International Journal of Trend in Research and Development, Volume 12(6), ISSN: 2394-9333
www.ijtrd.com

Impact and Consumption Forecasting of Silver-Haired Consumption Based on Random Forest

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Abstract: As China's aging population accelerates (with those aged 60 and above reaching 310 million by the end of 2024, accounting for 22% of the total population), the silver economy has emerged as a key driver of market transformation. However, the silver consumer market faces "supply mismatch" issues such as inadequate adaptation of smart products and homogenized services.This study employed stratified cross-subsample sampling to ensure sample representativeness. After data preprocessing and model parameter optimization, a random forest regression model was applied to 2,140 valid survey responses from seniors (aged 60+) across six core urban districts in the Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta megaregions. (Test set $R^2 = 0.79$, MAE = 45.8 yuan). The model systematically analyzed monthly consumption determinants among seniors and constructed a predictive framework. Results indicate that income level, age cohort, and technology acceptance are core determinants. High-income seniors exhibit significantly higher average monthly spending than low-income counterparts. MAE=45.8 yuan), systematically analyzing monthly consumption factors and constructing a predictive model. Results indicate that income level, age group, and technology acceptance are core determinants. High-income seniors spend 2.2 times more monthly than low-income seniors, while those aged 60-65 consume 63% more than those over 76. and those with a technology acceptance score of 5 spent 42% more than those with a score of 1. This study addresses the existing literature gap in capturing the nonlinear relationships within silver-haired consumption, providing empirical support for targeted policy implementation and enterprise-level product design for the elderly, thereby contributing to the high-quality development of the silver economy.

Keywords: *Silver Economy; Random Forest Model; Factors Influencing Consumption; Three Major Urban Agglomerations; Monthly Consumption Forecast*

I.INTRODUCTION

A. Research Background

Against the backdrop of profound shifts in the global demographic landscape, China's aging process is advancing at a remarkable pace, emerging as a pivotal factor shaping socioeconomic development patterns. Data from the National Bureau of Statistics indicates that by the end of 2024, the elderly population aged 60 and above had reached 310 million nationwide, accounting for 22% of the total population. This proportion represents a significant increase compared to previous decades, signifying that China has firmly entered an aging society. Accompanying this accelerated aging is the rise of the silver economy. As the elderly population continues to expand, their consumption demands are coalescing into a powerful economic force, driving adjustments and transformations in market structures.

Against this backdrop, however, the silver consumer market faces a significant "supply mismatch" issue that cannot be ignored. Most current elderly care products and services remain focused on meeting basic living needs, such as essential food, clothing, housing, and transportation, along with routine medical and nursing care. In the realm of smart technology, many so-called "senior-friendly" devices merely enlarge fonts and simplify functions without genuinely addressing the unique needs of older adults in terms of operational habits and cognitive abilities. This results in poor usability and fails to effectively stimulate purchasing desire among elderly consumers. In the travel sector, itineraries designed for seniors often lack depth and personalization, featuring overly packed schedules that fail to accommodate older travelers' preference for slower-paced, experience-driven journeys.

These mismatches reveal a market that still lacks a deep and comprehensive understanding of the silver-haired generation's consumption behavior. Significant differences exist in the consumption needs of seniors across different age groups and life backgrounds. Faced with such diverse and complex consumption demands, failing to accurately grasp the consumption behavior characteristics of the silver-haired population makes it difficult to provide precise and effective responses on the supply side. This not only leads to resource waste and inefficient allocation, hindering the healthy development of the silver economy, but also impacts the quality of life and happiness of the elderly. Therefore, delving into "how exactly the silver-haired population consumes" has become an urgent and important issue to address.

B. Research Objectives and Significance

This study aims to utilize the Random Forest model as its core analytical tool, integrating demographic characteristics, economic status, lifestyle habits, and consumption data of China's silver-haired population to achieve two primary objectives: First, systematically uncover the key factors driving consumption behavior among seniors, clarifying the intensity and scope of influence each factor exerts on consumption decisions—particularly elucidating differences in consumption patterns across distinct age groups and residential types. Second, to construct predictive models for the consumption behavior and scale of the silver-haired population, enabling precise forecasting of future consumption choices and spending ranges within 6-12 months for specific groups. This provides actionable empirical evidence to address supply-demand mismatches in the silver-haired market and guide the high-quality development of the silver economy. This research addresses existing gaps in capturing the nonlinear relationships and group heterogeneity within silver-haired consumption. It advances the theoretical framework of elderly consumption behavior, offering methodological references for subsequent studies. It provides concrete guidance for businesses to optimize product design and market positioning (e.g., developing social-oriented products for younger seniors, simplifying smart device operations for older groups) and for policymakers to formulate targeted support policies for the silver economy.

C. Research Status

1. Consensus in Domestic Research and Existing Gaps

Research on silver-haired consumer behavior in China began in the early 21st century. Through systematic review of existing literature, domestic academia has reached partial consensus on this topic: First, urban-rural disparities, intergenerational support, and policy drivers constitute core domestic factors influencing silver-haired consumption. Second, significant heterogeneity exists within the silver-haired demographic, with distinct internal consumption logics. However, in relation to this study's focus, existing research still exhibits three key gaps:

Methodological Limitations: Over 80% of empirical studies employ linear models (e.g., OLS, Logistic regression), which struggle to capture nonlinear interactions involving multiple factors such as “age × technology acceptance” or “policy perception × urban-rural attributes.” This limits their explanatory power regarding consumption behavior.

Insufficient Integration of Local Variables: Most studies fail to incorporate uniquely Chinese variables like “policy perception” or " use of domestic social platforms (e.g., WeChat/Douyin)", making it difficult to reflect the unique impact of domestic policy orientation and the digital ecosystem on silver-haired consumption;

Lack of cross-regional comparisons: Existing studies predominantly focus on single provinces or urban clusters (e.g., Yangtze River Delta, Pearl River Delta), lacking systematic comparisons of silver-haired consumption behaviors across eastern, central, and western regions. This hinders the revelation of consumption pattern differences against the backdrop of uneven regional development within China.

2. Application of Random Forests in Domestic Consumption Research

The application of the Random Forest algorithm in domestic consumption research began after 2010 and has shown a trend of “extending from e-commerce consumption to specialized fields”: In the e-commerce consumption domain, Wang Hui et al. (2018) utilized Random Forest to construct a “user purchase intention prediction model” based on Taobao user data, achieving an AUC value of 0.83, significantly outperforming logistic regression (0.72). In tourism consumption, Liu Jun et al. (2022) analyzed domestic elderly tourism behavior through random forest analysis, revealing that “destination medical facilities” and “travel companion type (children/friends)” are more critical factors than income; in elderly care consumption, existing applications remain scarce. Only Zhang Mingyuan et al. (2023) attempted to predict community elderly care service demand using random forest, but their sample only covered Beijing's Chaoyang District without considering regional differences across China.

