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Evaluating the Quality of Life of Empty Nesters by Means of Big Data and the Internet of Things

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This study uses the Internet of Things (IoT) and big data technology to construct a comprehensive assessment of the quality of life of empty nesters. By means of a questionnaire survey and data collected via IoT devices, the physical health, mental health, social support and financial status of empty-nesters were analyzed in detail. The results showed that the quality of life of the elderly with higher levels of depression and anxiety was significantly reduced, while the quality of life of the elderly with higher levels of family support, social activities and economic income was significantly better. In regard to physical health, heart rate, blood pressure, activity level and sleep quality have significant effects on quality of life, with activity level and sleep quality being particularly important. This study innovatively applies IoT and big data technologies for quality-of-life assessment, providing a multi-dimensional scientific basis for the development of targeted interventions. Despite the significance of the findings, the limitations of the sample size and data still need to be addressed by further research. In the future, the sample scope should be expanded, and quantitative and qualitative methods should be combined to conduct an in-depth exploration of the factors influencing empty nesters' quality of life, and devise intervention strategies to improve their quality of life significantly.

Keywords: empty nesters; Internet of Things; big data; quality-of-life assessment

1. INTRODUCTION

With the rapid development of society and the acceleration of the aging population process, the quality of life of empty nesters has gradually become the focus of social attention. In recent years, the number of empty nesters has been increasing, and the challenges of living alone have significantly affected their physical and mental health. Although previous research focused to some extent on the quality of life of empty nesters, comprehensive assessment methods for this special group are still lacking. The increasing application of IoT technology and big data analytics in health monitoring and evaluation offers new possibilities for a comprehensive assessment of the quality of life of empty nesters. The IoT technology collects the health data of the elderly in real time through smart devices, enabling the dynamic monitoring of the person's physical health status. Big data technology can be used to conduct in-depth analysis of large amounts of health data to reveal key factors affecting quality of life. The aim of this study is to build a life quality assessment model for empty nesters utilizing IoT and big data, and to conduct a comprehensive assessment comprising multiple dimensions such as physical health, mental health, social support and interaction, and financial status. Through scientific evaluation methods, it is expected that more effective intervention strategies can be devised by government and social entities to improve the quality of life of empty nesters.

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2. LITERATURE REVIEW

2.1 Definition and Status quo of Empty Nesters

Empty nesters are those elderly people who live alone or live only with their spouse because their children have left home.

In China, with the acceleration of the aging population process and social and economic development, the number of empty nesters has increased significantly, which has become a social problem that needs urgent attention. The main challenges faced by empty nesters include poor physical health, increased psychological loneliness and lack of social support.

Chang et al. (2022) pointed out that under the social ecosystem theory, the successful aging of empty nesters is affected by multiple factors, such as their financial position, health status and social integration [1]. By means of structural equation model analysis, Zhang et al. (2021) found that physical health, mental health and social support are the main factors affecting the quality of life of empty nesters in Shanxi Province [2]. Wang et al. (2021) found in their empirical study of Southwest China that chronic diseases and low social support are the key factors leading to the poor quality of life of empty nesters [3].

Cao and Lu (2021) studied the mediating and moderating role of loneliness in the relationship between social support and life satisfaction, emphasizing the importance of social support [4]. Li et al. (2022) discussed the multiple mediating effects of social capital on the self-rated health of rural empty nesters by improving sleep quality and alleviating psychological distress, further enriching the theoretical basis for research on the quality of life of empty nesters [5].

2.2 Research on Quality-of-Life Assessment

The study of quality-of-life assessment is an important area of academic research, involving the construction of an assessment index system and the application of assessment methods. Wen et al. (2021) applied big data and IoT technologies in financial credit evaluation and early warning, and proposed an evaluation model combining multidimensional data, which has important implications for the methods used to evaluate of quality of life [6]. Xu et al. (2024) proposed a balanced evaluation model of human resource allocation based on big data and IoT, and described the construction of an evaluation model [7].

Hou et al. (2020) studied the big data analysis algorithm of IoT based on machine learning, and pointed out the key role of big data analysis in quality-of-life assessment [8]. The big data processing framework for self-healing IoT applications proposed by Dundar et al. (2016) provides new technical support for quality-of-life assessment [9]. Pal et al. (2023) studied the intelligent task scheduling model of big data applications in hybrid networking and cloud environments, demonstrating the application potential of big data technology in complex evaluation systems [10].

