appropriate size is selected and the hash storage is taken instead of traditional sequential storage to improve search efficiency and compression speed. During the compression process, the dictionary is updated when a decrease in compression rate is detected, while commonly used single characters are saved and infrequently used dictionary entries are released to increase space utilization. In addition, the dictionary is not updated immediately after it is filled, but is adjusted according to the data duplication situation, and only updated when the compression rate increases.

Regarding the dictionary update frequency, this study introduces an adaptive triggering mechanism based on data repetition rate changes in the ILZW algorithm. When the data repetition rate decreases by more than 5% over ten consecutive compression processes, the system automatically triggers a dictionary update operation and uses a Markov prediction model to prioritize the elimination of dictionary entries that have not been referenced for nearly 30 minutes. When device resources are limited, the dictionary storage space is changed from a static array in traditional LZW to a linked hash table using a hash index structure. The least recently used (Least Recently Used, LRU) algorithm is employed to cache the access sequence of dictionary entries, thereby reducing memory fragmentation. Additionally, the study implements variable-length encoding for character compression, optimizing the byte count of a single dictionary entry from a fixed 3 bytes to a dynamic 1-4 bytes encoding, further reducing resource consumption.

To optimize bandwidth utilization, a priority scheduling mechanism is utilized to prioritize the key data transmission with high real-time requirements, such as abnormal heart rate alarm data, while compressing non-emergency data such as environmental monitoring and sending them in batches. The architecture and workflow of the priority scheduling mechanism are shown in Figure 3.

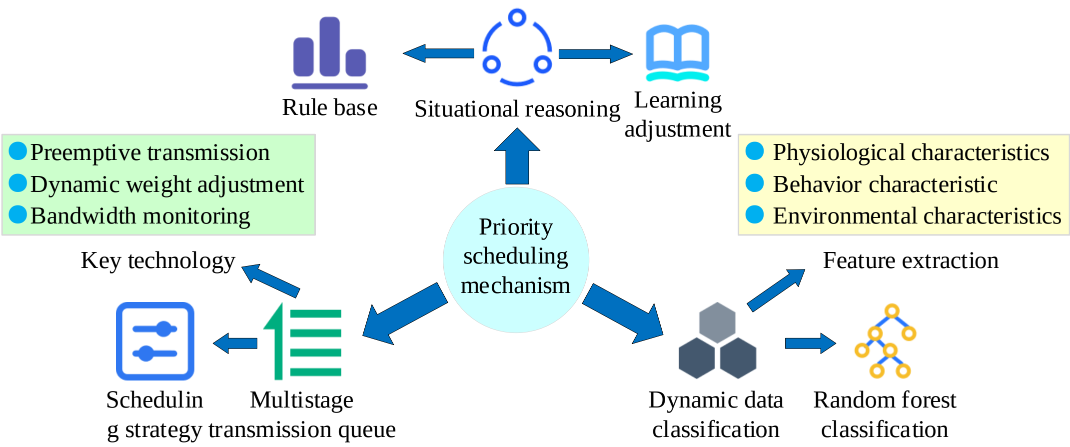


Figure 3: Architecture and workflow of priority scheduling mechanism

In Figure 3, the priority scheduling mechanism designed in the research works together through three core modules: dynamic data classification, multi-level queue management, and real-time contextual inference, to achieve intelligent hierarchical guarantee of data transmission. In dynamic data classification, feature extraction is performed on the raw sensor data stream, including physiological characteristics, behavioral characteristics, and living environment characteristics of disabled elderly people. The RF method is used to train datasets and annotate historical events such as falls and heart rate abnormalities. The acceleration variance, continuous heart rate anomaly, and residential environment temperature mutation rate of wearable devices are assigned different importance weights, and classification labels are output according to high, medium, and low priority. In multi-level transmission queue management, emergency situations such as fall alarms and cardiac arrest are set as high priority. Sleep apnea and high-temperature warning are set to medium priority. Temperature, humidity, lighting data, etc. are set as low priority. When a high priority event is identified, the current transmission task is immediately suspended, independent transmission paths are divided, and preemptive transmission is performed. The network utilization is calculated in real-time. When the bandwidth usage exceeds 80% and lasts for 5 seconds, the low priority queue is paused.

The RF training dataset is used to annotate historical events such as falls and abnormal heart rate. RF suppresses sensor data noise through multi-tree integration and voting mechanisms, adapting to the heterogeneity of physiological, behavioral, and environmental characteristics. Compared with XGBoost and CNN, RF is faster in inference speed for edge devices, meeting the real-time response requirement of fall detection within 50 ms. Additionally, RF supports variable-length time series data input, eliminating the need for fixed-window preprocessing required by CNN, making it suitable for deployment on low-power microcontrollers. The dataset includes 12,850 groups of annotated event data, covering six categories of priority events (falls, abnormal heart rate, etc.). Among them, 7,320 groups come from the clinical monitoring records of the geriatrics department at a hospital from 2021 to 2023. 3,610 groups are collected in real-time through sensor networks deployed in 15 households with disabled elderly individuals. The remaining 1,920 groups are from public datasets (the MIT-BIH Arrhythmia Database and the UR Fall Detection Dataset). The historical event data with annotations is divided into training, validation, and independent test sets in a ratio of 7:2:1, maintaining consistent sample proportions across categories. The training is conducted using Python's Scikit-learn library. During the training phase, the RF classifier model undergoes stratified 10-fold cross-validation to optimize model hyperparameters. In each fold of validation, the average accuracy of the model is calculated. The final model achieves an accuracy of 92.4% (±1.2%) on the independent test set.

To further evaluate the performance of the RF classifier, the study quantifies the model through feature importance score and confusion matrix. The study calculates the feature importance score based on the reduction of Gini impurity, and screens out the top 5 features with the highest contribution to classification, as shown in Table 2.

Table 2: Characteristic contribution

Feature category	Weighted score
Acceleration variance of wearable devices	0.32
The number of consecutive abnormal heart rates	0.28
The temperature fluctuation rate of the living environment	0.19
Standard deviation of nighttime activity duration	0.12
Gradient of light intensity variation	0.09

From Table 2, the contribution of acceleration variance to fall event detection is the highest, accounting for 32%, which verifies its core role in emergency event classification. In the confusion matrix verification, multiple classification confusion matrices are generated on the independent test set, and key indicators are shown in Table 3.

Table 3: Key indicator confusion matrix

True\Predicted	Fall (High-Priority)	Heart rate anomaly (High)	Sleep apnea (Medium)	Environmental anomaly (Low)	Normal (Low)
Fall	284	5	2	1	0
Heart rate anomaly	8	189	3	0	0
Sleep apnea	3	2	145	4	1
Environmental Anomaly	0	1	6	92	2
Normal	1	0	2	5	381

In Table 3, the model performs excellently in classifying five types of events. For high-priority events, the recall rate for fall detection is 98.3%, with an accuracy of 96.2%. The recall rate for abnormal heart rate is 94.5%, indicating that the model can accurately identify emergencies. For medium-priority events, the recall rate for apnea is 93.5%, with misjudgments mainly due to similar characteristics to high-priority events. For low-priority events, the recall rate for environmental abnormalities is 89.3%, with a normal state accuracy rate of 98.9% and a false positive rate of ≤2.8%. The overall classification accuracy is 91.7%, with a Macro-F1 value of 0.902, verifying the model's balanced performance across multiple categories. For task segmentation within the same priority category, a sub-priority dynamic evaluation model is designed to achieve refined scheduling through event urgency quantification indicators. Taking high-priority tasks as an example, the system extracts three core features: Response Time Threshold (RTT), Anomaly Gradient Physiological parameter (APG), and Historical Impact Factor (HIF), to construct an evaluation system. In RTT, the gold standard response time for cardiac arrest events is defined as ≤4 minutes (RTT=1), and the effective intervention time for fall alarms is defined as ≤10 minutes (RTT=2). Absolute time windows are allocated to different events using hardware timers. For APG, the rate of change in real-time heart rate relative to baseline values (ΔHR/minute) is calculated when heart rate is abnormal. When ΔHR> 50 bpm, it is marked as APG=1 (extremely critical). When 20 bpm <ΔHR ≤ 50 bpm, it is marked as APG=2 (high-risk). For HIF, based on the handling results of similar events over the past 30 days, if a timely response leads to complications, HIF=1. If a successful intervention is made, HIF=2. By integrating these features using a fuzzy logic controller, a sub-priority coefficient in the 0-1 range is output, with smaller values indicating higher priority.