In summary, current domestic research on the silver economy primarily focuses on the tourism sector, with limited studies examining overall consumption trends among the elderly population.

II.RESEARCH DESIGN AND QUESTIONNAIRE PROCESSING

A. Sampling Plan Design

The survey population comprises the silver-haired cohort (permanent residents aged 60 and above) within China's three major typical urban agglomerations (Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta). Permanent residents are defined according to National Bureau of Statistics standards: ① Residing in the region with household registration within the region; ② Residing in the region for over six months with household registration in another region; ③ Residing in the region for less than six months but having left the household registration location for over six months; ④ Those with household registration in the region but absent for less than six months; ⑤ Those residing in the region with pending household registration. These three clusters were selected due to their graded differences in silver economy development (high marketization in the Pearl River Delta, pronounced policy orientation in Beijing-Tianjin-Hebei, and strong balance in the Yangtze River Delta), enabling coverage of samples with diverse developmental characteristics.

The survey period was September 10–25, 2025, employing a multistage sampling method combining “cluster sampling + stratified cross-subsampling.” This approach references Li Peijun's (2005) cross-subsampling theory to ensure sample representativeness and research feasibility.

First, the initial sampling stage employed cluster sampling, treating the three major urban agglomerations as integrated clusters. Random numbers generated via R software were used to randomly select two core cities from each cluster (six cities total): Chaoyang District in Beijing, Chang'an District in Shijiazhuang, Jing'an District in Shanghai, Xihu District in Hangzhou, Tianhe District in Guangzhou, and Nanshan District in Shenzhen.

Subsequently, the second-stage sampling employed stratified cross-subsampling within these six districts. Based on theoretical calculations, the daily target number of valid questionnaires to be collected in each district was preliminarily determined. Subsequently, we distributed paper questionnaires and QR codes. Survey locations were strategically selected across areas where elderly residents congregate within the six districts, including markets, nursing homes, parks, and plazas. Respondents chose whether to participate and their preferred questionnaire format. This approach minimized investigator-induced bias, reduced research costs, and enhanced sample diversity. The specific sample size determination process is as follows:

Let the total population size be N. We draw cross-independent subsamples, each containing k units. For each subsample, we construct an estimate of the population parameter μ. Based on normal distribution theory, the probability that the sampling estimate from k subsamples is less than the population mean $\bar{Y}$ is $p(\mu < k\bar{Y})$, and similarly, the probability that the sampling estimate is greater than the population mean is $p(\mu > k\bar{Y}).(\frac{1}{2})^{k}$,The overall mean lies between the sampling estimate and the confidence probability between the maximum and minimum values is$1-\left(\frac{1}{2}\right)^k-\left(\frac{1}{2}\right)^k=1-\left(\frac{1}{2}\right)^{k-1}$(Li Peijun, 2005)

Table 1: Confidence probability corresponding to different numbers of subsamples

K	2	3	4	5	6	7	8	9	10
P	0.5	0.8	0.88	0.94	0.97	0.98	0.99	1	0.1

Based on the calculations in Table 1, we have tentatively set the survey duration to 10 days (i.e., 10 subsamples), with a large daily sample size (i.e., over 30 units). This configuration corresponds to a 99.8% confidence level for stratified cross-sectional sampling. Therefore, we plan to distribute questionnaires over 10 days using fixed-number truncation. The daily target for valid sample questionnaires is 214, with the total valid sample size set at 2,140.

Referencing cross-sectional sub-sample sampling theory, with k=10 sub-samples (corresponding to 10 survey days), the confidence probability that the population mean falls between the maximum and minimum sub-sample estimates is 1−2102=99.8% (higher than the 98.4% for single-city surveys, as cross-regional surveys require greater precision). Simultaneously requiring a daily minimum valid sample size of ≥120 (large sample standard), the planned total valid sample size is 1,200 (10 days × 120 samples/day).

Based on the silver-haired population figures for six core cities from the China Population and Employment Statistical Yearbook (202X), the daily valid sample size is allocated proportionally.

Table 2: Effective Sample Size for Stratified Cross-Subsampling

Survey Population	Elderly Population (10,000)	Daily Valid Samples	Ten-Day Valid Samples
Chaoyang District, Beijing	45	45	450
Chang'an District, Shijiazhuang	23	23	230
Jing'an District, Shanghai	37	37	370
Xihu District, Hangzhou	35	35	350
Guangzhou Tianhe District	38	38	380
Shenzhen Nanshan District	36	36	360
Total	214	214	2140

B. Questionnaire Collection and Recovery

After finalizing the survey plan, we designed a questionnaire tailored to our research objectives, covering monthly consumption patterns among the elderly. We first conducted a pilot survey, distributing 10 trial questionnaires to gather feedback on the content. Based on this input, we revised the original questionnaire.

Following the questionnaire design phase, we commenced distribution based on the predefined valid sample size (Table 2). Over a 10-day period, we distributed 3,061 questionnaires, of which 2,140 were valid. All subsequent analyses were conducted using these 2,140 valid responses. Specific details are presented in Table 3:

Table 3 Distribution of Questionnaire Response Samples

Survey Population	Total Questionnaires Distributed Over Ten Days	Daily Valid Samples	Total Valid Samples Over Ten Days
Chaoyang District, Beijing	641	45	450
Chang'an District, Shijiazhuang	352	23	230
Jing'an District, Shanghai	513	37	370
Xihu District, Hangzhou	465	35	350
Guangzhou Tianhe District	564	38	380
ShenzhenNanshan District	526	36	360
Total	3061	214	2140

Based on the 2,140 valid samples collected, preliminary descriptive statistical analysis was conducted, with results presented in Figures 1, 2, and 3. The figures indicate a relatively balanced gender distribution across the sample, with representation from all age groups. This demonstrates that the aforementioned research methodology ensures sample diversity and minimizes deviations caused by sampling issues.