2.3 Application of the Internet of Things in Health Monitoring

The application of IoT technology in health monitoring has been widely developed, which provides a new way for real-time collection and dynamic monitoring of health data. Saha et al. (2022) conducted a study on the quality of life of the elderly in India, indicating that IoT technology can significantly improve the accuracy and real-time performance of health monitoring, thereby improving the quality of life of the elderly [11]. da Silva et al. (2021) studied the application of IoT technology in the monitoring of falls and quality of life assessment, and found that IoT devices can significantly improve the sense of security and quality of life of the elderly [12].

Ahmadi et al. (2023) used a logistic regression model to analyze the factors affecting the quality of life of the elderly, emphasizing the important role of IoT technology in health monitoring, which can detect and deal with health risks in time [13]. Goes et al. (2020) proposed an assessment method for the quality of life of the elderly based on the assessment standards of the World Health Organization, and pointed out that IoT devices play a key role in the collection of health data, providing data support for comprehensive health assessment [14]. Bermejo et al. (2021) studied the readability of the quality-of-life assessment scale for the elderly and emphasized the importance of IoT technology in the application of the scale to improve the accuracy and reliability of the assessment results [15].

2.4 Application of Big Data Technology in Health Assessment

The application of big data technology in health assessment provides strong support for the comprehensive assessment of quality of life. Scherrer et al. (2022) explored the relationship between activities of daily living, depressive symptoms and quality of life, and pointed out the role of big data analysis in revealing complex health relationships, which can comprehensively analyze and evaluate the quality of life of the elderly [16].

Aydogan et al. (2022) studied the impact of COVID-19 on cognition, attention, memory, balance and quality of life in the elderly, and demonstrated the application of big data technology in health assessment, which can provide data support for public health policy making [17]. Wang et al. (2020) pointed out the importance of big data technology in the assessment of health-related quality of life through their study on the quality of life of elderly people in communities, enabling a comprehensive analysis of the health status of large groups of people [18].

Gunathilaka et al. (2023) developed a work-life quality scale suitable for elderly workers, emphasizing the application of big data technology in scale development and verification, and improving the science and accuracy of the scale [19]. Toselli et al. (2020) studied the relationship between body composition and the quality of life of the elderly in Italy, and demonstrated the application of big data analysis in health assessment, providing a scientific basis for improving the quality of life of the elderly [20].

Previous research has made substantial progress in the evaluation of the life quality of empty nesters; however, there are still several research gaps. For instance, studies focus mostly on examining the impact of a single factor, thereby failing to cover the multidimensional assessment of the quality of life of empty nesters. For example, comprehensive assessments of physical health, mental health, social support and economic status are lacking. Secondly, the traditional evaluation method has several limitations in terms of data collection and analysis, and it is difficult to achieve the dynamic monitoring and real-time evaluation of the health status of empty nesters. Although the IoT and big data technology have shown great potential in areas such as health monitoring and evaluation, their application in the assessment of the life quality of empty-nesters has not been fully developed, and relevant studies are unsystematic, fragments and specific.

By means of IoT technology, this study can achieve the real-time collection and dynamic monitoring of the health data of empty nesters and improve the accuracy and timeliness of the data. Secondly, combined with big data technology, many health data can be analyzed in depth to reveal the key factors affecting the quality of life of empty nesters, so as to build a more comprehensive and scientific assessment model. Finally, the aim of this study is conduct a comprehensive evaluation of the quality of life of empty nesters from multiple perspectives including physical health, mental health, social support and economic status, to provide more effective intervention strategies for the government and society and improve the overall quality of life of empty nesters.

3. RESEARCH DESIGN

3.1 Overall Design Framework

The aim of this study is to build a life quality assessment model for empty nesters based on IoT and big data, and comprehensively evaluate the life quality of empty nesters through a thorough analysis of multi-dimensional data. The research design adopts a quantitative research method, a questionnaire survey and data collected via IoT devices as the main means of data collection, combined with big data analysis technology, to conduct in-depth research on various dimensions of the life quality of empty nesters. By constructing a scientific evaluation index system and data analysis model, the key factors affecting the quality of life of empty-nesters were explored, and corresponding intervention strategies were proposed.

3.2 Data Source and Collection

3.2.1 Data Source

Two sources of data were used in this study: questionnaire data and data collected by IoT devices. Questionnaire survey data were obtained through quantitative questionnaires designed for empty nesters, with questionnaire items related to physical health, mental health, social support and financial status. The data collected by means of IoT mainly comes from intelligent health monitoring devices worn by empty nesters, which collect physiological indicators such as heart rate, blood pressure and activity level in real time.