In real-time situational reasoning, the long short-term memory network is used to learn the daily activity patterns of the elderly, and a relevant rule library is established. By predicting the behavior status for the next hour in real time, the transmission strategy of relevant data is preloaded. LSTM employs a two-layer stacked architecture. Based on the 24-hour activity trajectory data collected from ultra-wideband positioning systems, an input sequence with a time step of 60 is constructed using a sliding window mechanism (each time step corresponds to a 24-minute behavior segment). The network structure includes two 64-unit LSTM layers, which use layer normalization to enhance temporal feature extraction capabilities. The output layer predicts the behavior state for the next hour through a Sigmoid function. The training data comes from a behavioral trajectory dataset of 300 disabled elderly people for 6 consecutive months (with a total sample size of 2.16 million). The loss function L adopts the improved weighted binary cross entropy loss, as shown in equation (1).

$$L = -\frac{1}{N}\sum_{i=1}^{N}[\tau y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)] + \lambda\|\mathbf{W}\|_2 \quad (1)$$

In equation (1), N represents the total number of samples in the training batch, used to average the loss for each sample. y_i is the true label of the i-th sample. $\hat{y}_i$ indicates the prediction probability of the model for the i-th sample. τ is the positive class weight, used to amplify the loss contribution of rare anomalies, alleviating the class imbalance, and $\tau = 2.5$. λ is the regularization coefficient, controlling the strength of the L2 regularization term to prevent over-fitting. $\|\mathbf{W}\|_2$ is the L2 norm of the weight matrix, used to constrain model complexity. The model is deployed on NVIDIA Jetson Nano edge devices.

The collaborative mechanism between the rule base and situational reasoning learning achieves dynamic adjustment through a three-stage closed loop. First, the rule weights are dynamically updated based on LSTM learning from a 12-month historical event database to generate a priority weight evolution matrix. When the real-time inference result deviates from the pre-set value in the rule base by more than 15%, Bayesian optimization is triggered to adjust the priority threshold. Situational reasoning takes a reinforcement learning framework to update the convolution kernel parameters of the situational feature extractor every 24 hours, enhancing the ability to capture spatiotemporal features of complex behavioral patterns. The resource allocation strategy optimizes the bandwidth distribution ratio of the transmission queue according to the network utilization real-time heat map. When the number of concurrent medical devices exceeds 5, the TCP window size of the low-priority queue is automatically reduced from 64 KB to 16 KB, combined with an adaptive bandwidth compression algorithm to reduce transmission latency for emergency events.

3.2 Construction of an intelligent home care ecosystem for disabled elderly

In the process of building an intelligent elderly care ecosystem based on the IoT, it is crucial to adapt to the personalized needs of disabled elderly people and optimize system performance. The research method starts from two aspects: requirement identification and system adjustment, combined with design strategies and relevant technical means, to ensure that the system can flexibly respond to the specific situations, while maintaining long-term stable operation of the system. In terms of personalized demand adaptation, a data-driven framework for demand mapping and service customization is proposed, as shown in Figure 4.

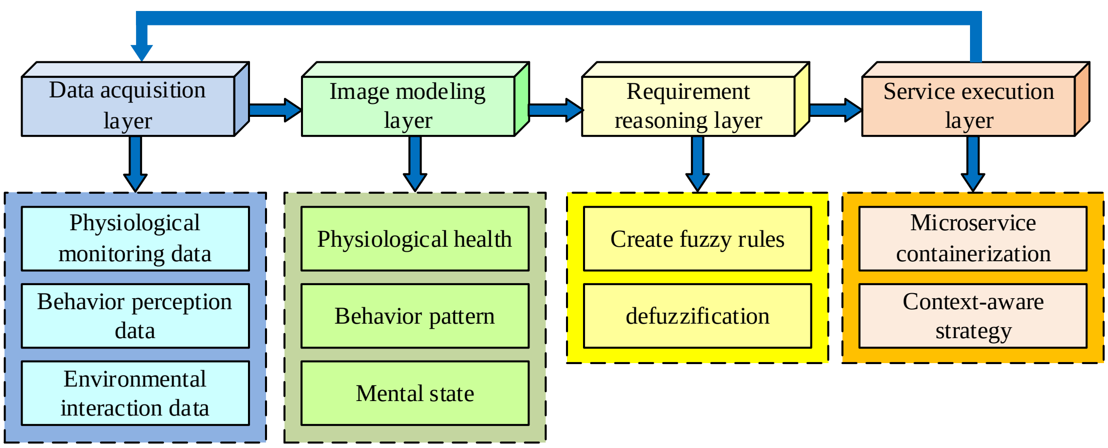


Figure 4: A data-driven framework for requirement mapping and service customization

From Figure 4, the framework first deploys multi-modal sensors to collect real-time physiological indicators, behavioral trajectories, and environmental data. The Dempster-Shafer evidence theory is used to fuse multi-source data, eliminate noise, and construct a unified temporal database [18]. By utilizing feature engineering to extract key indicators and combining online principal component analysis to dynamically update personalized state portraits, a multi-dimensional feature space covering physiology, behavior, and psychology is formed. The study employs a sliding window mechanism and an incremental learning strategy to achieve real-time personalized state mapping. Data windows are rolled every 5 minutes, with a capacity of 1,440 time-series data points. By extracting statistical features of physiological indicators, behavioral trajectories, and environmental parameters within the window, a user dynamic profile is constructed. To address data drift issues, online principal component analysis is used for dimensionality reduction and feature space updates. The study dynamically adjusts model parameters using the rank-1 correction formula of the covariance matrix, as shown in equation (2).

$$C_{\text{new}} = \delta C_{\text{old}} + (1-\delta)\frac{1}{V}\sum_{i=1}^{V}(x_i-\mu)(x_i-\mu)^T \quad (2)$$

In equation (2), C_{new} and C_{old} represent the covariance matrices before and after updates, respectively. δ is the forgetting factor and $\delta = 0.8$, used to reduce the weight of historical covariance matrices and control the model's adaptability to data drift. V is the sliding window size and $V = 1440$. x_i is the original observation value of the i-th data sample within the window. μ is the mean vector of all data within the window, used for centering processing. The time complexity for a single update is O(d) (where d is the feature dimension and d=15), which is much lower than the O(d^3) required for batch principal component analysis, making it suitable for real-time data stream processing.

The behavioral trajectory data collected by the sensor is first modeled using LSTM for temporal feature extraction, identifying behavior patterns related to psychological states. In the feature engineering phase, a behavioral feature vector is constructed, including behavioral entropy values, social activity levels, and environmental interaction frequencies. This vector is annotated and trained using the Simplified Geriatric Depression Scale (GDS-15) and the UCLA Loneliness Scale from psychometrics, forming a mapping model from behavioral data to psychological states. The output of the model is then fused through Dempster-Shafer evidence theory, ultimately forming a comprehensive state profile in multidimensional feature space that encompasses "physiological-behavior-psychological" aspects.

Based on a fuzzy logic inference engine, continuous data is transformed into fuzzy sets. Meanwhile, it matches the rule base constructed with expert experience to output demand categories and priority ratings. Specifically, the study normalizes three types of indicators: Physiological Abnormality Index (PAI), Behavioral Deviation (BD), and Environmental Risk Score (ERS), to the [0, 1] interval and processes them through triangular membership functions for fuzzification. For example, the high-risk membership function $\eta_{\text{high}}(x)$ for PAI is shown in equation (3).

$$\eta_{\text{high}}(x) = \begin{cases} 0 & x < 0.7 \\ \dfrac{x - 0.7}{0.2} & 0.7 \le x < 0.9 \\ 1 & x \ge 0.9 \end{cases} \tag{3}$$

In equation (3), x is the input value of PAI, which is quantitatively calculated from physiological indicators such as heart rate variability and blood oxygen saturation to assess the health risk level of disabled elderly individuals. The membership functions for BD and ERS are designed according to the fuzzy logic inference engine. The implementation method is consistent with that of PAI membership function. Mamdani fuzzy inference is used, and the center of gravity method is applied to resolve fuzziness, outputting a priority score ranging from 0 to 100. High priority ≥ 80, medium priority 50-79, and low priority <50. Some of the core rules in the rule base are shown in Table 4.