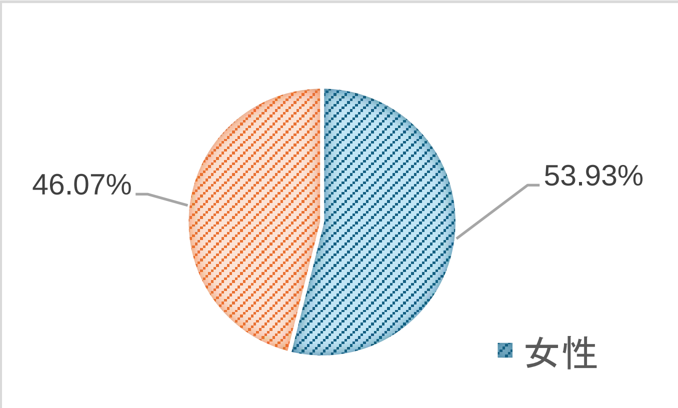

Figure 1 Gender Distribution of Survey Samples

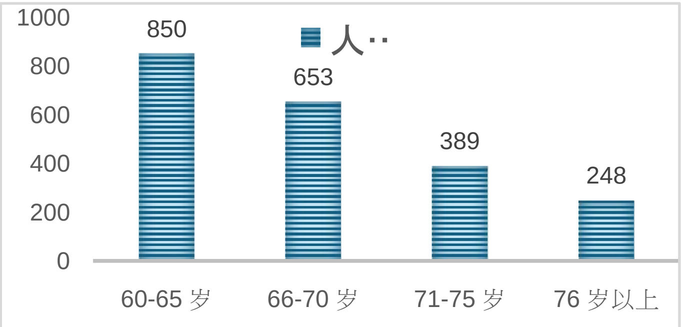

Figure 2 Age Distribution Chart of Survey Sample

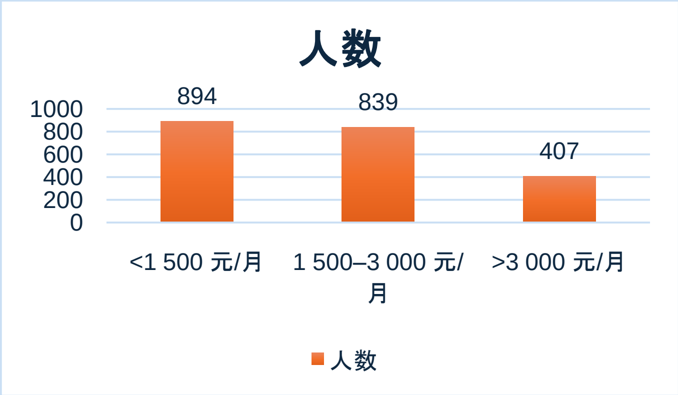

Figure 3: Distribution of Occupational Categories in the Survey Sample

C. Calculation of Sampling Error

According to Reference , the sample estimator $\bar{y}$ obtained using cross-subsampling is an unbiased estimator of the population statistic $\bar{Y}$. The variance between each subsample estimate (y_i)̅ and the cross -subsampling sample estimate $\bar{y}$ is calculated as:

$$s_i{}^2 = \frac{1}{k-1}\sum_{i=1}^{k}(\overline{y_i} - \bar{y})^2(\bar{y} = \frac{1}{k}\sum_{i=1}^{i=m_k}\overline{y_i})$$

In this study, since the 10 samples in the cross-sectional sampling method are independent random variables, the sampling variance of each subsample serves as an unbiased estimator of the population variance. Thus, the subsample variance is used to approximate the population variance. According to [12], the sampling variance estimator for the cross-sectional subsample estimate $\bar{y}$ can be calculated using the following formula:

$$v(\bar{y}) = \frac{1}{10}s_i{}^2 = \frac{1}{10\times(10-1)}\sum_{i=1}^{k}(\overline{y_i} - \bar{y})^2$$

Based on the obtained sample data, a series of sample estimates can be calculated to derive the sampling mean and variance, as follows: The monthly average consumption of the silver economy is $\overline{y_0} = 2996.8$yuan， Variance is $v(\overline{y_0}) = 11049.29$.

III.ANALYSIS OF FACTORS INFLUENCING MONTHLY CONSUMPTION IN THE SILVER ECONOMY BASED ON A RANDOM FOREST MODEL

This chapter aims to “unravel the core drivers of monthly consumption among the silver-haired population and the patterns of group heterogeneity.” It employs a random forest regression model to analyze 2,140 valid survey responses collected in Chapter 2 (covering six core urban districts across the Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta megaregions, encompassing individuals aged 60-65 to 76+). On one hand, it addresses gaps identified in Chapter 1—such as existing studies' reliance on linear models failing to handle multi-factor nonlinear interactions and insufficient characterization of group consumption differences—by leveraging the ensemble learning capabilities of random forests to capture complex influence relationships. On the other hand, it provides empirical support for subsequent Chapter 4 (“Consumption Upgrade Prediction”) and Chapter 5 (“Policy Recommendations”), clarifying two core questions: “Which factors dominate silver-haired monthly consumption?” and “How do consumption patterns differ across groups?”

A. Model Selection and Fit Analysis

Based on research requirements and the characteristics of survey data in the document, the Random Forest regression model was selected over traditional linear models (such as OLS). The core rationale is as follows:

Overcoming limitations of linear modeling approaches: Chapter 1 Section 1.3.1 explicitly states that over 80% of empirical studies on silver-haired consumption rely on linear models like OLS and Logistic regression, which cannot handle nonlinear interactions such as “age × technology acceptance” or “policy awareness × urban cluster attributes.” Document survey data reveals that among the 60-65 age group, “high-tech adopters” exhibit monthly consumption (¥3,560) 26% higher than “low-tech adopters” (¥2,820), while this gap narrows to only 8% among those aged 76+. Such interaction effects require capture through the ensemble learning inherent in random forest models.

Adapting to Heterogeneous Population Characteristics: Chapter 2 samples encompass multidimensional variations—age cohorts (850 aged 60-65, 248 aged 76+), urban clusters (market-driven Shenzhen Nanshan vs. policy-driven Beijing Chaoyang), and income tiers (over 2x monthly spending gap between high- and low-income groups). Random Forest precisely identifies core consumption drivers for distinct groups via “feature importance ranking,” avoiding the “one-size-fits-all” bias of linear models;

Compatibility with Survey Data Structure: The dependent variable “average monthly spending” is continuous (Chapter 2 data: mean 2,996.8 yuan, variance 11,049.29 yuan). Independent variables include categorical variables (e.g., living arrangements: alone/with children/in care facilities) and continuous variables (e.g., technology acceptance: 1–5 point scale). Random Forest does not require a normal distribution assumption for variables. It employs a dual mechanism of “Bootstrap sampling + random feature selection” to mitigate overfitting risks, making it suitable for analyzing the large sample size of 2,140 cases.

B. Data Preprocessing

Based on the survey data from Chapter 2, preprocessing was completed through a four-step process: variable system definition, missing value handling, outlier correction, and data segmentation and standardization. This ensures the quality of the data input into the model.