3.2.2 Data Collection Methods

The questionnaire survey data was collected using the random sampling method. A total of 1024 questionnaires were distributed throughout communities and nursing institutions where empty nesters tended to be in a city. In total, of 937 valid questionnaires were collected, with an effective recovery rate of 91.52%. The collection of data gathered by IoT devices was conducted by selecting 500 elderly people among the respondents, who wore smart health monitoring devices for continuous monitoring for three months. Ultimately, 487 valid data items were obtained, with an effective data rate of 97.40%.

The questionnaire data included the basic information of empty nesters (age, gender, education level, etc.), physical health status (chronic disease, frequency of medical treatment, etc.), mental health status (depression, anxiety, etc.), social support status (family support, social activities, etc.) and financial status (income level, living expenses, etc.). The data collected via IoT devices comprised physiological indicators such as heart rate, blood pressure, body temperature, activity level, sleep quality and so on.

3.3 Data Analysis Methods

Data analysis was conducted using quantitative analysis and SPSS.

4. CONSTRUCTION OF LIFE QUALITY ASSESSMENT MODEL FOR EMPTY-NESTERS BASED ON IOT AND BIG DATA

4.1 Construction of Evaluation Index System

Prior to constructing a life quality evaluation model for empty nesters, it is important to establish a comprehensive evaluation index system. Based on the literature review and survey results, the evaluation index system covers four main dimensions: physical health, mental health, social support, and economic status. Each dimension is further subdivided into several specific indicators.

Physical health dimensions include heart rate, blood pressure, body temperature, activity, sleep quality and other physiological indicators. The dimensions of mental health include depression score, anxiety score, subjective well-being and other psychological assessment indicators. The dimensions of social support include family support score, social activity score, community participation and other social interaction indicators. The financial status dimension comprises monthly income, living expenses, economic pressure and other financial status indicators.

To construct the evaluation index system, the analytic hierarchy process (AHP) was used to assign weights to each index. The specific steps are as follows:

(1) Construct a hierarchical structure model and decompose the target layer (quality of life of empty nesters) into the

criterion layer (four main dimensions) and the indicator layer (each specific indicator).

(2) Use the expert scoring method to compare each index in pairwise and construct the judgment matrix.

(3) Use the eigenvalue method to calculate the maximum eigenroot of the judgment matrix and its corresponding eigenvector, and obtain the weight of each index.

4.2 Collection and Processing of IoT Data

The acquisition and processing of IoT data is an important part of the evaluation model. The wearing of intelligent health monitoring devices by empty nesters enables certain physiological data to be collected in real time, such as heart rate, blood pressure, body temperature, activity level and sleep quality. Data is uploaded to the cloud via wireless transmission technology for storage and initial processing.

Data processing involves data cleaning, outlier detection, data standardization and other steps. Data cleaning removes the noise and invalid data generated during the acquisition process; outlier detection is used to identify and process anomalous data points by statistical methods. Data standardization is the normalization of data of different units and dimensions for subsequent analysis. The data processing formula is as follows:

(1) Data cleaning: the noise and invalid data in the data set $D = \{x_1, x_2, \ldots, x_n\}$ are filtered to obtain the cleaned data set, $D' = \{x'_1, x'_2, \ldots, x'_m\},\ m \leq n$.

(2) Outlier detection: the triple standard deviation method is used to calculate the mean μ and standard deviation σ of each data x_i. If $|x_i - \mu| > 3\sigma$ is satisfied, it is determined to be an outlier and processed.

(3) Data standardization: Each data x_i is normalized to obtain standardized data, as shown in the following formula (1).

$$z_i = \frac{x_i - \mu}{\sigma} \tag{1}$$

4.3 Construction of Big Data Analysis Model

The construction of a big data analysis model involves data feature extraction, model selection and training, model evaluation and so on. First, key features are extracted from the IoT data and questionnaire data through feature engineering. Commonly-used feature-extraction methods include principal component analysis (PCA), Feature Selection and so on.

Based on feature extraction, a suitable machine learning model is selected for training and evaluation. Common machine learning models include linear regression, logistic regression, support vector machines (SVM), Random Forest, and neural networks. Cross-validation was used to evaluate the model during model training to avoid overfitting.

Assuming the random forest model is selected, the construction process of the model is as follows:

(1) Data set partitioning: the data set D is divided into training set D_{train} and test set D_{test}. Generally, 80% of the data is used for training and 20% is used for testing.