Table 4: Some of the core rules in the rule base

Rule ID	Conditions (Input Variables)	Priority Level	Weight	Example Scenarios	Conflict Resolution
R1	PAI≥0.9 (High-Risk) and BD≥0.7 (High Deviation)	Emergency	1.0	Heart rate surge (0.92) +Prolonged immobility (0.85)	Independent transmission path, preemptive response
R2	ERS≥0.8 (High-Risk) and PAI ≥0.7 (Medium-Risk)	Emergency	0.9	Excessive CO (0.85) +Respiratory anomaly (0.78)	Priority stacking of service combinations
R3	0.7≤PAI<0.9 (Medium-Risk) and 0.5≤ERS<0.8 (Medium-Risk)	High	0.7	Sleep apnea (0.75) +High-temperature alert (0.65)	Dynamic load balancing allocation
R4	BD<0.3 (Low Deviation) and ERS<0.4 (Low-Risk)	Low	0.2	Normal activity (0.15) +Stable environment (0.25)	Delayed processing or batch transmission

In Table 4, the rule base covers the dynamic mapping relationship between input conditions and output priority. For example, when PAI ≥ 0.9 and BD ≥ 0.7, the system determines it as an emergency event (weight 1.0) and directly triggers a preemptive response for fall alarm services. The library contains a total of 52 expert experience rules, which achieve service orchestration through weighted summation and dynamic conflict resolution mechanisms. The service orchestration layer adopts a micro-service architecture and deploys functional modules such as fall detection and voice broadcasting in Kubernetes containers to optimize resource scheduling strategies [19]. Service orchestration divides the system into independent service modules, each communicating through RESTful API. The average code length per service is less than 500 lines, and the deployment image size is less than 100 MB. Kubernetes automatically adjusts the number of replicas based on load. For example, the fall detection service reduces to one replica when concurrent traffic drops at night and expands to three replicas during the day, thereby improving resource utilization. Through Kubernetes containerized deployment, the system can dynamically allocate computing resources based on real-time needs, while achieving independent updates and version management of service modules. The fault isolation mechanism ensures that a single-point service failure does not affect other functions. Combined with the mixed integer programming model to optimize service combinations, it meets the diverse needs of elderly individuals living at home, ensuring low latency and high efficiency.

The constraint of the mixed integer programming model is used to realize the service combination with low latency and high energy efficiency. The model is shown in equation (4).

$$\min \sum_{s=1}^{S} c_s \cdot n_s + \sum_{t=1}^{T} d_t \cdot l_t \tag{4}$$

In equation (4), n_s represents the number of deployment replicas for service s, and $s \in \{1, 2, \ldots, S\}$. c_s is the unit operating cost of service s, determined by service complexity and resource consumption. d_t is the delay sensitivity coefficient of task t, reflecting the task's tolerance to delay. The coefficient for emergency alarm tasks is 10. For every 1ms increase in delay, the cost increases by 10 units. l_t is the end-to-end delay of task t, and $t \in \{1, 2, \ldots, T\}$. Under the constraints of mixed integer programming models, low latency and high-efficiency service composition can be achieved. The closed-loop feedback mechanism analyzes service performance through gradient boosting tree analysis, such as response speed, elderly satisfaction, etc., and corrects inference rules and weight parameters in reverse to continuously improve system adaptability. In terms of system optimization, a multi-objective optimization based load balancing strategy is proposed to address the diversity and potential instability of IoT equipment in home environments. The framework of this strategy is shown in Figure 5.

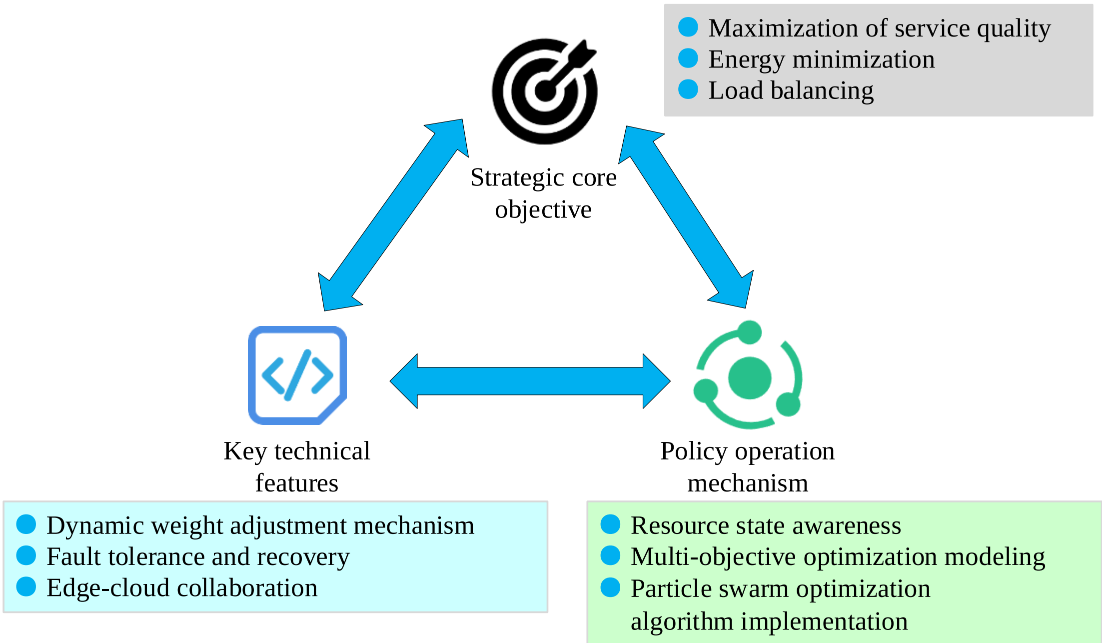


Figure 5: Load balancing policy framework based on multi-objective optimization

As shown in Figure 5, this strategy aims to minimize energy consumption, and balance load. By monitoring the network in real-time, it continuously collects key indicators such as computing load, communication delay, and remaining power of IoT equipment. Future task requirements are predicted based on historical data. The objective function of energy consumption minimization and load balancing is shown in equation (5).

$$\begin{cases} \min E = \sum_{j}^{n} (P_j \cdot T_j) \\ \min L = \sqrt{\frac{1}{n} \sum_{j=1}^{n} (C_j - \bar{C})^2} \end{cases} \tag{5}$$

In equation (5), E and L are the total energy consumption of the system and the load balancing index, respectively. n is the total number of edge nodes. P_j and T_j are the average power and active time of node j, respectively. C_j and $\bar{C}$ are the real-time load and its average value of node, respectively. The constraints are shown in equation (6).

$$\begin{cases} E_j \geq E_{\min} \\ C_j \leq C_{\text{th}} \end{cases} \tag{6}$$

In equation (6), $E_{\min}$ is the threshold of remaining power of the device, and $E_{\min} = 20\%$. C_{th} is the threshold of node load, and $C_{\text{th}} = 80\%$. Simultaneously, the task is divided into three categories: urgent, routine, and backend, and the priority scheduling rule is established for each task. Urgent tasks are prioritized for allocation to low delay nodes, while routine tasks are dynamically allocated based on load balancing principles, and backend tasks are delayed or handed over to the cloud. The PSO algorithm is used to simulate the intelligent search process of biological populations, iteratively evaluating the comprehensive performance of different resource allocation schemes in dimensions such as service quality, energy consumption, and load balancing, and gradually approaching the optimal solution [20]. In the PSO algorithm, each particle represents the task allocation scheme, and the dimension is the number of edge nodes. The position $X_{ij} \in (0,1)$ of the particle indicates whether the task is assigned to the node. The fitness function is shown in equation (7).

