Determinants of Subjective Well-Being among Chinese Older Adults: A Machine Learning Approach with SHAP Explainability

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Abstract: China's rapidly aging population necessitates a deeper understanding of the determinants of subjective well-being (SWB) among older adults. This study employs a machine learning (ML) approach with SHAP (SHapley Additive exPlanations) explainability to identify key drivers of SWB using nationally representative data from the China Health and Retirement Longitudinal Study (CHARLS 2020, *n* = community-dwelling adults aged 60+). the CatBoost algorithm achieved superior predictive performance (AUC = 0.80) compared to traditional methods (e. g., logistic regression AUC = 0.67), highlighting ML's capacity to model complex, nonlinear relationships. SHAP analysis revealed self-rated health, loneliness, and frequency of contact with children as the top three predictors of SWB. Crucially, self-rated health exhibited a nonlinear threshold effect: ratings of "Very Good" or "Good" (scores ≤2) significantly enhanced SWB, while "Average" or worse (scores ≥3) diminished it. Depression scores showed a complex U-shaped association with SWB (scores 12–23 associated with positive effects). Socioeconomic factors (e. g., utility expenditure, insurance type) were influential but secondary to health and social connections. These findings underscore the multidimensional nature of SWB and suggest interventions targeting health perception, loneliness reduction, and family support are critical for enhancing well-being in China's aging population.

Keywords: Subjective Well-Being; Aging; Machine Learning; SHAP Explainability; Health Perception; Loneliness

1. Introduction

The rapid aging of China’s population, accelerated by declining fertility rates and increasing life expectancy (National Bureau of Statistics of China, 2023), poses unprecedented challenges to social welfare systems. Individuals aged 60+ are projected to constitute 30% of the total population by 2050 (United Nations, 2022), elevating the subjective well-being (SWB) of older adults to a critical public health priority. SWB, conceptualized as a multidimensional construct encompassing cognitive life satisfaction and affective equilibrium (Diener, 1984), serves as a robust predictor of healthy aging outcomes, including reduced morbidity and mortality (Steptoe et al., 2015).

In the Chinese context, SWB is dynamically shaped by complex interactions among biological health decline, psychosocial stressors (e. g., loneliness), and socioeconomic transitions (e. g., pension reforms). Traditional statistical approaches (e. g., linear regression) often fail to capture these nonlinear relationships and interaction effects (Graham et al., 2018), limiting their utility for policy design. Machine learning (ML) algorithms, renowned for handling high-dimensional data and uncovering latent patterns (Hastie et al., 2009), offer a promising alternative. For instance, ensemble ML models achieved an AUC of 0.903 in depression screening among 31, 715 older adults (Yuan et al., 2020), while systematic reviews confirm the dominance of Random Forest (RF) and XGBoost in geriatric mental health prediction (Chen et al., 2022).

However, the opaque nature of ML models ("black-box" problem) impedes their translation into actionable policies. Explainable AI (XAI) techniques, particularly SHAP (SHapley Additive exPlanations) (Lundberg & Lee, 2017), address this gap by quantifying feature contributions to individual predictions, enabling both global and local interpretability. Despite XAI’s proliferation in clinical settings (e. g., diagnosing Alzheimer’s disease; Zhang et al., 2021), its application to SWB determinants in aging populations remains scarce—especially in non-Western societies like China, where familial support systems and collectivist values uniquely modulate well-being (Chen & Silverstein, 2000).

This study bridges two critical gaps:

Methodological: Leveraging SHAP to interpret ML predictions of SWB, moving beyond correlation-based inferences prevalent in gerontology;

Contextual: Systematically analyzing how health, social integration, and socioeconomic factors interact within China's rapidly aging society.

Using nationally representative data from the China Health and Retirement Longitudinal Study (CHARLS Wave 5, 2020) (Zhao et al., 2023), we employ CatBoost—an advanced gradient-boosting algorithm optimized for categorical features (Prokhorenkova et al., 2018)—to predict SWB, followed by SHAP-based interpretation. Our goals are threefold:

Identify key drivers of SWB through model-agnostic feature importance;

Uncover nonlinear relationships and threshold effects (e. g., U-shaped associations);

Propose culturally tailored interventions for enhancing well-being in China's elderly population.