(2) Model training: The random forest model is trained on the training set D_{train}, and multiple decision trees are constructed, and each tree is trained on a randomly-selected feature subset.

(3) Model evaluation: Model performance was evaluated on test set D_{test}, and indexes such as mean square error (MSE) and determination coefficient R^2 were used for evaluation.

The mathematical expression of the random forest model is shown in formula (2) below.

$$f(x) = \frac{1}{N} \sum_{i=1}^{N} h_i(x) \tag{2}$$

Where, $f(x)$ is the final prediction result, N is the number of decision trees, and $h_i(x)$ is the prediction result of the i decision tree.

4.4 Verification and Optimization of the Evaluation Model

The verification and optimization of the evaluation model is the key step taken to ensure the accuracy and reliability of the model. The verification model compares the predicted value with the actual value, and calculates the error indicators, such as mean square error (MSE), root mean square error (RMSE), and mean absolute error (MAE).

The specific steps of model verification are as follows.

(1) Model validation: The error between the model prediction results and the actual value is calculated using the test set. Commonly-used error index formulas are shown in formulas (3), (4) and (5).

Mean square error:

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{3}$$

Root mean square error:

$$\text{RMSE} = \sqrt{\text{MSE}} \tag{4}$$

Average absolute error:

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{5}$$

Where, y_i is the actual value, $\hat{y}_i$ is the predicted value, and n is the number of samples.

(2) Model optimization: According to the model verification results, the model is optimized. Common optimization methods include adjusting model parameters, adding feature engineering, and selecting more suitable data

Table 1 Overview of Physiological Data.

Indicator	Sample Size (n)	Average Score
Heart Rate (bpm)	487	76.34 ± 8.45
Blood Pressure (mmHg)	487	124.56 ± 14.23
Body Temperature (°C)	487	36.72 ± 0.47
Activity Level (steps)	487	6321.78 ± 1534.67
Sleep Quality Score	487	7.45 ± 1.23

preprocessing methods. Taking the random forest model as an example, the performance of the model can be optimized by adjusting the number of trees, depth of trees, sample weights and other parameters.

(3) Model robustness test: To verify the robustness of the model, different data sets and different sampling methods can be used for verification to ensure the stability and reliability of the model in different environments.

Through model verification and optimization, the final evaluation model built has high accuracy and reliability and can provide a scientific basis for the assessment of the quality of life of empty nesters. The validation and optimization process of the model not only ensures the accuracy of the evaluation results, but also provides data support for subsequent intervention strategies.

Through the construction of the evaluation index system, the collection and processing of the IoT data, the construction of the big data analysis model, and the verification and optimization of the evaluation model, a comprehensive, scientific and reliable model for the evaluation of the quality of life of empty nesters is formed. The model can effectively evaluate the quality of life of empty nesters and provide a scientific basis for improving their quality of life.

5. EVALUATION RESULTS FOR LIFE QUALITY OF EMPTY NESTERS BASED ON INTERNET OF THINGS AND BIG DATA

5.1 Physical Health Assessment Results

5.1.1 Physiological Index Analysis

The physiological index data collected by IoT devices provides an important basis for evaluating the physical health status of empty nesters. Through the analysis of data such as heart rate, blood pressure, body temperature, activity level and sleep quality, the results shown in Table 1 were obtained.

As shown in Table 1 above, the mean value of heart rate data is 76.34 beats/min, and the standard deviation is 8.45, indicating that the heart rate of most empty nesters is within the normal range, but the heart rate of some elderly people fluctuates greatly, which may be related to an unstable health status. The mean blood pressure was 124.56 mmHg, and the standard deviation was 14.23. Some elderly people had hypertension problems. The mean temperature was 36.72°C and the standard deviation was 0.47, which was basically within the normal range. The average daily activity was 6321.78 steps, and the standard deviation was 1534.67, indicating that some elderly people were not active enough. The mean sleep quality score was 7.45, and the standard deviation was 1.23. Some elderly people reported poor sleep quality.

5.1.2 Chronic Diseases and Health Conditions

Chronic diseases are important factors affecting the health of empty-nesters. 63.41% of empty-nesters suffered from at least one chronic disease, of which high blood pressure, diabetes and arthritis were the most common. The existence of chronic diseases significantly reduces the quality of life of the elderly, and those with chronic diseases generally have a lower physical health score. The results are shown in Figure 1.