$$\text{Fitness} = \beta \cdot (\frac{E}{E_0}) + \gamma \cdot L \quad (7)$$

In equation (7), β and γ are fixed weights (experimentally verified to achieve optimal energy consumption and load balancing), and $\beta = 0.6 / \gamma = 0.4$. E_0 is the initial total energy consumption. The algorithm takes 20 particles, with a maximum of 100 iterations, and an acceleration constant $c_1 = c_2 = 2.0$. Parameter selection is based on the sensitivity analysis results from reference [20], aiming to balance convergence speed and global search capability. Within 50 iterations, the objective function value stabilizes, with a standard deviation less than 5%, indicating that the convergence meets real-time scheduling requirements. The time complexity of the PSO algorithm is O(N T D), where D=2 (dimension of the objective function). The average time for a single optimization at an edge node is 12.3ms (edge node computation), meeting real-time requirements. The system triggers the PSO algorithm by monitoring network utilization in real-time. First, it suspends low-priority queues to release bandwidth resources. By dynamically adjusting the particle swarm parameters, the inertia weight is temporarily increased to 0.7 to accelerate the search.

The algorithm introduces a dynamic weight mechanism, which automatically increases the energy-saving weight when the device has low power, and focuses on optimizing response speed during peak service periods, achieving flexible trade-offs between multiple objectives. At the critical technical level, edge nodes handle real-time tasks and cache data, globally optimize resource parameters in the cloud, and combine backup path switching to ensure service continuity in fault scenarios. The home intelligent elderly care ecosystem for disabled elderly is shown in Figure 6.

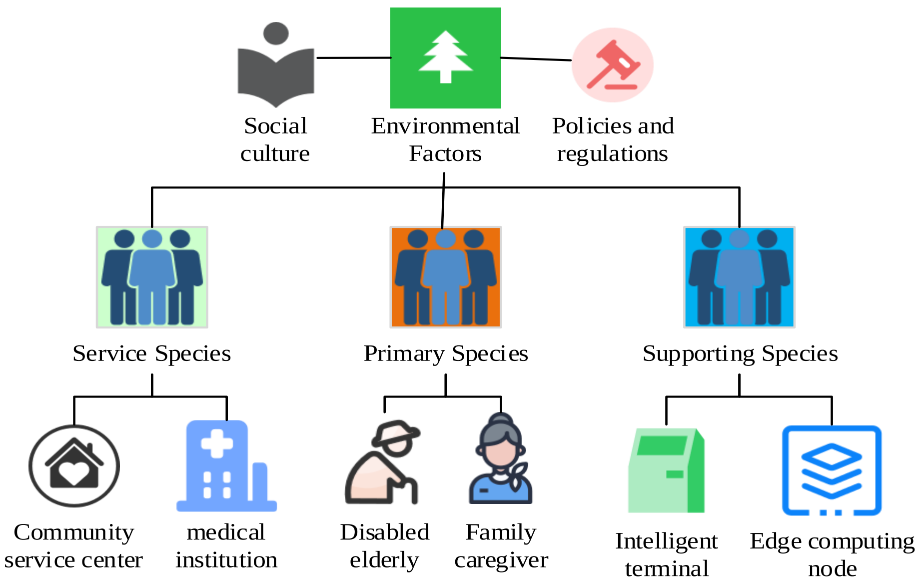


Figure 6: Ecosystem of smart home care for the disabled elderly

In Figure 6, the intelligent elderly care ecosystem is a collaborative network that integrates technology, services, and environmental elements with disabled elderly people as the core, and achieves sustainable operation through dynamic resource allocation and value exchange. The system population consists of a core population, a support population, and a service population. The core population includes the elderly and family caregivers, who generate driving data through wearable equipment and interactive behaviors. Family caregivers report abnormal behaviors of elderly individuals through mobile applications. The system triggers priority scheduling after verifying with sensor data. Health reports generated by the system are annotated, and feedback data is used to optimize feature weights in the fall detection algorithm through a gradient enhanced tree model, improving prediction accuracy. When family caregivers submit medication adherence reports, the system synchronously updates the R&D database of pharmaceutical companies and the risk assessment model of insurance companies, forming a collaborative value stream of "family-enterprise-insurance."

The support population is composed of IoT hardware, edge computing nodes, and network technology to achieve multi-modal data collection. The service population connects hospitals, communities, supermarkets, and other institutions, and maps demand to cross domain services based on reinforcement learning. The community service center receives health monitoring data from the system in real-time through block links. This includes abnormal physiological indicators of elderly individuals, high-risk behavioral events, and environmental alerts. It also coordinates medical resources and public services within the community. For example, when the system predicts that an elderly person has a fall risk exceeding the threshold over the next 2 hours, the community service center will dispatch the nearest community nurse with a portable monitor to intervene.

Environmental factors ensure that the system complies with social ethics through policy interfaces and cultural adaptation modules. This ecosystem supports the ecological cycle through information flow and value flow. Information flow relies on online learning to achieve cross institutional knowledge sharing, while blockchain records data contribution for incentive distribution. Information flow includes real-time vital signs stream, behavioral pattern analysis stream, and environmental control command stream. The real-time vital signs stream transmits data such as heart rate and blood oxygen collected by wearable devices, with an end-to-end average delay of 83 ms, meeting the requirement for emergency response within 100 ms. The behavioral pattern analysis stream transmits behavioral trajectory segments generated by ultra-wideband positioning systems, with a peak delay of 1.2 s and a daily update cycle of 15 minutes per session. The environmental control command stream issues temperature control commands in JSON format, with an average delay of 210 ms and a feedback delay of 380 ms. The study aims to achieve sustainable motivation for multi-party collaboration through designed incentive mechanisms. The system records the data contribution values of all participants through blockchain, with quantifiable metrics including the volume of sensor data uploaded, service response frequency, and collaboration node efficiency. The government dynamically allocates subsidies based on contribution values. For example, communities receive an additional 5% of their annual budget for every 100 care tasks completed. Pharmaceutical companies pay 0.5% of their R&D revenue as data usage fees for each 100,000 anonymized health data entries. Families with data contribution values exceeding 500 can redeem free health check-ups or drug discount coupons. Pharmaceutical companies, due to shortened R&D cycles from the data, must return 12% of cost savings in the form of "medication points," where 1 point equals 1 RMB and can be used to offset medication costs. Hospitals reduce the annual fall rate among insured users to <5%, and insurance companies pay hospitals 3% of their annual premiums as a collaboration reward.

An economic closed loop is built through value streams. In the quantification of insurance industry value, the system dynamically adjusts premium strategies by reducing health risk events. Based on the proportion of risk reduction, insurers offer a 5%-8% premium discount, with a discount rate of 2% for every 10% decrease in risk rate. In practice, the cumulative discount rate can reach up to 8%. Pharmaceutical companies accelerate R&D through anonymized health trend data, while agreeing to purchase equipment worth 0.5 million RMB for every 10,000 RMB saved in R&D costs, forming a sustainable ecosystem model of "risk sharing-data sharing-benefit feedback." This ecological architecture breaks through the linear logic of traditional IoT by establishing multi-directional feedback and adaptive adjustment mechanisms, truly integrating technology into the social collaboration system, improving service accuracy, and reducing system resource redundancy. The system deployment hardware is shown in Table 5.

