User Profiling of Smartphone Use Among Older Adults from a Digital Divide Perspective

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Abstract

[Purpose/Significance] From the perspective of the new media digital divide, constructing user personas for older adults to uncover differences in behavioral habits and demand characteristics regarding smartphone usage among various elderly groups, and providing more tailored services for each segment, is of significant importance for enhancing the quality of life of older adults and addressing the challenges of an aging society. [Method/Process] Based on foundational data obtained through questionnaire surveys and in-depth interviews, we constructed a user persona tag system encompassing smartphone usage behaviors across various functions, including social interaction, leisure entertainment, and digital life, and employed factor analysis and K-Means clustering methods for empirical analysis of the survey data. [Results/Conclusion] According to the characteristics of the user persona tags, older adult smartphone users can be classified into five categories: traditional lifestyle, basic applications only, consumption cautious, pragmatic, and keeping pace with the times. By identifying the typical features of each segmented group and proposing more personalized and targeted service strategy recommendations, this helps actively promote the resolution of the digital divide issue among older adults.

Full Text

User Portrait of Elderly People's Smartphone Usage from a Digital Divide Perspective

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Abstract

[**Purpose/Significance**] This study constructs user portraits of elderly smartphone usage from the new media digital divide perspective, explores behavioral habits and demand characteristics across different elderly groups, and provides more precise services for each segment. This is crucial for improving elderly quality of life and addressing aging society challenges. [**Method/Procedure**] Based on questionnaire surveys and in-depth interviews, we construct a user portrait labeling system encompassing smartphone social interaction, leisure entertainment, and digital life functions. Factor analysis and K-Means clustering methods conduct empirical analysis on survey data. [**Results/Conclusions**] According to user portrait labeling features, elderly smartphone users can be categorized into five groups: traditional lifestyle, basic application-oriented, consumption-cautious, pragmatic, and technology-embracing. By exploring typical characteristics of each segment, we propose personalized and targeted service strategies that can actively promote resolution of the digital divide faced by the elderly.

Keywords: User Portrait; Digital Divide; Elderly Group; Smartphone Usage

Population aging has become an increasingly prominent issue in China. The Fifth Plenary Session of the 19th Central Committee elevated "actively responding to population aging" to a national strategy, demonstrating the government's high priority on aging-related work. According to data released by the National Bureau of Statistics on January 17, 2024, by the end of 2023, there were 296.97 million people aged 60 and above nationwide, accounting for 21.1% of the total population; among them, 216.76 million were aged 65 and above, representing 15.4% of the total population. During the "14th Five-Year Plan" period, China's elderly population proportion is expected to reach 15%, entering a stage of moderate aging, and it is projected that by 2030, China will enter a super-aged society with over 20% of the population being elderly [1]. These figures indicate that China is already facing a relatively severe population aging problem.

In recent years, smartphones have become increasingly pervasive, gradually integrating into and reshaping the daily lives of the elderly, emerging as an important tool in their modern lives. According to a survey conducted at the Third China Population and Development Forum, more than half of the elderly population aged 65 to 69 use smartphones; in the 70 to 79 age group, the proportion reaches 31.2% [2]. The popularization and application of smartphones have brought numerous benefits to the elderly, not only improving their quality of life but also enhancing their social interaction and daily convenience.

However, the elderly have long remained in a relatively disadvantaged position in the digitalization process, with a prominent digital divide existing between them and younger groups. Compared with young people, the proportion of elderly using smartphones for WeChat communication and search engines is significantly lower. A 2020 survey showed that usage rates of WeChat and search engines among non-elderly people were 88.9% and 27.4%, respectively, while corresponding rates for the elderly were only 26.2% and 4.4% [3]. This digital divide may cause difficulties for the elderly in information acquisition, service access, and social interaction, thereby affecting their quality of life and social participation. Alleviating the digital divide among the elderly is therefore crucial for improving their quality of life, safeguarding their rights and interests, promoting social integration, and addressing the challenges of an aging society.

How to accurately uncover the usage patterns and demand dilemmas of elderly smartphone use has become a focal concern for policymakers and product designers. User portraits, widely applied in e-commerce, healthcare, tourism, and other fields, are well-suited for addressing the elderly digital divide. As an increasingly mature tool in data analysis, user portraits can accurately extract comprehensive user information, providing targeted guidance for product design, service optimization, and strategy recommendations. Accordingly, this paper constructs an analytical process model for elderly smartphone usage behavior portraits, conducts empirical research based on questionnaire and interview data, deeply explores behavioral habits and demand characteristics across different elderly user groups, and proposes precise, differentiated strategic recommendations for each segment. This research deepens understanding of the elderly digital divide, provides foundational support for policymakers to formulate more scientific and objective measures, and enables relevant enterprises and institutions to optimize product design and services to better meet elderly needs, helping them actively and correctly integrate into the new media environment and smart society, thereby enhancing their sense of gain, happiness, and security in information-based development.