5.2 Results of Mental Health Assessment

5.2.1 Analysis of Depression and Anxiety Levels

Mental health status was assessed using depression scores and anxiety scores. As shown in Table 2 below, the mean depression score of empty-nesters was 3.45, and the standard deviation was 1.78. The mean anxiety score was 2.98 and the standard deviation was 1.64. As shown in Table 2, older adults with higher levels of depression and anxiety generally reported lower quality of life, showing the important impact of mental health issues on the quality of life of empty nesters.

5.2.2 Influencing Factors of Mental Health

Mental health is influenced by a variety of factors, including social support, financial stress and physical health. Family support scores and social activity scores were significantly positively correlated with mental health, while financial stress and physical health problems were significantly negatively correlated with mental health. As shown in Figure 2, older adults who received greater family support and were active in social activities had lower levels of depression and anxiety.

5.3 Results of Social Support and Interaction Assessment

5.3.1 Family Support Status

Family support has an important impact on the quality of life of empty nesters. As shown in Table 3, the mean of the family support score was 4.12 and the standard deviation was 0.89. Most empty nesters received some degree of family support,

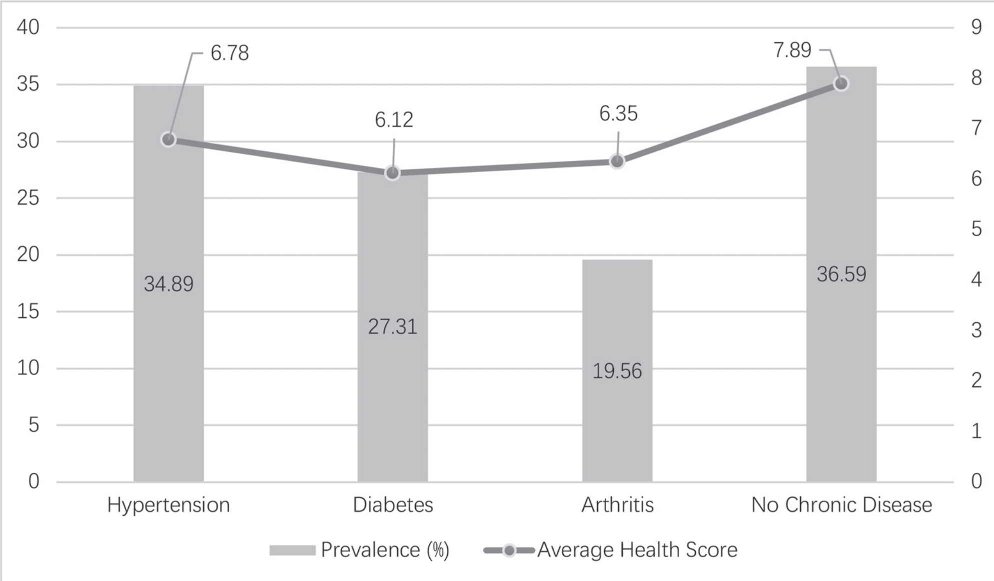

Figure 1 Chronic Disease Status.

Table 2 Overview of Mental Health Data.

Indicator	Sample Size (n)	Mean $\pm$ Standard Deviation
Depression Score	937	3.45 ± 1.78
Anxiety Score	937	2.98 ± 1.64

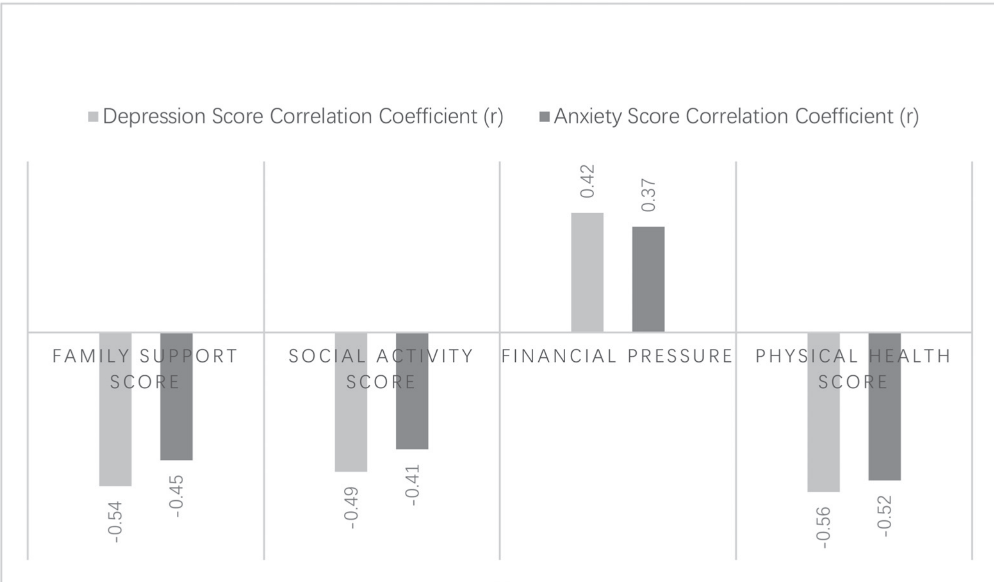

Figure 2 Correlation Analysis of Factors Influencing Mental Health.