Table 5: System deployment hardware equipment

Device Category	Device Model	Quantity	Unit Price (RMB)	Function Description
Physiological Monitoring Sensors	HUAWEI Watch D	3 units	1,999	Real-time collection of physiological parameters (heart rate, blood oxygen, body temperature, etc.), supporting Bluetooth 5.0 communication.
	Sleepace Rest Smart Mattress	1 unit	3,999	Monitors sleep cycles, body movement frequency, and respiratory rate; transmits data through Wi-Fi.
Environmental and Behavioral Sensors	HC-SR501 Infrared Sensor	5 units	25	Detects human activity trajectories, deployed in living rooms, corridors, and other areas.
	FlexiForce A201 Pressure Mat	3 units	150	Monitors pressure distribution in sitting/lying positions, placed on seats and bedding surfaces.
	MQ-7/MQ-2 Gas Sensors	2 units	80	Detects CO and smoke concentrations, deployed in kitchens and bedrooms.
Positioning and Communication Equipment	Ultra-Wideband (UWB) Positioning Tag	6 units	300	Achieves centimeter-level positioning accuracy with UWB technology (coverage: 10m).
	Raspberry Pi 4B (8GB)	1 unit	899	Edge computing node integrating sensor gateway and local data processing modules.
Interactive Devices	Voice Interaction Terminal	1 unit	1,299	Supports voice commands for emergency calls, health inquiries, and other functions.
Network Equipment	Wi-Fi 6 Router	1 unit	599	Provides 2.4G/5G dual-band coverage and supports Mesh networking expansion.
Others	Smart Pill Box	1 unit	199	Monitors medication adherence with integrated RFID tag recognition.

The hardware devices in Figure 5 are arranged in a grid pattern (1m×1m grid) in the home environment. In the bedroom of the disabled elderly person, pressure pads are laid along the edge of the bed to monitor the pressure distribution during sitting and lying positions in real time. Smart mattresses are deployed under the bed to collect sleep cycles and respiratory rates. Gas sensors are installed near the headboard to monitor CO and smoke concentrations in real time. An infrared sensor is placed at the entrance of the bathroom to detect human entry and exit activities, while humidity sensors are installed on the ceiling to dynamically monitor environmental humidity to prevent slipping risks. A Ultra-Wideband (UWB) positioning base station is installed in the corner of the wall to achieve centimeter-level positioning with the UWB tags worn by the elderly. Infrared sensors are deployed in the corridor area to track daily activity trajectories. Gas sensors are installed near the gas pipes in the kitchen to provide real-time warnings of gas leaks. Temperature sensors are installed in the cabinet area to monitor abnormal high temperatures to prevent fires. The Raspberry Pi 4B edge computing node is placed in the center of the living room as the sensor gateway and local data processing core. The total deployment cost for a single household is approximately 11,842 RMB.

3.3 Data security and privacy

Regarding user data security issues, the study adopts a three-tier privacy protection mechanism to ensure data safety. The SHA-256 algorithm is used at the data collection end to irreversibly encrypt sensitive information such as names, ID numbers, and addresses, retaining only non-identifiable data directly related to health management (such as age, gender, and medical history codes). All sensor data, after preprocessing by edge nodes, is accessible to authorized researchers for the anonymized dataset, while healthcare institutions must obtain temporary keys approved by an ethics committee to access the data. Data transmission takes TLS 1.3 protocol encryption, and storage servers are deployed in data centers that meet ISO 27001 standards. Physical storage devices undergo regular security audits, and decommissioned equipment is physically destroyed. Considering the possible sensor deception problem, a unique digital certificate is assigned to each IoT device. The edge node verifies the legitimacy of the device through two-way TLS protocol, and the device signature based on elliptic curve digital signature algorithm is attached during data collection to prevent forged data.

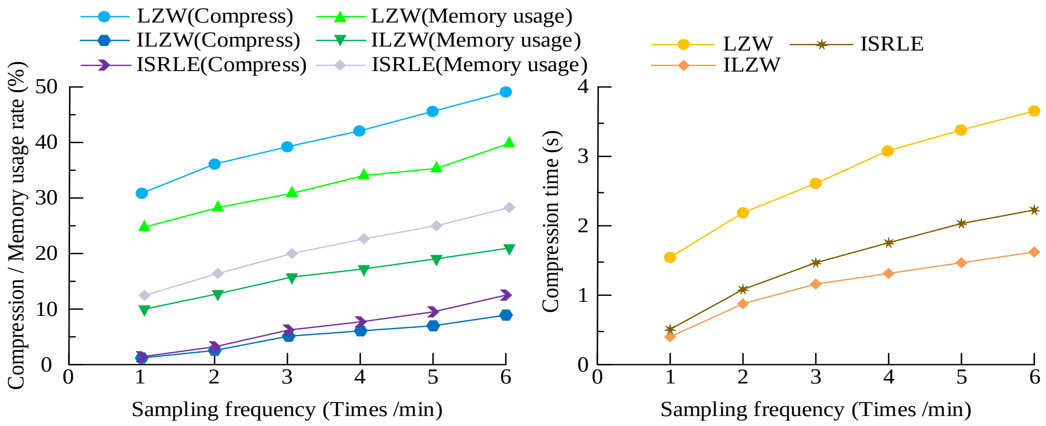
In response to the threat of network hijacking, the communication link is encrypted using TLS1.3 protocol, with keys rotated daily, and traffic anomalies are monitored in real-time through an LSTM model. For designs not fully encrypted, the primary considerations are the compatibility of resource-constrained devices and the real-time nature of emergency services. Low-power sensors take lightweight Corrected Block Tiny Encryption Algorithm to encrypt key fields, prioritizing alarm data transmission, with encryption concentrated at edge nodes. Non-sensitive data is transmitted in plaintext after de-identification, while sensitive data is protected through both AES-256 and homomorphic encryption, ensuring a balance between data integrity and privacy security [21].

Considering the potential conflict of interest, the study records all data contributions and service responses on the blockchain, labels data streams, and ensures that responsibility is traceable. When data abuse is detected, the smart contract automatically freezes access to it and triggers an audit process. In potential ethical issues, the system provides an informed consent form at deployment, clearly labeling data sharing parties and exit clauses. Any new service provider must obtain written authorization before joining. Family members can track in real-time which institutions access and use the data through a blockchain browser, with the system generating monthly data usage reports via email.

4 Results

4.1 Key technology performance optimization verification

To verify the effectiveness of the ILZW algorithm in lossless compression of data, the DHT11 humidity sensor is used to collect indoor humidity data at different frequencies for 3 days, and the collected data is compressed using the algorithm. At each sampling frequency, the compression algorithm is tested independently for 100 times, and the compression rate, memory occupancy rate and compression time are recorded for each run. The final result is the average of 100 runs. The performance of the current latest Improved Shared Run Length Coding (ISRLE) data compression method at different sampling frequencies is shown in Figure 7 [22]. In the performance testing of the ILZW algorithm, a sampling frequency of up to 6 times per minute is used, aiming to simulate the comprehensive frequency after data preprocessing at edge nodes. In practical applications, after initial screening by edge nodes to filter out duplicate and invalid signals, the transmission frequency of some non-urgent data is below 6 times per minute, forming a gradient data transmission system with one time per minute at night. Figures 7 (a) and 7 (b) show the data compression rate, memory usage, and compression time of different methods, respectively.



(a) Data compression rate and memory usage of LZW algorithm before and after improvement

(b) Compression time of LZW algorithm before and after improvement

Figure 7: Performance of each method at different sampling frequencies

In Figure 7 (a), with the increase of device sampling frequency, the data compression rate and memory usage of the LZW algorithm before and after improvement also increased. The data compression rate and memory usage of ILZW were lower than LZW throughout the entire testing process. When the sampling frequency was 6 times/min, the data compression rate and memory usage of ILZW were 8.92% and 21.87%, respectively, while the data compression rate and memory usage of LZW were 49.01% and 39.98%, respectively. The data compression rate and memory usage of the ISRLE method were basically the same as those of the ILZW when the sampling frequency was low. As the sampling frequency gradually increased, the gap between ISRLE and ILZW widened. At a sampling frequency of 6 times /min, the data compression rate and memory usage of ISRLE were 12.51% and 27.52%, respectively, which were 3.59% and 5.65% higher than the research method. As shown in Figure 7 (b), the compression time of ILZW at different sampling frequencies was lower than that of the comparison method. At the sampling frequency of 6 times /min, the compression time of ILZW was 1.65 s, while that of ISRLE and LZW was 2.24 s and 3.72 s, respectively. The compression time of the research method was reduced by 55.65% compared with the traditional method. The improved algorithm reduces data compression rate and compression time by optimizing preprocessing and storage strategies.