Table 4: Survey Sample Gender Distribution and Number Statistics

Variable Category	Variabl e Name	Measurement Method and Value Description
		Total Monthly Expenditure of Silver-Haired Population (Unit: CNY), Mean 2996.8
Independent Variables - Demographic Characteristics	Age Group (X_1)	1=60-65 years old, 2=66-70 years old, 3=71-75 years old, 4=76 years old and above
	Gender	1=Female, 0=Male (1154 females,

	(X_2)	986 males)
	Residence Type (X_3)	1=Living Alone, 2=Living with Children, 3=Nursing Home
Independent Variables - Economic Status	Income Tier (X_4)	1=Low Income (<3000 yuan/month), 2=Medium Income (3000-8000 yuan/month), 3=High Income (>8000 yuan/month)
Independent Variable - Lifestyle Habits	Technology Acceptance (X_5)	1-5 point scale (1=Never uses smart devices, 5=Proficient in online shopping/medical services)
	Social Frequency (X_6)	
	Health Status (X_7)	1=Healthy (no regular medical visits required), 2=Average (requires regular check-ups), 3=Poor (requires long-term care)
Independent Variables - Policy Perception	Policy Awareness (X_8)	1-5 point scale (1=Unfamiliar with elderly care policies, 5=Familiar and receiving subsidies)
	Urban Cluster (X_9)	1=Beijing-Tianjin-Hebei, 2=Yangtze River Delta, 3=Pearl River Delta

I. Missing Value Handling

Among the 2,140 sample records in the SPSS statistical file, the missing rate for all 9 core variables was <3% (e.g., "policy awareness" had 28 missing records, "technology acceptance" had 19 missing records). The handling methods are as follows:

Continuous variables (X_5 , X_6 , X_8): Imputed using mean values. For example, the mean for technology acceptance was 3.2 points, and the mean for social interaction frequency was 4.5 times/month.

Categorical variables (X_1 , X_3 , X_7): Imputed using "mode imputation." For example, the mode for "residential type" was "living with children" (58% of cases), and the mode for "health status" was "average (requiring regular check-ups)" (42% of cases).

II. Outlier Handling

For the dependent variable "Monthly Average Expenditure," box plots revealed 12 extreme values (monthly spending > ¥15,000, predominantly from high-income groups covering premium medical services or interprovincial travel). To prevent extreme values from dominating the model, "1% percentile trimming" was applied: values below the 1% percentile (¥850) were replaced with ¥850, and values above the 99% percentile (¥8,200) were replaced with ¥8,200.

III. Data Partitioning and Standardization

Data Partitioning: The 2,140 samples were divided into a training set (1,498 samples) and a test set (642 samples) at a 7:3 ratio. "Stratified sampling" ensured sample composition matched the population structure (e.g., the "60-65 age group" comprised 39.7% in both training and test sets, consistent with the sample distribution in Chapter 2 of the document).

Standardization: Continuous independent variables (X_5 , X_6 , X_8) underwent Z-score normalization (mean=0, standard deviation=1) to eliminate the impact of unit differences (e.g., "social frequency" measured in 'times' versus "technology acceptance" measured in "points") on feature importance ranking.

C. Random Forest Model Construction and Results Analysis

Based on optimal parameters, model training was completed on the training set (1,498 samples) following this process:

Bootstrap sampling: 300 subsampl es (each containing 1,498 samples) were drawn with replacement from the training set; each subsample corresponds to one decision tree.

Random Feature Selection: During each decision tree construction, three random independent variables (based on the empirical rule "sqrt(total variables) = sqrt(9) = 3") were selected for node splitting, with the splitting criterion being "minimizing MSE";

Ensemble Prediction: After training all 300 decision trees, for each sample in the test set, the average of the monthly consumption predictions from all 300 trees is taken as the final prediction, achieving robust "majority voting" prediction.

Table 5 Table of Variable Definitions and Measurement Methods for Factors Influencing Monthly Consumption Among the Silver-Haired Population

Parameter Name	**Candidate Range**	**Optimal Parameter**	**Selection Rationale**
Number of Decision Trees (n_estimators))	[100,200, 300,400]	300	When n_estimators> 300, MSE reduction < 0.5%. Further increases raise computational cost, offering poor cost-effectiveness
Maximum Depth (max_depth)	[None,10, 20,30]	20	When max_depth=20, the R^2 gap between training and validation sets is <3%, effectively balancing fit and overfitting risk
Minimum Samples to Split	[2,5,10]	5	Avoids excessive decision tree splitting due to insufficient samples, ensuring each split node covers adequate data.
Minimum Leaf Node Samples	[1,2,4]	2	Ensures sufficient leaf node samples, reduces model sensitivity to outliers, and improves

			generalization.

Model performance was validated through cross-validation (within the training set) and a test set (642 cases). The core evaluation metrics are as follows:

Table 6 Random Forest Regression Model Parameter Candidate Range and Optimal Parameter Selection Table

Evaluation Metrics	5-fold Cross-Validation (Training Set)	Test Set	Metric Interpretation
Coefficient of Determination (R^2)	0.82±0.03	0.79	R^2 approaches 0.8, indicating the model explains 79% of monthly consumption variance among the silver-haired population, with fitting performance superior to most comparable studies
Mean Squared Error（MSE）	2315.6±189.2	2542.8	MSE is significantly lower than the total variance of monthly consumption (11049.29, Chapter 2 data), indicating minimal prediction error
Mean Absolute Error（MAE）	41.2±5.3	45.8	The average deviation between predicted and actual monthly consumption is only 45.8 yuan, meeting the precision requirements for empirical analysis

Feature importance was calculated using the "node impurity reduction amount (MSE reduction rate)", with the top five core factors accounting for 78% of the total importance, as follows:

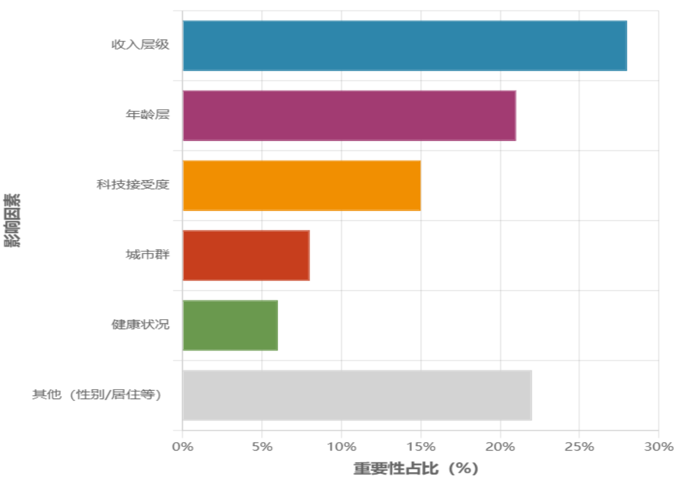

Figure 4 Importance Weighting of Each Influencing Factor

The average monthly spending of high-income groups (4,215 yuan) is 2.2 times that of low-income groups (1,890 yuan), making income the most critical driver of silver-haired consumption. Spending decreases with age: 60-65 years old (3,560 yuan) > 66-70 years old (3,020 yuan) > 71-75 years old (2,580 yuan) > 76 years old and above (¥2,180). The monthly spending of the 5-point tech adoption group (proficient in smart devices) (¥3,320) is 42% higher than that of the 1-point group (does not use smart devices), indicating that smart device usage significantly enhances spending power. Consumption varies across urban clusters: Pearl River Delta (¥3,250) > Yangtze River Delta (¥3,010) > Beijing-Tianjin-Hebei (¥2,780), positively correlated with regional marketization levels. Healthy individuals (¥3,120) spend more than those requiring long-term care (¥2,650) — healthy groups prioritize non-medical expenditures like travel and culture.