but some still reported insufficient family support. Family support was significantly positively associated with quality of life, and older adults who received strong family support had higher quality of life scores.

Social activities are an important way for empty nesters to maintain social interactions. The mean and standard deviation of social activity scores were 3.76 and 1.12, indicating that most empty nesters were able to participate actively in social activities. The frequency and quality of social activities are closely related to mental health and overall quality of life. Active social activities can significantly improve the mental health level and life satisfaction of the elderly.

5.4 Results of Economic Status Assessment

5.4.1 Analysis of Income Level and Source

Financial status is assessed by monthly income and living expenses. As shown in Table 4, the mean monthly income of empty nesters is 3,145.67 yuan, and the standard deviation is 1213.45 yuan. The mean of living expenses is 2456.89 yuan, and the standard deviation is 987.56 yuan. The main sources of income are pensions, child support and savings. Older adults with higher income levels had higher quality-of-life scores, indicating that financial status had a significant impact on quality of life.

Table 3 Overview of Family Support Data.

Indicator	Sample Size (n)	Mean ± Standard Deviation
Family Support Score	937	4.12 ± 0.89
Social Activity Score	937	3.76 ± 1.12

Table 4 Overview of Financial Status Data.

Indicator	Sample Size (n)	Mean ± Standard Deviation
Monthly Income (¥)	937	3145.67 ± 1213.45
Living Expenses (¥)	937	2456.89 ± 987.56

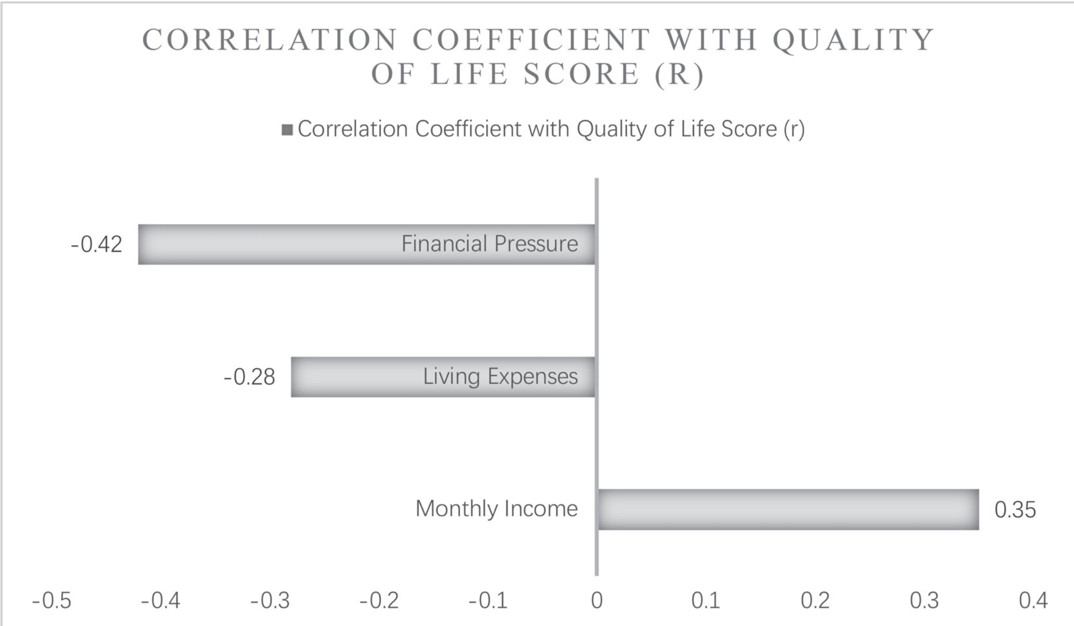

Figure 3 Analysis of the Impact of Financial Status on Quality of Life.