In terms of algorithm complexity, the time complexity of the traditional LZW algorithm is O(n), where n is the length of the input data. The ILZW algorithm optimizes the average time complexity to O(n/k) through a hash storage structure and dynamic dictionary adjustment strategy, where k is the length of repeated pattern units formed during the preprocessing stage through difference calculation ($k \geq 2$). The time complexity of ISRLE is O(n), but it requires additional processing for shared repetitive patterns. In terms of space complexity, the traditional LZW takes a fixed dictionary, resulting in a space complexity of O(m), where m is the maximum number of entries that the dictionary can store. The ILZW reduces the space complexity to O(m/α) through hash indexing and dictionary item elimination mechanisms, with $\alpha = 1.25$ being the experimental-determined dictionary space compression coefficient. The space complexity of ISRLE is O(1), but it requires pre-allocated buffer storage for shared patterns.

To further verify the performance of ILZW in different network scenarios, the aforementioned data compression algorithm is tested under four typical network scenarios. In high packet loss scenarios, the random packet loss rate ranged from 0.1% to 5%. In dynamic rate scenarios, the data rate fluctuated between 0.017 Hz and 2 Hz. In mixed jitter scenarios, a delay of 150 ms ± 50 ms and an instantaneous packet loss rate of 10% to 15% were added. The performance of each method under various network conditions is shown in Table 6.

Table 6: Performance of each method under different network conditions

Network Condition	Algorithm	Compression Rate	Data Recovery Rate	Memory Peak (MB)
Ideal Network (0% packet loss)	ILZW	8.92%	100%	21.87
	LZW	49.01%	100%	39.98
	ISRLE	12.51%	100%	27.52
5% Packet Loss	ILZW	9.8%	90.2%	23.12
	LZW	51.3%	68.4%	41.23
	ISRLE	13.7%	72.1%	29.84
Dynamic Rate (0.017→2 Hz)	ILZW	11.3%	94.7%	24.75
	LZW	53.8%	75.2%	43.67
	ISRLE	15.4%	80.3%	31.02
Mixed Jitter	ILZW	10.5%	87.6%	22.98
	LZW	55.1%	61.9%	44.15
	ISRLE	14.2%	65.4%	30.19

As shown in Table 6, in an ideal network, the compression rate of ILZW (8.92%) was 40.09% lower than that of LZW (49.01%), but 3.59% higher than that of ISRLE (12.51%). ILZW enhances data repetition recognition through difference preprocessing and dynamic dictionary adjustment. Under dynamic rate scenarios, the compression rate of ILZW fluctuated by only ±2.38%, while that of ISRLE fluctuated by ±2.9%, demonstrating better adaptability to non-uniform data. At high packet loss rates (5%), the data recovery rate of ILZW was consistently higher than that of LZW and ISRLE. This is thanks to its differential preprocessing technique, which reconstructs lost information through the correlation of adjacent data. In terms of peak memory usage, compared with LZW, ILZW reduced memory consumption by 45%-48%. Compared with ISRLE, it reduced memory consumption by 17%-22%. ILZW adopts a linked hash table and dynamic dictionary item elimination mechanism, reducing memory fragmentation and making it suitable for resource constrained medical IoT devices.

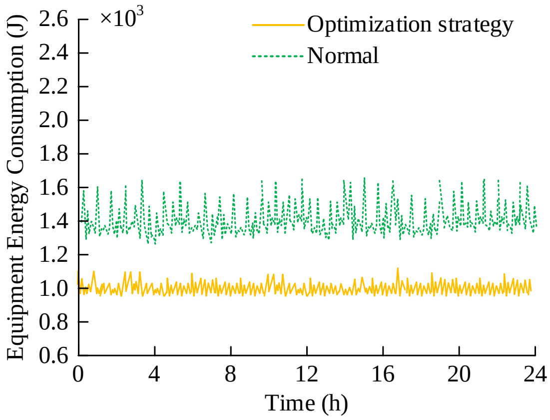
To verify the practical effectiveness of the proposed priority scheduling mechanism, comparative experiments are conducted on typical scenarios such as normal networks, bandwidth limitations, and network jitter. The experiment is conducted in the home environments of 15 disabled elderly individuals, with 20-25 IoT devices deployed per household. The edge node is Raspberry Pi 4B. Network conditions are simulated using Mininet-WiFi. The normal network bandwidth is 100 Mbps (download) / 50 Mbps (upload). In the bandwidth-limited scenarios of simulated NB-IoT, the limit is 5 Mbps (download) / 2Mbps (upload). The network jitter introduces random delays Linux tc tools (averaege of 150 ms, standard deviation of 50 ms) and burst packet loss using. Each test is repeated 100 times, and the data represents the average. By systematically comparing the three indicators of time delay, data arrival rate, and failure rate of critical event, it is verified whether the priority scheduling mechanism has a positive impact on data transmission. The study strictly adheres to the Helsinki Declaration and relevant provisions of the Personal Information Protection Law, completing ethical review and informed consent procedures before implementation to ensure the rights and data security of incapacitated elderly individuals. The research protocol is reviewed and approved by the ethics committee of a first-affiliated hospital affiliated with a domestic university, meeting clinical research ethical standards. The ethics committee focuses on reviewing the non invasiveness of data collection, the safety of service interventions, and privacy protection measures, confirming that the study does not pose direct physiological risks and that all technological applications are aimed at improving the quality of life of older adults. Regarding user data security issues, the study adopts a three-tier privacy protection mechanism to ensure data safety. The SHA-256 algorithm is used at the data collection end to irreversibly encrypt sensitive information such as names, ID numbers, and addresses, retaining only non-identifiable data directly related to health management (such as age, gender, and medical history codes). All sensor data, after preprocessing by edge nodes, is accessible to authorized researchers for the anonymized dataset, while healthcare institutions must obtain temporary keys approved by an ethics committee to access the data. Data transmission uses TLS 1.3 protocol encryption, and storage servers are deployed in data centers that meet ISO 27001 standards. Physical storage devices undergo regular security audits, and decommissioned equipment is physically destroyed. The subjects have basic communication skills or legal guardians to make decisions on their behalf, and they voluntarily participate and sign a written informed consent. The network performance indicators before and after introducing priority scheduling mechanism are shown in Table 7.

Table 7: The statistics of network performance indicators before and after using the priority scheduling mechanism

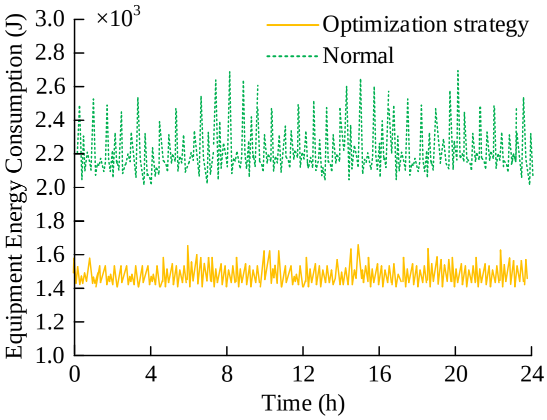
Test scenario	Use the priority scheduling mechanism			Don't use priority scheduling mechanism		
	Time delay (ms)	Data arrival rate (%)	Failure rate of critical events (%)	Time delay (ms)	Data arrival rate (%)	Failure rate of critical events (%)
Normal network	235.73±18.24	99.84	0.03	420.19±35.67	89.37	1.34
Bandwidth limited	485.26±42.31	97.13	0.17	1,200.63±35.67	63.82	5.19
Network jitter	785.34±68.57	93.41	0.26	>2,000	38.72	9.83
High load medical equipment	1180.28±92.45	85.19	0.48	>2,000	41.31	12.37
Multi-user concurrency (5 terminals)	635.79±55.12	89.36	0.34	1,580.24±120.36	55.63	4.76
Mixed emergency	705.43±50.89	87.64	0.39	1,420.79±110.41	60.12	3.96

As shown in Table 7, the priority scheduling mechanism exhibited significant advantages in various network scenarios. In terms of time delay, this mechanism generally reduced delay by 50% to 70%. For example, under normal network conditions, the delay was reduced from 420.19 ms to 235.73 ms, and under network jitter, the delay was optimized from >2,000 ms to 785.34 ms. In extreme high-load scenarios, the delay is improved from >2,000 ms to 1,180.28 ms. The data arrival rate was increased by 20% to 50%, especially when bandwidth was limited, from 63.82% to 97.13%. The failure rate of critical events decreased, with the failure rate in high-load medical equipment scenarios dropping from 12.37% to 0.48%, mixed emergency situations dropping from 3.96% to 0.39%, and network jitter scenarios being controlled from 9.83% to 0.26%. This mechanism ensures priority processing of critical tasks through dynamic resource allocation and improves data reliability under complex conditions such as network instability, resource constraints, and concurrency pressure.