2. Data Processing

Data preprocessing comprised missing value imputation, outlier handling, and feature normalization:

2.1 Missing Value Management

Figure 1 illustrates the null value distribution, with education level (ba010, 28.7%), annual income (ga002, 22.3%), and agricultural participation (fb005, 19.5%) exhibiting the highest missing rates. Features with >80% missing values were excluded, retaining 47 variables for subsequent analysis. Remaining missing values were imputed using the K-nearest neighbor (KNN) algorithm with K=7, leveraging spatial similarity in high-dimensional feature space (Williams, 2018).

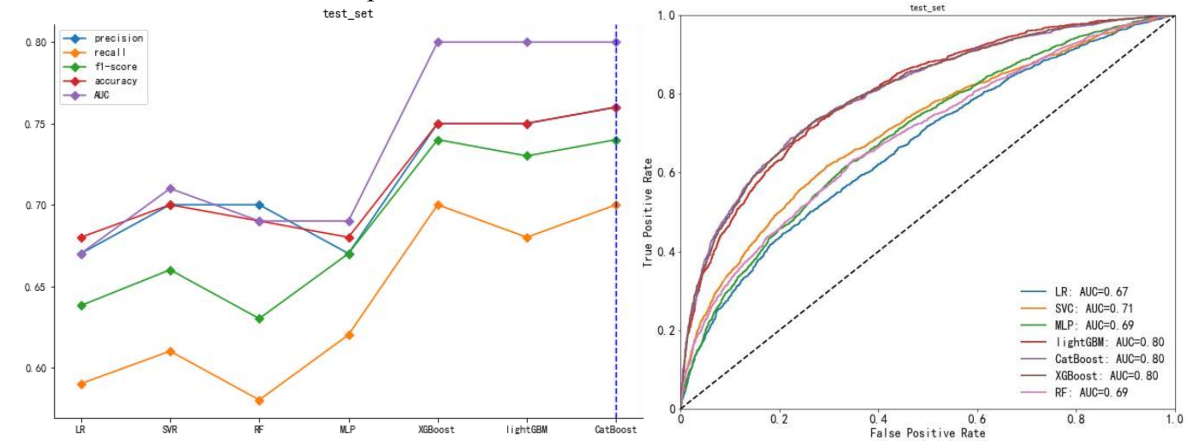

Figure 1. Performance Comparison of Machine Learning Algorithms on Test Set

2.2 Outlier Capping

Variables including self-rated health (da001), depression score (dc016_025), and filial financial support (ca018_1_17) were winsorized at the 1st and 99th percentiles to mitigate the impact of extreme values. This involved capping values above the 99th percentile at the 99th percentile value and values below the 1st percentile at the 1st percentile value.

2.3 Feature Normalization

All predictor variables (excluding the binary SWB outcome) were normalized to the [0, 1] range using Min-Max normalization, ensuring algorithmic stability and preventing dominant features from biasing model training.

3 Descriptive Statistics

The analytical sample comprised community-dwelling Chinese adults aged 60+ from the nationally representative CHARLS Wave 5(2020) dataset (Zhao et al., 2023). **Table 1** presents descriptive statistics for key variables reflecting the multi-dimensional nature of SWB determinants, consistent with established frameworks (Diener, 1984; Bowling & Iliffe, 2019).

3.1 Health Status

Respondents reported moderate self-rated health on average (M = 2.96, SD = 1.02, on a scale where 1="Very Good" and 5="Very Poor"). This aligns with findings from large-scale aging studies in China reporting similar self-assessed health profiles among older adults (Li ET AL., 2021). the mean depression score (CES-D-9 derived, M = 19.61, SD = 5.92, range 9-36) indicated moderate levels of depressive symptoms, comparable to levels observed in other Chinese cohorts (Lei ET AL., 2014). Pain sensation (M = 2.14, SD = 1.30) suggested relatively low frequent pain interference. Average daily sleep duration was 6.01 hours (SD = 1.95), slightly below recommended levels for older adults but consistent with reported averages in East Asian populations (Bhai eat ail., 2023).