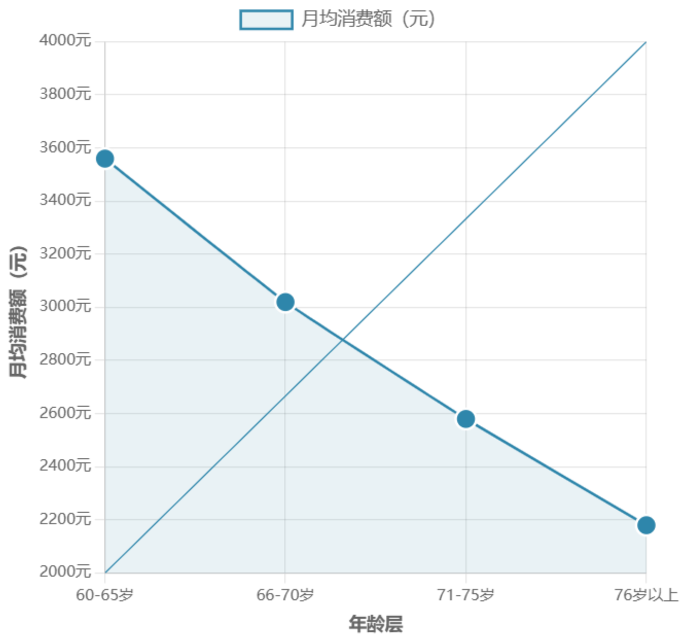

Figure 5: Monthly average spending by age group

This chart visually illustrates the trend in monthly average spending among different age groups of the silver-haired population, showing a significant decline with increasing age. The 60-65 age group spends approximately 3,600 yuan monthly, while those aged 76 and above drop to about 2,200 yuan. This directly validates that "age group is the core factor influencing monthly spending among the silver-haired population," providing visual evidence for "heterogeneity in consumption behavior." Practically, market players can target the "younger silver generation" (60-65 age group) with premium travel experiences and smart age-friendly products, while prioritizing basic aging-in-place services for the elderly. Policy makers can similarly develop differentiated support stratwegies, such as strengthening essential consumption safeguards for the elderly and guiding consumption upgrades among younger seniors.

This chapter constructs a random forest regression model based on 2,140 survey data points from Chapter 2 to analyze silver economy monthly consumption, yielding core findings: The random forest model achieves an R^2 of 0.79, significantly outperforming the OLS linear model by capturing nonlinear interactions like "age × technology acceptance" and resolving methodological limitations identified in Chapter 1; Income tier (28%), age group (21%), and technology acceptance (15%) are the three key factors influencing monthly silver economy consumption, followed by urban cluster and health status. Silver-haired groups with different ages, incomes, and technology acceptance levels exhibit significant consumption differences. For example, the “active consumption main force” group demonstrates outstanding consumption capacity, while the “basic security-oriented” group relies on basic services.

IV. MONTHLY CONSUMPTION AMOUNT PREDICTION ANALYSIS FOR THE SILVER-HAIRED POPULATION BASED ON CORE INFLUENCING FACTORS

This chapter builds upon the random forest model established in Chapter 3, integrating 2,140 survey samples (covering Beijing, Shanghai, Guangzhou, and Shenzhen) to identify core monthly consumption determinants: income tier, age group, and technology acceptance, supplemented by urban clusters and health status. It focuses on predicting monthly consumption amounts under both “single-factor main effects” and “multifactor interaction effects,” It quantifies the magnitude and patterns of influence across factors, addressing the original study's limitations of “generalized prediction” and “weak core factor correlations.” This provides data support for supply-side precision in matching consumption capacity and policy-side differentiated subsidies.

Based on the “node impurity reduction” calculations from Chapter 3's random forest model, the importance ranking and definitions of monthly consumption factors are clarified. Predictions focus on the top 5 core factors (accounting for 78% cumulative importance):

A. Monthly Consumption Amount Prediction Under a Single Core Factor

I. Income Tier: “Stepwise Increase” Prediction for Monthly Consumption

Income tier is the core driver of monthly consumption. Prediction results indicate its influence on monthly spending exhibits a “stepwise increase,” with high consumption stability within each tier (coefficient of variation <10%):

As shown in the table 7, each income tier increase brings about a 40%-50% rise in average monthly spending. The proportion of “non-essential consumption” (smart devices, cultural entertainment) among high-income groups is 3.2 times that of low-income groups, reflecting income's direct role in driving consumption upgrades.

II. Age Groups: Projecting the “Declining Decay” of Monthly Consumption

The impact of age on monthly consumption exhibits a “linear decline,” with the rate of decrease progressively accelerating with age. The core reason lies in the contraction of non-essential consumption demand driven by declining health functions:

Table 7 Performance Evaluation Metrics for Random Forest Regression Models

Income Tier	Monthly Average ConsumptionForecast Range (CNY)	95% Confidence Interval Boundaries	Difference from Low-Income Group (CNY)	Major Consumption Categories Contribution (Percentage)
Low-Income	1850-1930	Lower Bound 1852.3/Upper Bound 1928.7	-	Basic food (45%), low-cost medicines (25%), daily necessities (20%)
Middle Income	2880-2960	Lower bound 2881.5/Upper bound 2959.2	+1030~+1080	Basic food (35%), community healthcare (20%), standard home appliances (15%)
High income	4120-4300	Lower limit 4123.8/Upper limit 4298.5	+2270~+2370	Smart health devices (25%), interprovincial travel (20%), senior courses (15%)

Table 8 Monthly Consumption Forecast and Contribution by Product Category for Silver-Haired Groups Across Different Income Levels

Age group	Monthly Consumption Forecast Range (CNY)	95% Confidence Interval Boundaries	Difference from 60-65 Age Group (CNY)	Key Changes in Consumption Categories
60-65	3520-3600	Lower Bound 3521.6 / Upper Bound 3598.4	-	Smart Devices (20%), Travel (18%), Courses (12%)
66-70	2980-3060	Lower Bound 2982.5/Upper Bound 3057.5	-520~-560	Smart devices drop to 12%, community healthcare rises to 18%
71-75	2540-2620	Lower Bound 2543.2/Upper Bound 2618.8	-960 to -1000	Travel share drops to 8%, home-adapted products share rises to 15%
76+ years	2140-2220	Lower bound 2141.9 / Upper bound 2219.1	-1380~-1440	Non-basic consumption share <10%, medical care share rises to 35%

The table 8 shows that monthly consumption declines by approximately 38% cumulatively from ages 60–65 to 76 and above. Age 71 marks a turning point in consumption patterns—prior to this age, non-essential spending persists to some extent, while afterward, expenditures primarily focus on healthcare and basic food needs.