To evaluate the impact of the load balancing strategy based on multi-objective optimization on the energy consumption of IoT equipment and verify their actual effectiveness at different time periods, the study deploys multiple IoT equipment in a home environment. The energy consumption test is conducted on equipment operating in normal mode, and a balancing strategy is applied under the same initial conditions. Each household includes 3 wearable devices (HUAWEI Watch D, 1.5W), 1 smart mattress (Sleepace Rest, 3W), 5 infrared sensors (HC-SR501, 0.065W), 3 pressure pads (FlexiForce A201, 0.1W), 2 gas sensors (MQ-7/MQ-2, 0.8W), and 1 edge node (Raspberry Pi 4B, 6W). During the day (6:00-22:00), it simulates a scenario with multiple devices running concurrently (5 terminals online simultaneously, occupying 70% bandwidth), while at night (22:00-6:00), it operates in a low-load state (bandwidth usage ≤30%). The energy consumption data of 24 whole points is recorded every day for 7 consecutive days, and the power consumption of the equipment is collected in real time using a high-precision power meter. The result is the average value of 15 households. The energy consumption changes of the device during the day and night are shown in Figure 8. Figure 8 (a) shows the energy consumption change at night when using the load balancing strategy, and Figure 8 (b) shows the energy consumption change during the day.



(a) The curve of total energy consumption of equipment at night with time



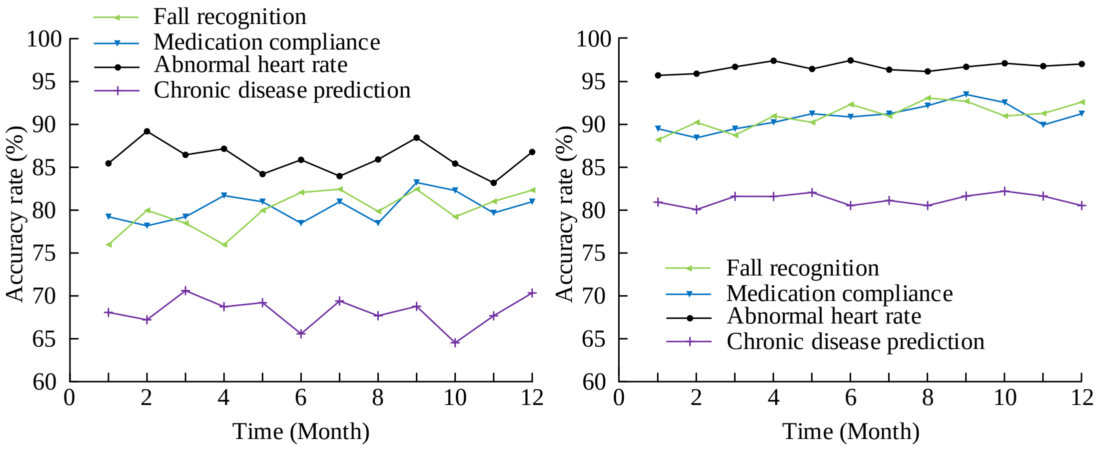
(b) The curve of total energy consumption of equipment during the day with time

Figure 8: Energy consumption of the equipment during the day and night

According to Figure 8 (a), without using load balancing strategy, the average energy consumption at night was $1.42\times10^3\pm85$J (95%CI: 1.38×10^3-1.46×10^3J), while the average energy consumption after using this strategy was $1.03\times10^3\pm42$J (95%CI: 1.01×10^3-1.05×10^3J), which was 27.46% lower than that without using the load balancing strategy. This strategy also reduced the fluctuation range of energy consumption. In Figure 8 (b), the energy consumption increased during the day. The average energy consumption without load balancing strategy was $2.24\times10^3\pm112$J (95%CI: 2.18×10^3-2.30×10^3J), while the average energy consumption after using this strategy was $1.55\times10^3\pm55$J (95%CI: 1.52×10^3-1.58×10^3J). The load balancing strategy can reduce the energy consumption and maintain energy stability. This is because the dynamic task scheduling strategy prioritizes critical tasks, while non-urgent tasks are delayed or transferred to the cloud, reducing the continuous high-load operation time of devices and increasing the proportion of idle or sleep modes. Secondly, the day-night differentiated strategy adjusts the device sampling frequency, combining spatial partitioning to optimize sensor layout, reducing redundant data collection, and extending low-power periods. The multi-objective balancing mechanism based on PSO algorithm monitors device load and power in real-time, dynamically allocating tasks to low-latency nodes or the cloud, and automatically increasing energy-saving weights when devices have low power.

4.2 Health management and ecosystem applications

To evaluate the effectiveness of the intelligent elderly care ecosystem in improving health management efficiency, a 12-month controlled experiment is designed, and relevant data is collected regularly every month. A single-group self-contrast design is adopted to carry out a longitudinal control experiment on 30 disabled elderly people (average age 72.5±6.8 years) for 13 months, including one month at baseline (before system deployment) and 12 months at dry period (system operation). The changes in health management efficiency before and after applying the intelligent elderly care ecosystem are shown in Figure 9. Figure 9 (a) shows the health management performance statistics before applying the system, and Figure 9 (b) shows the health management performance statistics after applying the system. The data represents the monthly average of 30 disabled elderly individuals over a 12-month intervention period. Each monthly dataset is based on three repeated measurements (one in early, mid, and late each month), with the final result being the average of 36 observations. A paired *t*-test is used to analyze the differences between the baseline period and the intervention period, with a significance level set at α=0.05. p<0.05 is considered statistically significant.

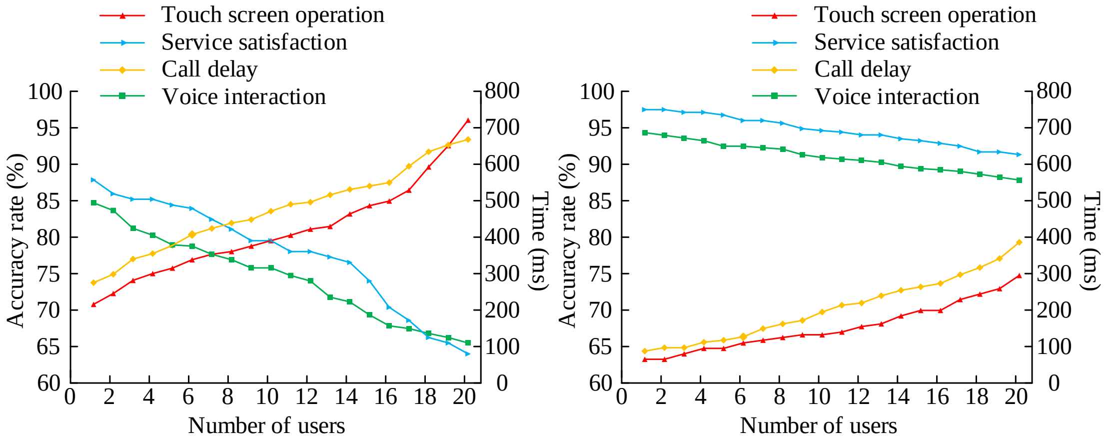


(a) Trends in health management performance over time before ecosystem application

(b) Trends in the health management effectiveness of an applied ecosystem over time

Figure 9: Changes of health management efficiency before and after the application of intelligent elderly care ecosystem

According to Figure 9 (a), when the proposed system was not used, the different health management performance indicators of disabled elderly people fluctuated greatly in different time periods. The average accuracy of chronic disease prediction, medication compliance, fall recognition accuracy, and abnormal heart rate were 67.73%, 81.95%, 79.96%, and 86.85%, respectively. According to Figure 9 (b), after using the system, the fluctuations of various health management performance indicators of disabled elderly people were reduced at different time periods, and all health management performance indicators were improved. The average values of each indicator were 81.54%, 90.32%, 91.06%, and 96.62%. The prediction accuracy of chronic diseases increased by 13.81% (t=8.92, p<0.001), the compliance rate of medication reached the standard, at 8.37% (t=6.54, p<0.01), the recognition accuracy of falling down increased by 11.10% (t=9.15, p<0.001), and the alarm rate of abnormal heart rate increased by 9.77% (t=7.83, p<0.01). The relationship between user experience and the number of concurrent tasks is shown in Figure 10. Each test of the number of concurrent tasks is run independently 50 times, and the result is the average of the 50 runs. Figures 10 (a) and 10 (b) respectively show the relationship between user experience and the number of users before and after applying the system.