5.4.2 Impact of Financial Status on Quality of Life

As shown in Figure 3, the impact of financial status on quality of life is mainly reflected in financial stress and financial security. Seniors with high income levels and low financial stress had higher quality of life scores, while seniors with high financial stress reported lower quality of life. Financial status indirectly affects the overall quality of life of empty nesters as it can determine mental health and social participation.

Through comprehensive analysis of physical health, mental health, social support and economic status, it is found that these factors have a significant impact on the quality of life of empty-nesters. In terms of physical health, physiological indicators such as heart rate, blood pressure, body temperature, activity level and sleep quality have an important impact on quality of life; in particular, chronic illness has a significant negative impact on physical health. In terms of mental health, older people with higher levels of depression and anxiety have lower quality of life, and family support and social activities can significantly improve mental health. In terms of social support, family support and active participation in social activities play an important role in improving the quality of life of empty-nesters. In terms of status, income level and economic pressure have a significant impact on the quality of life, and the elderly with higher income and lower financial pressure have a higher quality of life.

5.5 Comprehensive Scoring Discussion

This section presents and discusses the scores for quality of life of empty nesters, based on the results of correlation analysis and multiple regression analysis. The overall quality of life score was influenced by several factors, including depression score, anxiety score, family support score, social activity score, monthly income score, heart rate, blood pressure, body temperature, activity level and sleep quality score.

The correlation analysis results shown in Table 5 indicate that there is a significant correlation between the variables. The correlation coefficient between depression score and anxiety score was 0.67, indicating a strong positive correlation between the two. At the same time, the depression score was negatively correlated with the family support score, social activity score, activity level and sleep quality score, and the correlation coefficients were −0.54, −0.49, −0.32 and −0.56, respectively. This suggests that greater family support, frequency of social activities, activity levels and better sleep

Table 5 Correlation Analysis Results.

Variable	Depression Score	Anxiety Score	Family Support Score	Social Activity Score	Monthly Income (¥)	Heart Rate (bpm)	Blood Pressure (mmHg)	Body Tempera-ture (°C)	Activity Level (steps)	Sleep Quality Score
Depression Score	1	0.67	−0.54	−0.49	−0.23	0.15	0.20	0.05	−0.32	−0.56
Anxiety Score	0.67	1	−0.45	−0.41	−0.21	0.18	0.23	0.07	−0.28	−0.52
Family Support Score	−0.54	−0.45	1	0.63	0.32	−0.12	−0.15	−0.04	0.35	0.48
Social Activity Score	−0.49	−0.41	0.63	1	0.29	−0.10	−0.13	−0.02	0.32	0.45
Monthly Income (¥)	−0.23	−0.21	0.32	0.29	1	−0.05	−0.07	−0.01	0.20	0.25
Heart Rate (bpm)	0.15	0.18	−0.12	−0.10	−0.05	1	0.58	0.08	−0.23	−0.15
Blood Pressure (mmHg)	0.20	0.23	−0.15	−0.13	−0.07	0.58	1	0.12	−0.25	−0.17
Body Temperature (°C)	0.05	0.07	−0.04	−0.02	−0.01	0.08	0.12	1	−0.09	−0.05
Activity Level (steps)	−0.32	−0.28	0.35	0.32	0.20	−0.23	−0.25	−0.09	1	0.37
Sleep Quality Score	−0.56	−0.52	0.48	0.45	0.25	−0.15	−0.17	−0.05	0.37	1

Table 6 Multiple Regression Analysis Results.

Independent Variable	Standardized Regression Coefficient (β)	t-value
Depression Score	−0.42	−6.75
Anxiety Score	−0.37	−5.89
Family Support Score	0.41	6.23
Social Activity Score	0.38	5.74
Monthly Income (¥)	0.29	4.56
Heart Rate (bpm)	−0.17	−2.98
Blood Pressure (mmHg)	−0.19	−3.12
Body Temperature (°C)	−0.04	−0.78
Activity Level (steps)	0.32	5.13
Sleep Quality Score	0.45	7.21
p-value	<0.001	

quality contribute to lower levels of depression. Similar negative correlations were found between anxiety scores and family support scores, social activity scores, activity levels, and sleep quality scores, with correlation coefficients of −0.45, −0.41, −0.28, and −0.52, respectively.