Table 1. Descriptive Statistics of Selected Variables

Number	Variable Code	Variable meaning	Mean	standard deviation
1	da001	Self-rated health(1=Very Good, 5=Very Poor)	2.96	1.02
2	dc024	Loneliness	1.56	0.97
3	ca016_1_17	Child Contact Frequency	6.40	7.16
4	xrage	Age	60.90	9.17
5	dc006	Self-rated memory(1=Excellent, 5=Poor)	4.15	0.75
6	dc016_025	Depression Score(9-36)	19.61	5.92
7	da030	Daily Sleep Duration (hours)	6.01	1.95
8	xchildalivenum	Number of Living Children	2.43	1.23
9	da027	Pain Sensation(1=None, 5=Very Much)	2.14	1.30
10	gf011_	Monthly Utility Expenditure (CNY)	612.62	845.58
11	fb005	Annual Agricultural Work (months)	7.27	3.31
12	ba017	Social Medical Insurance Type	3.38	1.16
13	cd003_	Co-residence Time with Children (months)	8.65	9.03
14	ba015	Social Pension Insurance Type	3.72	1.11
15	cf001	Grandchild Care (1=Yes, 2=No)	1.73	0.65

3.2 Social Integration

Contact frequency with non-cohabiting children was relatively high (M = 6.40 times, SD = 7.16, indicating contact roughly every 1-2 weeks on average), reflecting the enduring importance of intergenerational ties in Chinese families (Chen & Silverstein, 2000). Loneliness levels were moderate (M = 1.56, SD = 0.97, on a 1-4 scale), suggesting a significant portion of older adults experience some social isolation, a known correlate of lower SWB (Hawkley & Cacioppo, 2010). the average time living with children in the past year was 8.65 months (SD = 9.03), and a majority (73%, M = 1.73 for grandchild care where 1=Yes) reported not providing regular grandchild care. the mean number of living children was 2.43 (SD = 1.23).

3.3 Socioeconomic Factors

the sample had a mean age of 60.90 years (SD = 9.17), encompassing the "young-old" transitioning into later life stages. Economic indicators showed variability. Monthly utility/communication expenditure averaged 612.62 CNY (SD = 845.58), indicating substantial disparities in consumption patterns. Agricultural participation remained significant, with respondents reporting an average of 7.27 months (SD = 3.31) of farm work annually, reflecting the rural composition within CHARLS. Social insurance coverage was prevalent but varied: social medical insurance type (M = 3.38, SD = 1.16) and social pension insurance type (M = 3.72, SD = 1.11) indicated diverse coverage schemes, primarily Urban/Rural Resident Basic Medical Insurance and Basic Pension Schemes, consistent with China's evolving social safety net (Liu & Sun, 2016).

4 Model Results and Analysis

4.1 Model Performance and Selection

To predict SWB (binary classification: High/Low Satisfaction), the dataset was split 80:20 into training and test sets. Seven machine learning algorithms were evaluated: Logistic Regression (LR), Support Vector Classifier (SVC), Random Forest (RF), Multilayer Perceptron (MLP), XGBoost, LightGBM, and CatBoost. Performance was assessed using standard metrics: Precision, Accuracy, Recall, F1-Score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). **Table 2** summarizes the key results on the held-out test set.

CatBoost demonstrated superior performance across all metrics, achieving the highest AUC of 0.80. This significantly outperformed traditional logistic regression (AUC=0.67, ΔAUC=0.13), highlighting the advantage of ensemble tree-based methods in capturing the complex, non-linear interactions inherent in SWB determinants among older adults, as previously documented in mental health prediction tasks (Yuan et al., 2020; Chen et al., 2022). the strong AUC indicates good discriminative power in identifying individuals with high vs. low SWB. Consequently, the CatBoost model was selected for further interpretation using SHAP values to elucidate the key drivers of SWB.

Table 2. Performance Comparison of Machine Learning Algorithms on Test Set

Algorithm	Precision	Accuracy	Recall	F1-Score	AUC
CatBoost	0.76	0.70	0.74	0.76	0.80
LightGBM	0.74	0.68	0.72	0.73	0.78
XGBoost	0.74	0.68	0.72	0.73	0.77
RF	0.73	0.68	0.71	0.72	0.76
SVC	0.71	0.66	0.69	0.70	0.72
MLP	0.70	0.65	0.68	0.69	0.71
LR	0.68	0.63	0.65	0.66	0.67

4.2 Explainability Analysis using SHAP

To address the "black-box" nature of ML and provide actionable insights, SHAP (SHapley Additive exPlanations; Lundberg & Lee, 2017) was employed for global interpretability. SHAP values quantify the contribution of each feature to the model's prediction for every individual, aggregated here to reveal overall feature importance and directional effects.