(a) The relationship between the user experience before the application system and the number of users

(b) The relationship between the user experience after the application system and the number of users

Figure 10: Relationship between user experience and the number of concurrent tasks

As shown in Figure 10 (a), with the increase of the number of users, the response time of device touch screen operation and the average delay of emergency calls both improved. When the number of users was 20, they were 735.24±58.72 ms and 681.76±82.31 ms. The success rate of device voice interaction and user satisfaction with personalized services showed a downward trend, reaching 65.55% and 64.21% respectively when the number of users was 20. In Figure 10 (b), the proposed system improved user experience. The device touch screen operation response time and the average delay of emergency call decreased to 295.37 ms±22.45 ms (Δ=439.87 ms, t=12.58, and p<0.001) and 390.06 ms±35.68 ms (Δ=291.70 ms, t=13.64, and p<0.001) when the number of users was 20. The success rate of voice interaction and user satisfaction with personalized services was 87.68% and 92.11% (Δ=22.13%, 27.90%, and p<0.01), respectively. The improvement of relevant evaluation indicators before and after adopting the elderly care ecosystem is shown in Table 8. The data in the table is the cumulative average of 30 elderly people during the 12-month intervention period.

Table 8: Comparison of relevant evaluation indicators before and after applying the elderly care ecosystem

Evaluation Dimension	Specific Indicator	Pre-Implementation Data	Post-Implementation Data	Improvement
Health Monitoring Coverage	Real-time physiological parameter rate	52.3% (manual records)	98.5% (auto-monitoring)	+88.34%
Hygiene Response Time	Excrement disposal delay	Average 15 min-30 min	≤3 s	-99.7%
Pressure Ulcer Incidence Rate	Monthly rate (bedridden patients)	37% (severe cases: 21%)	7.8% (no severe cases)	-78.9%
Urinary Tract Infection Rate	Monthly infection rate	28.6%	10.9%	-61.9%
Psychological Stress Index	Caregiver anxiety score	6.8 (severe stress)	3.2 (mild stress)	-52.9%
Daily Care Time	Caregiver time investment	4.2 h	1.5 h	-64.3%
Position Change Compliance Rate	Bedridden repositioning compliance	58% (manual tracking)	97% (system alerts)	+67.2%
Aspiration Incident Rate	Feeding-related aspiration incidents	22 times/month	3 times/month	-86.4%
Joint Mobility Maintenance	Range of Motion (ROM) retention rate	61% (passive exercises)	89% (active assistive training)	+45.9%
Skin Microclimate Management	Moisture-associated skin damage (MASD)	34%	9%	-73.5%
Assisted Mobility Safety	Falls during transfers (per 100 moves)	17 incidents	0.8 incidents	-95.3%
Economic cost	Average monthly nursing expenses	9,354 RMB	3,547 RMB	-62.1%

According to Table 8, the real-time physiological parameter rate increased from 12.3% to 98.5% (t=22.3, p<0.001), relying on IoT sensors to achieve all-weather tracking of health indicators, which was about 7 times more efficient than manual detection. In terms of preventing complications, the pressure ulcer incidence rate decreased by 78.9% (t=20.5, p<0.001), and the aspiration incident rate decreased by 86.4%. The falls during transfers decreased by 95.3% (t=23.5, p<0.001). The average monthly care cost includes the cost of human care and medical consumables. After using the elderly care ecosystem, the working hours of human care were reduced, and the number of medical consumables used by intelligent monitoring was reduced. The average monthly care cost was reduced by 56.4% compared with before the system was used (t=18.7, p<0.001). The system has formed a synergistic effect in three aspects: health risk control, functional maintenance, and reducing nursing burden through a closed-loop management system.

5 Discussion

Compared with reference [6], the intelligent elderly care ecosystem proposed in this study reduces the delay of emergency events from 1200 ms to 235 ms through a dynamic priority scheduling mechanism, and optimizes the failure rate of critical tasks from 5.19% to 0.39%. This improvement is attributed to multi-level queue management and real-time context reasoning, which dynamically identifies task urgency using a RF classifier and predicts future behavior states with LSTM, pre-allocating transmission resources accordingly. Compared with the average recall rate of 89.7% in the reference [8], this study enhances the fall detection recall rate to 98.3% through a heterogeneous sensor fusion strategy, while keeping the false alarm rate below 2.8%. In terms of energy optimization, the single-function device in the reference [14] consumes 1.5 W. This study reduces the day and night power consumption by 30.8% and 27.5%, respectively, through a multi-objective PSO algorithm that coordinates edge node loads. This difference stems from the dynamic resource scheduling strategy. When network utilization >80%, low-priority queues are paused, and backup path switching is enabled to reduce energy waste caused by redundant transmissions.

In the design of the ecological closed-loop architecture, the research focuses on quantifying data contribution through blockchain to incentivize pharmaceutical companies, insurance firms, and other stakeholders to form a value exchange network. Traditional solutions (such as mental health services provided by Li et al. [9]) rely solely on unidirectional data flow. The ecosystem proposed in this study takes a gradient boosting tree-based service effectiveness analysis model to continuously optimize rule library weights. The static rule library in reference [8] struggles to adapt to behavioral drift issues in disabled elderly individuals. To address home network jitter problems, the study improves key data transmission success rates from 63.8% to 97.1% through hybrid a network protocol and adaptive channel allocation, outperforming industrial IoT solutions (SanchezIborra, which reduces energy consumption by 40%, but has not been verified in home scenarios [11]).

6 Conclusion

To meet the needs of home-based elderly care for disabled individuals, this study integrated data collection, transmission, and intelligent service modules through a layered architecture. A multi-modal sensor network was deployed to achieve physiological behavioral environmental data fusion perception. The ILZW compression algorithm was proposed, and a dynamic priority scheduling mechanism was designed. An intelligent elderly care ecosystem based on the IoT was constructed, forming a closed-loop management system based on multi-objective optimization load balancing strategy. The study applied this system to the home-based elderly care scenario for disabled individuals and compared it with traditional home-based elderly care methods. The results showed that the compression rate of ILZW decreased by 40.09% and the compression time shortened by 55.65% at a sampling frequency of 6 times/min. The dynamic priority scheduling mechanism reduced the transmission delay of key data in network jitter scenarios by 61.3% and increased the data arrival rate to 97.13%. The multi-objective optimization strategy reduced device day and night energy consumption by 30.8% and 27.5%, respectively. In terms of health management effectiveness, the accuracy of chronic disease prediction increased to 81.5%, the pressure ulcer incidence rate decreased by 78.9%, the nursing cost decreased by 62.1%, and the user satisfaction reached 92.11%. After integrating IoT technology and ecological architecture, a multi-party collaborative value network for elderly care services was constructed, achieving precise monitoring, rapid response, and dynamic resource allocation, which provides a reusable technological paradigm and social collaboration model for addressing the aging. The personal data collected by IoT equipment has not yet been systematically managed for privacy and security. Future research will explore new privacy protection technologies based on homomorphic encryption, which can ensure the security of user privacy data while balancing system performance and long-term stability.

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