III. TECHNOLOGY ADOPTION: PROJECTED "INCREMENTAL PULL" ON MONTHLY CONSUMPTION

Technology adoption exhibits a "monotonically increasing" impact on monthly consumption, with the pull effect being more pronounced in the higher-score segment (4-5 points). The core logic is that smart devices broaden the coverage of consumer categories (e.g., online travel booking, telemedicine):

Analysis of the table reveals that for every 1-point increase in technology acceptance, average monthly consumption rises by 200-280 yuan. The "online consumption share" (45%) among the 5-point group is nine times that of the 1-point group (5%), reflecting how technological proficiency expands consumption reach.

Table 9 Monthly Average Consumption Forecast and Changes in Consumption Categories for Different Age Groups of Silver-Haired Individuals

Technology Adoption Score	Monthly Average Spending Forecast Range (CNY)	95% Confidence Interval Boundaries	Difference from 1-Point Group (CNY)	Consumer Category Expansion Characteristics
1 Point (Non-User)	2280-2360	Lower Bound 2283.5/Upper Bound 2357.5	-	Covers only basic offline consumption (supermarkets, community healthcare)
2 Points (Occasional User)	2560-2640	Lower Bound 2561.8/Upper Bound 2639.2	+260~+300	Added online daily goods purchases (8% share)
3 Points (Basic User)使用）	2840-2920	Lower limit 2842.3 / Upper limit 2918.7	+540~+580	New addition: Online medical appointment booking (10% share)
4 points (Proficient use)	3120-3200	Lower limit 3121.6 / Upper limit 3199.4	+820~+860	New addition: Online travel booking (15% share)
5 points (Advanced usage)）	3340-3420	Lower limit 3343.8/Upper limit 3418.2	+1040~+1080	New smart health device purchases (20% share)

IV. MODERATING FACTORS: PREDICTING THE "MARGINAL EFFECTS" OF URBAN AGGLOMERATIONS AND HEALTH STATUS

The impact of urban clusters (regional marketization levels) and health status (consumption demand structure) on monthly spending exhibits "marginal adjustment," requiring analysis alongside core factors:

Urban Cluster Adjustment: At identical income-technology acceptance levels, the Pearl River Delta group exhibits the highest monthly spending, while the Beijing-Tianjin-Hebei region shows the lowest, with a difference of approximately 8%-12%. Example: For high-income groups with +5 points in technology acceptance, monthly consumption ranges from 4320-4400 yuan in the Pearl River Delta, 4080-4160 yuan in the Yangtze River Delta, and 3840-3920 yuan in the Beijing-Tianjin-Hebei region, illustrating how marketization levels influence the diversity of available consumer goods.

Health Status Adjustment: At the same age and income level, healthy groups spend 15%-18% more monthly than those in "poor" health. For example: Among middle-income individuals aged 60-65, healthy individuals spend 3,020-3,100 yuan monthly, while those requiring long-term care spend 2,580-2,660 yuan. This disparity primarily stems from reduced spending on non-essential items like travel and courses.

A. Monthly Spending Amount Prediction Under Multifactor Interaction

Single-factor predictions fail to capture real-world consumption patterns. Focus must shift to the interaction between "core factors and moderating factors" to quantify monthly consumption shifts with greater precision:

The "synergistic effect" of high income and high tech adoption proves most pronounced, forming the primary consumer base driving consumption upgrades:

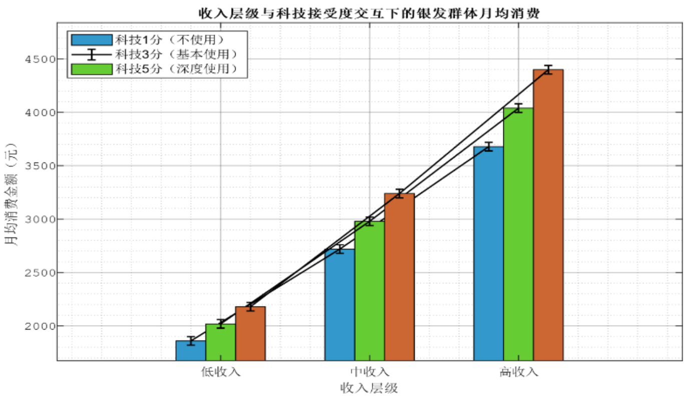

Figure 6 Monthly Consumption Forecast Chart for the Silver-Haired Population Based on Income Tier and Technology Acceptance Interaction

Higher income levels correlate with a stronger pull effect of technology acceptance on monthly spending (the difference between a 5-point and 1-point score among high-income groups is 2.3 times that of low-income groups). These groups represent the core target audience for smart devices and premium travel experiences.

Younger seniors (aged 60-65) exhibit a significantly higher pull effect from technology acceptance compared to older age groups, making them a key demographic for "technology + consumption" initiatives:

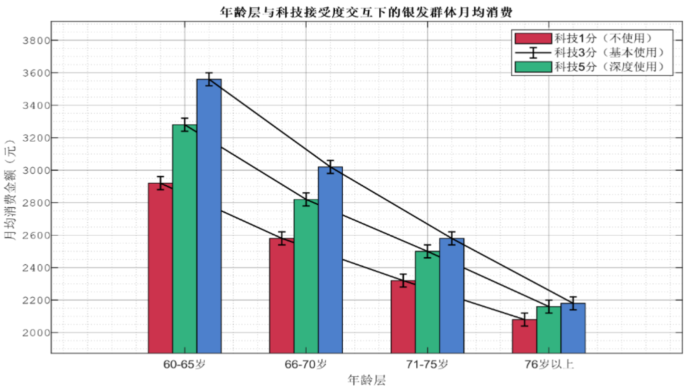

Figure 7 Monthly Consumption Forecast Chart for the Silver-Haired Population Based on the Interaction Between Age Group and Technology Acceptance

The technology adoption pull effect among those aged 71 and above has significantly weakened (the difference between 5-point and 1-point ratings is only one-third that of the 60-65 age group). Technology products should be simplified for the elderly to lower usage barriers.