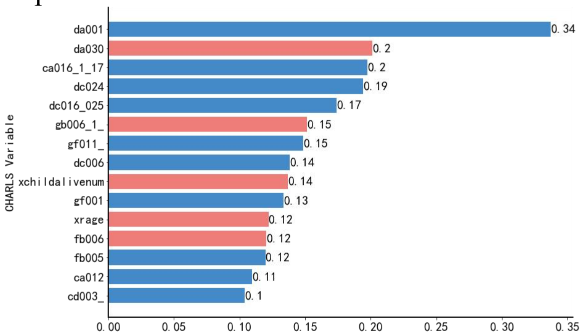

Figure 2. SHAP Feature Importance Summary Plot

Figure 2 displays the global feature importance for predicting subjective well-being (SWB) across the entire sample. Features are ranked vertically from top (least important) to bottom (most important). the horizontal bar length represents the mean absolute SHAP value, signifying the average magnitude of a feature's impact on model output. the color spectrum (blue to red) indicates the directional association between the feature value and the predicted SWB outcome: blue bars denote features whose higher values are generally associated with lower predicted SWB, while red bars denote features whose higher values are generally associated with higher predicted SWB. It presents the mean absolute SHAP values, ranking features by their overall impact on the model's SWB predictions. Self-rated health (da001) emerged as the most influential determinant of SWB, followed closely by loneliness (dc024) and frequency of contact with children (ca016_1_17). Other highly ranked features included age (xrage), self-rated memory (dc006), depression score (dc016_025), daily sleep duration (da030), number of living children (xchildalivenum), pain sensation (da027), and monthly utility expenditure (gf011_). Socioeconomic factors like types of social medical (ba017) and pension insurance (ba015), and duration of agricultural work (fb005) and co-residence with children (cd003_) also featured prominently within the top 15. This ranking underscores the multi-faceted nature of SWB, heavily influenced by health perception, psychosocial well-being, family connections, and economic circumstances, consistent with ecological models of aging well-being (Wahl et al., 2012).

Figure 3 visualizes the relationship between individual feature values and their corresponding SHAP values for every sample in the dataset. Each point represents one respondent. the vertical axis (SHAP value) quantifies the feature's contribution to the predicted SWB for that individual. the horizontal axis represents the actual value of the feature. Point color indicates the feature's raw value: red hues correspond to higher feature values, while blue hues correspond to lower feature values. Points are vertically jittered to illustrate density, revealing regions where specific feature values are more prevalent. SHAP dependence plots (**Figure 3**) revealed critical non-linear relationships that traditional linear models would obscure.