1.1 Elderly Digital Divide

The concept of the digital divide can be traced back to the 1990s, referring to the gap between groups with internet access and those without. Based on existing literature, this paper defines the digital divide as "the gap between countries and between groups within countries caused or widened by the development and application of information and communication technologies" [4]. Age represents one of the most important driving factors of the digital divide, and the elderly digital divide has attracted considerable scholarly attention in recent years [5]. The elderly digital divide refers to the information gap and trends caused by differences in information acquisition, network technology mastery, and innovation capacity between elderly users and other age groups during digital transformation [6]. It profoundly affects elderly social life, psychological well-being, and social integration, with main manifestations including the access gap, usage gap, and knowledge gap [4, 6]. Wan Xin [7], employing grounded theory, demonstrates that subjective dilemmas such as restricted access, avoidance, and refusal create numerous obstacles for rural elderly new media adoption. Lu Jiehua and Wei Xiaodan [8] note that regarding the usage gap, the elderly face limitations in new media functions such as APP installation and WeChat Pay, resulting in generally low network skills; regarding the knowledge gap, frequent encounters with digital fraud and misinformation lead to far lower efficiency in information acquisition, understanding, and application compared with other age groups.

Smartphones integrate communication, entertainment, learning, and other functions, becoming indispensable in modern life. However, for the elderly, smartphones have become a major obstacle to digital society integration, exacerbating the digital divide with younger groups. Scholars have conducted empirical research on the elderly digital divide regarding WeChat usage, digital reading, Douyin short videos, and mobile payment. For example, Zhang Xiaojing [9], through questionnaires and interviews with 110 Wuhan elderly, concludes that technological fear and rigid thinking prevent some elderly from accepting WeChat, while physical condition and passive access degree are main influencing factors. Tan Xiaoyun [10] uses in-depth interviews and the UTAUT model to analyze how elderly users' Douyin usage intention and digital feedback intention significantly affect usage behavior, with age, education, and physical condition playing moderating roles. Yan Sanjiu and Zheng Tongtong [11], based on questionnaire research with 47 Shanghai elderly, conclude that optimizing mobile payment processes, encouraging family intergenerational technical support, and enhancing mobile payment security can promote elderly digital integration. Additionally, Li Siyue [12], from a social support perspective, finds that younger relatives provide the most information, emotional, and instrumental support in bridging the smartphone digital divide, significantly affecting elderly subjective well-being. Wu Si [13] notes that society conceals its control over elderly smartphone usage under the guise of care, while the elderly themselves, constrained by family resources and emotional needs, continuously cede their own power.

1.2 Elderly User Portrait

A user portrait, as a labeled representation of user information [14], collects and analyzes multi-dimensional user data (demographics, behavioral preferences, consumption patterns, etc.) to extract comprehensive and accurate user information, enabling user value mining and providing precision marketing, recommendations, and personalized services [15-16]. As virtual user models constructed from behavior data, consumption habits, and preferences, user portraits have been widely applied in e-commerce, healthcare, transportation, and online public opinion [17-20], helping enterprises and organizations better meet user needs and improve service quality and efficiency.

China's population aging trend has significantly intensified in recent years. With the expanding elderly population, changing consumption habits and behavior patterns, and deepening digital life, research on elderly user portraits has become increasingly important. Elderly user portraits refer to comprehensive descriptive models of elderly groups constructed from basic attributes (age, gender, health status), behavioral characteristics (digital device habits, online behavior), consumption patterns, interests, and psychological needs. Such portraits help enterprises, government agencies, and service providers understand elderly needs more accurately, enabling more considerate and convenient products and services. Currently, only a few scholars have focused on elderly user portrait research. Yu Wangyang [21] and Duan Jiacun [22] respectively construct precision push systems for elderly sports services and online health services based on user portrait technology to improve service quality and satisfaction. He Zhenyu [23] constructs a hierarchical label user portrait model to achieve deep mining of elderly care service data, verifying feasibility with real platform data. Liu Di [24] constructs a user portrait model for library elderly group information literacy, analyzing current status and influencing factors and proposing corresponding strategies. Kuang Yalin [25] employs Stimulus-Organism-Response (S-O-R) theory to construct a user portrait of barriers to elderly digital integration, providing empirical reference for understanding and solving elderly dilemmas in digital transformation. Li Jiaxing [26] analyzes WeChat log data, finding low usage frequency, interaction levels, and skill mastery among elderly WeChat users, while highly educated elderly groups show higher activity levels.

1.3 Literature Review

Although a few scholars have begun examining elderly user portraits, this field remains in its infancy [23]. Existing research mostly focuses on specific domains (sports services, online health services, library services), verifying effectiveness and providing valuable experience. With technological progress and social development, more elderly are integrating into digital life, making the elderly digital divide increasingly prominent and presenting new opportunities and challenges for user portrait research.