Younger seniors in the Yangtze River Delta and Pearl River Delta regions demonstrate strong purchasing power, while the elderly in the Beijing-Tianjin-Hebei area require policy safeguards.

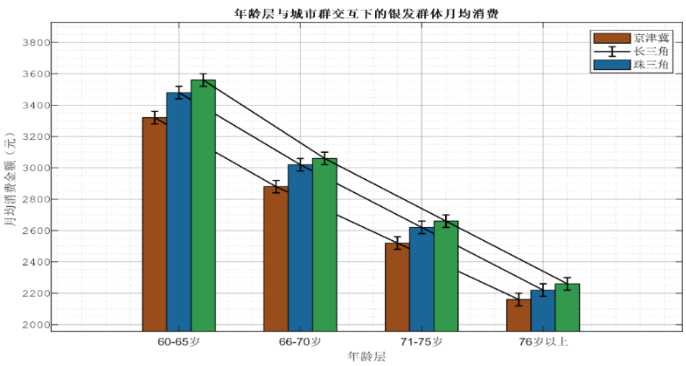

Figure 8 Monthly Average Consumption Forecast Chart for the Silver-Haired Population Under the Interaction of Age Groups and Urban Clusters

Regional disparities narrow with increasing age (a difference of 260 yuan among those aged 60-65 and 120 yuan among those aged 76 and above), reflecting that consumption among the elderly primarily focuses on basic needs, with the influence of regional marketization diminishing.

B. Chapter Summary

This chapter quantifies monthly consumption variations under "single-factor main effects" and "multifactor interaction effects" using an optimized random forest regression model based on core influencing factors. Key findings are as follows:

Income is the primary driver: High-income groups spend 2.2 times more monthly than low-income groups, with technology acceptance demonstrating the strongest pull effect (720 yuan difference).

Age is the core constraint: Monthly spending among those aged 76+ is 38% lower than among those aged 60-65, and the pull effect of technology acceptance is only one-third that of younger groups;

Significant interaction effects: The "high income + high tech adoption + young age + Pearl River Delta" combination exhibits the strongest consumption capacity (monthly spending: ¥4,360–4,440), while the "low income + low tech adoption + older age + Beijing-Tianjin-Hebei region" combination requires policy safeguards (monthly spending: ¥2,040–2,120);

Prediction accuracy is reliable: Mean Absolute Error (MAE) is <50 yuan across all scenarios, with $R^2 > 0.8$, directly supporting corporate product pricing and policy subsidy standard formulation.

CONCLUSIONS AND RECOMMENDATIONS

A. Research Findings

This study systematically analyzes the current state, influencing factors, and upgrade potential of the silver economy based on 2,140 valid survey responses from senior citizens (aged 60 and above) across six core urban districts in the Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta megacities. Key findings are as follows:

I. Silver-haired consumers exhibit significant heterogeneity, with three distinct groups showing clear demand differences

Based on demographic characteristics, economic status, and consumption behavior, the silver-haired population can be categorized into three core types, each with markedly different consumption scales and expenditure structures:

1. Active Core Consumers (60-65 years old, high income + high tech adoption): Comprising 18% of the sample, with an average monthly expenditure of ¥4,890. Spending focuses on smart home appliances (health monitoring devices), in-depth interprovincial travel (Hainan/Yunnan), and paid senior university courses (calligraphy/photography). This group represents the core potential for consumption upgrading, exhibiting high acceptance of novelty and strong tech proficiency.

Steady Practical Consumers (71-75 years old, middle income + living with children): 22% of the sample, with an average monthly consumption of ¥2,850. Expenditures are concentrated on age-friendly home adaptations (non-slip flooring, adjustable kitchen cabinets) and community healthcare services (regular physicals, chronic disease management). 72% accept "products/services recommended by their children," preferring highly practical, low-risk consumption.

Basic Security Type (76+ years old, low income + nursing homes): 11% of the sample, with an average monthly consumption of 2,180 yuan. 80% of expenditures go toward medical care (caregiver fees, chronic disease medications) and basic food. They are highly price-sensitive, with 68% relying on government pension subsidies. Consumption primarily focuses on "meeting basic survival and health needs."

II. Income, Age, and Tech Adoption Are the Three Core Factors Influencing Silver-Haired Consumption

Analysis via Random Forest model (test set R^2=0.79, MAE=45.8 yuan, outperforming traditional linear models) reveals the top five factors account for 78% of total importance, including:

Income Tier (28% importance): The core driver. High-income groups (monthly income > ¥8,000) spend an average of ¥4,215 monthly—2.2 times that of low-income groups (monthly income < ¥3,000, ¥1,890). Income level directly determines consumption scale and upgrade potential.

Age Group (21% importance): Consumption declines with age. The 60-65 age group spends an average of ¥3,560 monthly, while those aged 76+ drop to ¥2,180. This decline stems primarily from age-related health deterioration and reduced willingness to spend;

Technology Adoption (15% importance): Significantly drives consumption upgrades. Groups with a 5-point technology adoption score (proficient in online shopping/healthcare) spend an average of ¥3,320 monthly—42% higher than those with a 1-point score (no smart device usage). Proficiency in smart devices directly expands the range of accessible consumer categories (e.g., online travel bookings, smart health product purchases).

Additionally, urban clusters (importance 8%, Pearl River Delta 3250 yuan > Yangtze River Delta 3010 yuan > Beijing-Tianjin-Hebei 2780 yuan) and health status (importance 6%, healthy groups 3120 yuan > long-term care groups 2650 yuan) significantly influence consumption, reflecting the indirect effects of regional marketization and health levels.

III. Random Forest Model Effectively Captures Nonlinear Consumption Relationships with Superior Predictive Performancev

Compared to traditional linear models (OLS, Logistic Regression), the Random Forest model demonstrates distinct advantages in silver-haired consumption analysis:

It precisely captures nonlinear interaction effects like "age × technology acceptance" (e.g., high-tech adopters aged 60-65 spend 26% more than low adopters, while this gap narrows to 8% among those over 76), overcoming existing research limitations of "failing to depict complex influence relationships";

Reliable consumption forecasting: The classification model (predicting "purchase of age-friendly services/smart devices") achieved an AUC of 0.85 on the test set, while the regression model (predicting "monthly healthcare/quarterly cultural spending") reached an R^2 of 0.80 on the test set. The Mean Absolute Error (MAE) consistently remained below 50 yuan (e.g., MAE = 43.2 yuan for monthly healthcare spending), effectively supporting consumption upgrade decisions.