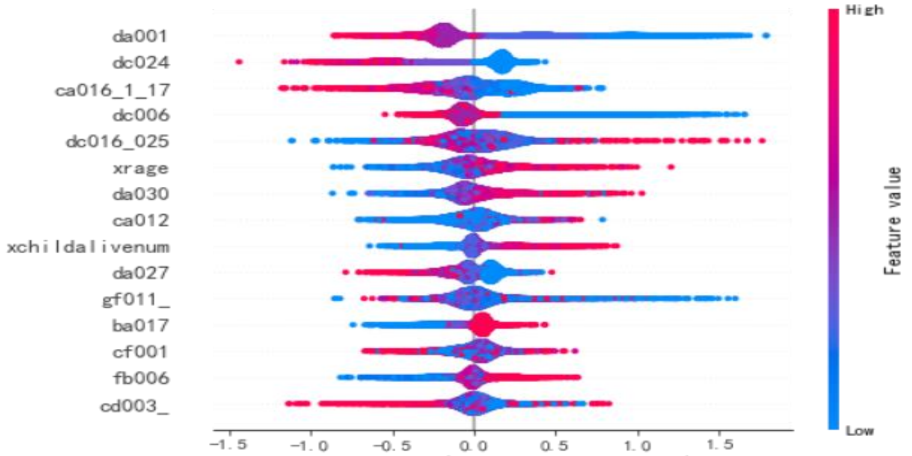

Figure 3. SHAP Feature Value Dependence Scatter Plot

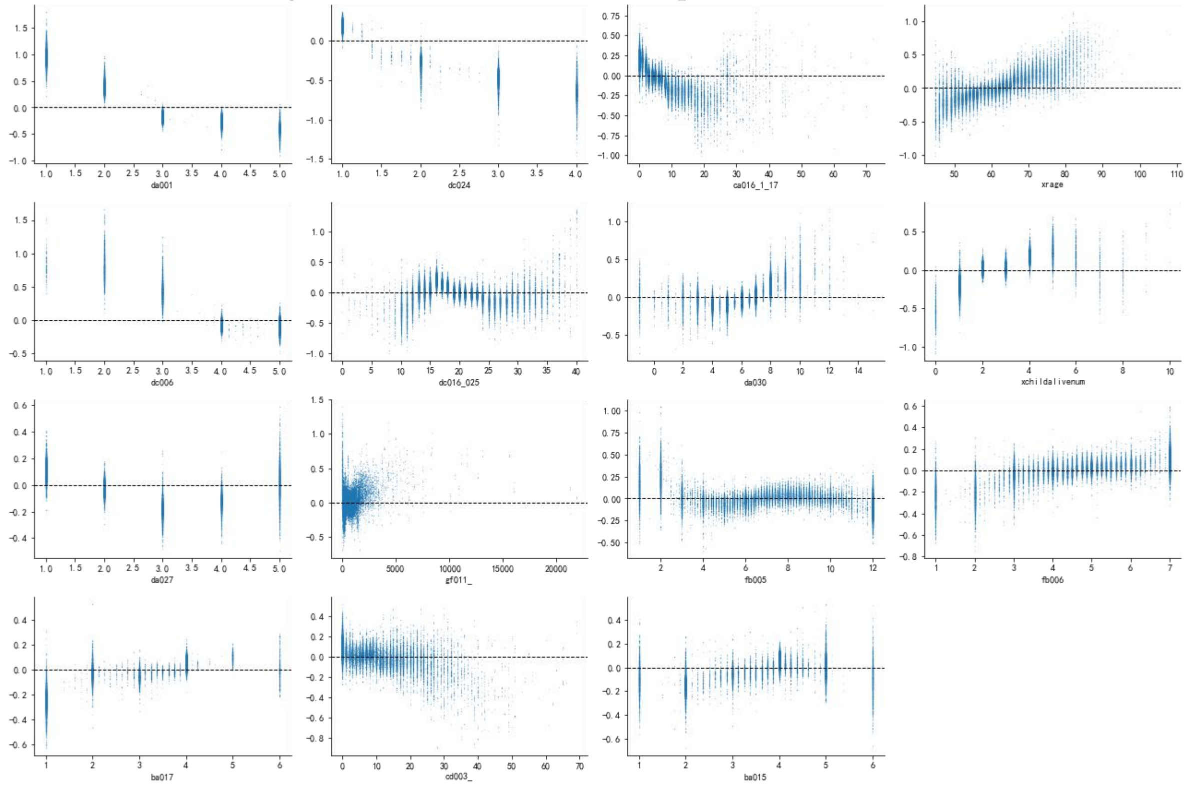

Figure 4: SHAP Dependence Plots

Figure 4 depicts the marginal effect of individual features on the model's predicted SWB output. Each plot isolates one feature. the horizontal axis shows the feature's actual value, and the vertical axis shows the SHAP value. Each point represents one respondent. A SHAP value greater than 0 indicates that the specific feature value exerts a positive influence on the predicted SWB for that individual, pushing the prediction towards higher well-being. Conversely, a SHAP value less than 0 indicates a negative influence, pushing the prediction towards lower well-being. For instance, the plot for Self-rated Health (da001) demonstrates a clear threshold effect: values ≤ 2 (corresponding to "Very Good" or "Good" ratings) consistently yield positive SHAP values (enhancing predicted SWB), whereas values ≥ 3 (corresponding to "Average", "Poor", or "Very Poor" ratings) consistently yield negative SHAP values (diminishing predicted SWB).

Self-rated health exhibited a clear threshold effect exhibited a clear threshold effect. Ratings of "Very Good" or "Good" (scores ≤ 2) had a strong positive impact on SWB. However, ratings of "Average" or worse (scores ≥ 3) exerted a significant negative impact. This aligns with research emphasizing the strong link between perceived health and life satisfaction in later life, where even moderate declines can substantially impact well-being (Hybels et al., 2014).

Higher loneliness scores consistently decreased SHAP values (reducing predicted SWB), confirming the robust negative association between loneliness and SWB established in gerontological literature (Hawkley & Cacioppo, 2010; Yang & Victor, 2011). Even feelings occurring "Not much" (1-2 days) had a less positive impact than "Rarely or never".

More frequent contact generally boosted SWB (positive SHAP values), particularly at lower frequencies (scores < ~8, indicating contact at least monthly). the positive effect diminished or became slightly negative at very high frequencies, potentially indicating dependency or burden, though this requires further investigation.