Multiple regression analysis results presented in Table 6 show the influence of each factor on the quality-of-life score. The regression results show that depression and anxiety have significant negative effects on quality-of-life score. The standardized regression coefficients were −0.42 and −0.37, and the T-values were −6.75 and −5.89, respectively, with significance less than 0.001. Family support score and social activity score had a significant positive impact on quality-of-life score, with standardized regression coefficients of 0.41 and 0.38, and T-values of 6.23 and 5.74, respectively, with significance less than 0.001. Monthly income, activity level and sleep quality scores also had significant positive effects on QOL scores, with standardized regression coefficients of 0.29, 0.32 and 0.45, and T-values of 4.56, 5.13 and 7.21, respectively, with significance less than 0.001. Heart rate and blood pressure had a negative effect on quality-of-life score, with standardized regression coefficients of −0.17 and −0.19, and T-values of −2.98 and −3.12, respectively, with significance less than 0.001.

The results of correlation analysis and multiple regression analysis lead to the following conclusions:

(1) Mental health (depression and anxiety scores) has a significant negative impact on quality of life. Higher levels of depression and anxiety significantly reduced the quality-of-life scores of empty nesters.

(2) Social support (family support score and social activity score) has a significant positive impact on quality of life. Greater family support and active participation in social activities significantly improved the quality-of-life scores of empty nesters.

(3) Financial status (monthly income) has a significant positive impact on quality of life. Higher income levels significantly improved the quality-of-life scores of empty-nesters.

(4) Physical health status (heart rate, blood pressure, activity level and sleep quality score) has a significant impact on quality of life. Among them, higher activity and good sleep quality significantly improved the quality-of-life score of empty nesters, while higher heart rate and blood pressure had a negative impact on quality of life. The effect of body temperature on quality of life is not significant, which may be related to the fact that the body temperature of most elderly people is within the normal range.

The overall quality-of-life score of empty nesters is affected by many factors. Mental health, social support, financial status and physical health all have significant effects on quality of life. The quality of life of empty nesters can be significantly improved by enhancing family support and social activities, improving mental health, increasing financial income, and maintaining good physical health. The analysis results can provide a scientific basis for formulating targeted intervention strategies to comprehensively improve the quality of life of empty nesters.

In summary, through the IoT and big data analysis, the quality of life of empty nesters can be comprehensively evaluated. Physical health, mental health, social support and economic status are the main factors affecting quality of life. The stability of physiological indicators, the management of chronic diseases, the improvement of mental health level, family support and active involvement in social activities, and a good financial position all play an important role in improving the quality of life of empty nesters.

6. DISCUSSION

The results of the study show that through the application of IoT and big data technology, the quality of life of empty nesters can be comprehensively evaluated and a variety of factors affecting the quality of life can be determined. Mental health, social support, economic status and physical health all have significant effects on quality of life. Older adults with scores for depression and anxiety had significantly lower quality of life, while higher scores for family support and social activities significantly improved the quality of life of older adults. The quality-of-life score of the elderly with higher income level is also greater, which shows the important influence of financial status on the quality of life. In addition, physiological indicators such as heart rate, blood pressure, activity and sleep quality have significant effects on quality of life, with the positive effects of activity and sleep quality on quality of life being particularly prominent.

The study demonstrated the effectiveness and feasibility of using IoT and big data technologies for health monitoring and assessing the quality of life of the elderly. These technologies can collect and analyze the physiological and behavioral data of the elderly in real time, provide a comprehensive health status assessment, and provide a scientific basis for improving the quality of life of this sector of the population. Through comprehensive analysis of multi-dimensional data, key factors affecting quality of life can be more accurately identified, and targeted interventions can be developed.

Like most studies, this one has several shortcomings: (1) The sample size is limited, and the generalizability of the research results needs to be further verified. While the sample covers multiple types of empty nesters, due to geographical and cultural differences, empty nesters in different regions may face different quality-of-life issues. (2) The research data were collected from questionnaires and IoT devices, and are limited by the accuracy and completeness of the data. Some of the self-reporting by elderly people may have subjective biases, and the data collection of IoT devices in certain environments may also be less than optimal. (3) The study adopted a quantitative analysis method, but did not conduct an on-depth exploration of the social and psychological mechanisms behind the quality of life of empty nesters.

The future development direction mainly includes the following aspects. (1) The sample size can be expanded to cover empty-nesters in more geographical and cultural backgrounds to improve the universality and representativeness of the research results. (2) Quantitative and qualitative research methods can be combined to gain an in-depth understanding of the complex mechanism underlying the quality of life of empty nesters through in-depth interviews and focus groups. (3) More intelligent and diversified data acquisition technologies can be explored, such as wearable devices, smart home systems, etc., to improve the accuracy and real-time performance of data. (4) Intervention studies can be conducted to design and implement targeted intervention measures based on the evaluation results to determine their effects on the quality of life of empty nesters.

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