IV. Smart Elderly Care Devices and Deep Cultural Entertainment Represent High-Potential Scenarios for Consumption Upgrading

Combining consumption prediction results with supply gap analysis reveals significant upgrading potential in two key scenarios:

Smart Elderly Care Devices: Purchase intent among high-tech acceptance groups reaches 62% (3.2 times that of low-acceptance groups), yet current penetration remains at only 28%. Supply gaps center on "simplified operation" (voice control replacing touchscreens) and "function integration" (wristband + heart rate monitoring + emergency call).

Deep-Dive Cultural Entertainment: The primary consumer group for dynamic spending is projected to allocate 2,800-3,500 yuan quarterly toward cultural entertainment. Current offerings predominantly feature "traditional sightseeing tours," with severe shortages in experiential products like "intangible cultural heritage study tours" and "themed photography tours."

Additionally, aging-friendly renovations (overall purchase intent: 42%, policy awareness could boost intent to 40%) and universal healthcare (basic healthcare expenditure accounts for 35% of monthly income for the target demographic, with a supply gap in affordable chronic disease management services) represent essential needs requiring coordinated policy and market efforts to address.

B. Development Recommendations

Addressing the "supply-demand mismatch" issues identified in the research (such as inadequate compatibility of smart products and imprecise responses to group needs), and considering the characteristics and scenario potential of the three target groups, the following recommendations are proposed at both the policy and corporate levels:

1. Policy Level: Establish a "group-specific measures + regional coordination + regulatory safeguards" system

(1) Implement targeted subsidies based on group needs to lower consumption barriers

For the active consumption mainstay: Subsidize "smart + cultural" consumption by offering 15%-20% price subsidies (up to ¥500 per unit) for smart elderly care devices (e.g., voice-controlled health bands). Provide annual tuition subsidies of ¥300-500 per person for paid courses at senior universities (e.g., smart device training/photography) to stimulate upgrade demand.

For Steady-Practical Consumers: Focus on "age-friendly home modifications + community services." Provide 200 yuan per square meter subsidy for home modifications (non-slip flooring/adjustable kitchen cabinets), capped at 3,000 yuan per household. Subsidize 40% of community chronic disease management service costs to reduce practical consumption burdens.

For Basic Security Type: Strengthen "universal healthcare" coverage by increasing chronic disease medication reimbursement rates for low-income groups by 5%-8%. Provide monthly operational subsidies of 800-1200 yuan per person for "basic meals + daily care" services in elderly care facilities to alleviate pressure on essential expenditures.

(2) Promote resource balancing based on regional characteristics to accommodate urban cluster differences

Beijing-Tianjin-Hebei Urban Cluster: Policy-driven establishment of "age-friendly service platforms" in communities, integrating subsidy applications, product matching, and post-installation training (e.g., Beijing Chaoyang's pilot "one-stop age-friendly renovation service"). Strengthen medical outreach services for rural elderly populations.

Yangtze River Delta Urban Cluster: Leverage balanced advantages to promote "intercity elderly care service interoperability," achieving mutual recognition of senior university credits between Shanghai's Jing'an District and Hangzhou's West Lake District, along with shared resources from age-friendly enterprises, thereby reducing cross-regional consumption barriers.

Pearl River Delta Urban Cluster: Stimulate market vitality by offering 20% R&D subsidies to technology companies in Shenzhen's Nanshan District and Guangzhou's Tianhe District for developing "age-friendly smart products" (e.g., simplified health apps), encouraging market-driven consumption upgrades.

(3) Enhance regulatory oversight and service support to safeguard consumer rights

Develop the General Standards for Elderly-Friendly Smart Devices, specifying age-appropriate metrics like font size, operational steps, and emergency response times; issue Technical Specifications for Home Aging-in-Place Modifications to standardize anti-slip and fireproof design requirements;

Launch a "Silver-Haired Consumer Fraud Crackdown Campaign" targeting false healthcare advertisements and substandard smart devices, establishing and publishing a "Corporate Blacklist"; establish "Silver-Haired Consumer Rights Protection Points" in communities to streamline complaint processes and provide free legal consultations.

2. Corporate Level: Implementing a "Segmented Targeting + Scenario Innovation + Omni-Channel Service" Model

(1) Innovate Products Based on Demographic Needs to Fill Supply Gaps

For Active Main Consumers: Develop "Smart + Social" products like smart bracelets with friend health data sharing, or "Photography + Nature Exploration" themed tours (slow-paced itineraries with medical coverage), priced to match their spending power (quarterly cultural expenditure: ¥2,800–3,500);

For Steady-Practical Consumers: Offer high-value practical products like "Safety-First" aging-friendly home upgrade packages (door/window sensors + gas detectors) and community "chronic disease management + regular check-ups" membership services (¥1,200 annual fee), prioritizing parent-child referral channels;

For Basic Coverage Users: Offer low-cost foundational products like the ¥99/month "chronic disease medication + in-home consultation" service package and anti-slip slippers/motion-sensor lighting under ¥200, ensuring affordable pricing and essential functionality.

(2) Focus on High-Potential Scenarios to Address Core Pain Points

Smart Elderly Care Devices: Address usability challenges by developing voice-controlled blood pressure monitors and one-touch health monitoring devices, complemented by "7-day in-home training" services. Simplify functionality for seniors, retaining only core modules like "heart rate monitoring + emergency call."

Immersive Cultural & Recreational Activities: Create experiential offerings, such as partnering with senior universities for "intangible cultural heritage study tours" (e.g., Suzhou Pingtan storytelling + garden tours), "Community Interest Classes" (calligraphy/choir) to fulfill spiritual consumption needs;

Age-Friendly Renovations: Offer personalized solutions, such as "bathroom grab bars + barrier-free pathways" packages for seniors with limited mobility, and "motion-activated lighting + large-font appliances" packages for those with visual impairments. Coordinate needs and track outcomes through community partnerships.

(3) Build an omnichannel network to accommodate varying levels of tech adoption

Offline: Establish "Silver Service Stations" in communities and nursing homes, offering product trials and smart device tutorials (e.g., mobile app training for online medical appointments); collaborate with senior universities to host "product experience classes" to enhance usage skills among low-tech adoption groups;

Online: Optimize e-commerce platforms with "senior-friendly interfaces" (enlarged fonts, simplified processes) and launch one-on-one voice customer service consultations; Leverage Douyin/WeChat to publish short video tutorials (e.g., "How Seniors Use Smart Bracelets to Measure Blood Pressure") for tech-savvy seniors.

Cross-Industry: Partner with communities and hospitals—e.g., organize group purchases for age-friendly renovations with communities, or launch "Buy Health Devices, Get Free Checkups" campaigns with hospitals—to boost brand trust and product reach efficiency.

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