Scores within the mid-range (approximately 12-23) were associated with positive SHAP values (contributing to higher predicted SWB), while scores below 12 or above 23 were associated with negative SHAP values. This challenges simplistic linear assumptions and suggests that mild-moderate symptom levels within this cohort might reflect engagement or normative stress, not necessarily low SWB, or could relate to measurement nuances. This warrants careful clinical and contextual interpretation (Kohler et al., 2017).

Contrary to some stereotypes, older age within this cohort (60+) was generally associated with higher predicted SWB (positive SHAP values), particularly after age 60, potentially reflecting adaptation or cohort effects. Lower age (<60) showed a slight negative association.

Sleep durations below 6 hours were associated with negative SHAP values, while durations of 6 hours or more generally had a positive impact, supporting the known U-shaped relationship between sleep and well-being in aging (Zhai et al., 2023).

Higher monthly utility/communication expenditure (a proxy for consumption capacity) positively influenced SWB, highlighting the role of economic security (Ng et al., 2019). the type of social insurance showed mixed SHAP effects, reflecting the complexity and varying adequacy of different schemes in China (Liu & Sun, 2016).

The SHAP analysis confirms the paramount importance of perceived health and psychosocial factors (loneliness, family contact) for SWB in Chinese older adults. Crucially, it reveals significant non-linearities and thresholds (especially for health, depression, and contact frequency) that are essential for understanding the dynamics of SWB and designing effective interventions. While socioeconomic factors are important, their influence, as captured by this model and explainability method, appears secondary to health and social connection in this specific predictive context, though they remain vital for overall well-being and policy.

5 Conclusions and Limitations

5.1 Conclusions

This study leverages machine learning to decode the determinants of subjective well-being among Chinese older adults, yielding three key findings. First, the CatBoost model outperformed traditional algorithms (e. g., logistic regression) in predicting SWB, with an AUC of 0.80, highlighting ML's utility in capturing complex socioeconomic and health-related relationships (Figure 2). Second, SHAP analysis identified self-rated health (da001), loneliness (dc024), and frequency of contact with children (ca016_1_17) as the most influential factors. Notably, self-rated health exhibited a nonlinear association with SWB: scores ≤2 (indicating "very good" or "good") positively impacted SWB, while scores ≥3 (indicating "average" or worse) had negative effects (Figure 5), aligning with prior research on health-perceived well-being dynamics (Hybels et al., 2014). Third, socioeconomic factors such as social insurance types and consumption expenditures showed significant associations with SWB, underscoring the role of economic security in aging well (Ng et al., 2019). From a policy perspective, our findings suggest that interventions to enhance SWB should prioritize reducing loneliness (e. g., community-based social programs) and improving access to healthcare and social security. the nonlinear relationship between depression and SWB (depression scores 12–23 showed positive effects, while scores outside this range were negative; Figure 5) warrants further clinical investigation, as it challenges the assumption of a linear depression-well-being correlation (Kohler et al., 2017). Community-based interventions (e. g., social prescribing programs linking isolated elders to group activities) could mitigate loneliness, while telehealth expansion may improve health perception among rural elderly.

5.2 Limitations and Future Directions

This study has several limitations. First, the cross-sectional design of CHARLS 2020 data restricts causal inference, precluding insights into temporal dynamics of SWB (e. g., how changes in health or social connections impact well-being over time). Second, the sample primarily consists of community-dwelling older adults, potentially underrepresenting vulnerable groups (e. g., those in long-term care facilities or rural areas with limited resources). Third, while we included 41 variables, unmeasured factors like cultural values (e. g., filial piety norms) and neighborhood environment quality may influence SWB but were not captured in the dataset (Zhang & Hayflick, 2020).

Future research could address these gaps by: 1) Employing longitudinal data to model SWB trajectories; 2) Incorporating qualitative methods to explore cultural and contextual influences; 3) Validating findings across different aging populations (e. g., urban vs. rural, older vs. oldest-old); 4) Integrating real-time data (e. g., wearable device metrics) to enrich physiological correlates of SWB. Additionally, cross-cultural comparisons using ML models could illuminate how socioeconomic systems and cultural norms shape aging well-being globally, enhancing the generalizability of Chinese findings to international contexts.

Acknowledgments

Research for this paper was partially supported by the 2024 Innovation Project of Guangxi Graduate Education (XYCSR2024073) with no commercial support. APC waiver is requested.

Availability of Data

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

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