Current elderly digital divide research primarily focuses on single smartphone functions (WeChat, Douyin, mobile payment) or general overall analysis of usage intention influencing factors and governance measures. In reality, different elderly groups (by age, education, income, etc.) may exhibit significant differences in usage characteristics and behavioral habits across various smartphone functions (WeChat, Douyin, mobile payment). Ignoring user characteristic differences and lacking community feature research can lead to conclusions and recommendations with weak specificity and operability. Based on the digital divide perspective, this study constructs a user portrait labeling system covering smartphone social interaction, daily travel, leisure entertainment, and other functional usage capabilities, employs factor analysis and K-Means clustering to classify elderly users, deeply explores typical characteristics of each segment, and portrays complete group profiles. This research helps accurately understand different elderly group needs, provides references for personalized recommendations and precision services, helps the elderly better integrate into the digital era, and promotes elderly social integration and development.

2.1 User Portrait Tag System

Establishing a user tag system is the core component of constructing elderly user portraits, aiming to simplify complex multi-dimensional user information into an easily understandable and applicable feature set through labeling, thereby achieving clear characterization and insight into individual and group characteristics. As shown in Table 1 , this paper constructs a user portrait labeling system for elderly smartphone usage across three dimensions: basic attributes, usage barriers, and usage capabilities. 1) **User attribute tags** describe natural elderly attributes, including gender, age, education, occupation, income level, income source, health status, and smartphone usage duration. 2) **Usage barrier tags** describe obstacles elderly face when using smartphones, including technical operation, vision/touch, and psychological fear barriers. 3) **Usage behavior tags** describe the degree and habits of elderly usage of various smartphone functions, covering a wide range from basic communication (WeChat voice/video chat) to advanced applications such as leisure entertainment, mobile payment, and exercise learning—important indicators for evaluating whether the elderly effectively use smartphone technology to meet daily life and learning entertainment needs.

Smartphone usage behavior indicators represent the focus of this study, containing 14 sub-indicators covering elderly user functions such as social interaction, daily travel, and leisure entertainment, forming an evaluation system reflecting usage frequency of various smartphone functions. This labeling system enables in-depth understanding of elderly smartphone function usage, identifying potential usage barriers and training needs. This not only helps provide more personalized and targeted technical support and services for the elderly but also provides important references for age-friendly smartphone product design, promoting inclusive technology development and enabling more elderly to enjoy technological progress benefits.

2.2 Main Research Methods

Given current research limitations on elderly digital divide user portraits, this paper constructs a user portrait model for analyzing elderly smartphone usage behavior from the digital divide perspective. The main research methods are as follows.

(1) Factor Analysis. Factor analysis is an effective data dimensionality reduction method that summarizes multiple potentially highly correlated variables through a few latent factors, simplifying complex data structures while revealing underlying relationships [27]. In this study, elderly smartphone usage behavior portrait indicators are numerous and may be strongly correlated, requiring factor analysis to refine them into several uncorrelated core factors, improving research efficiency and enhancing explanatory power.

(2) Cluster Analysis. Cluster analysis is an unsupervised learning method that divides data sets into multiple groups (clusters) based on similarity, ensuring high within-cluster similarity and significant between-cluster differences. The K-Means clustering method is simple, efficient, and commonly used in user portrait group division research [26-28]. This paper uses K-Means clustering to classify elderly smartphone user groups to more accurately understand behavior patterns and demand characteristics of various groups, providing a foundation for personalized recommendations and precision services.

(3) Cross-tabulation Analysis. Cross-tabulation analysis examines correlations between two or more categorical variables. In this paper, elderly users' personal attributes (age group, education, etc.) and group categories are categorical variables. Generating cross-tabulation tables and conducting correlation tests can reveal potential relationships between personal attributes and group categories. Based on cross-tabulation data, Pearson chi-square (^{2}) statistical tests are calculated. If the corresponding probability p-value is less than the significance level (e.g., 0.05), the null hypothesis is rejected, concluding that the two categorical variables are correlated.

2.3 User Portrait Model Construction Process

Based on elderly smartphone usage data, this study constructs a user portrait model. The process, shown in Figure 1 [Figure 1: see original paper], includes five steps: data collection, data preprocessing, data dimensionality reduction, user classification, and user portrait feature extraction.

(1) Data Collection. This study uses questionnaire surveys and in-depth interviews to obtain basic user information. Questionnaires systematically collect various information on elderly basic attributes, usage capabilities, and usage barriers regarding smartphone usage. Simultaneously, representative elderly users are selected for face-to-face in-depth exchanges to further understand specific behaviors, attitudes, and feelings during smartphone usage, flexibly obtaining real thoughts and experiences and supplementing information missed in questionnaires.

(2) Data Preprocessing. Preprocessing involves data cleaning (removing invalid questionnaires, handling outliers, unifying formats), data organization (categorical sorting, encoding conversion, missing value handling), and descriptive statistical analysis of basic elderly smartphone usage information.

(3) Data Dimensionality Reduction. Data standardization is performed on numerous smartphone usage behavior indicator variables. First, factor analysis applicability is evaluated, then principal component analysis extracts common factors, followed by factor rotation to enhance interpretability, and specific names are assigned to each factor.

(4) User Group Classification. Based on core factors extracted from factor analysis, this paper uses K-Means clustering to classify elderly smartphone users, dividing them into different groups to identify differentiated behavior patterns of different elderly groups.

(5) User Portrait Feature Extraction. Correlation between elderly users' basic attributes and group categories is analyzed. Based on significantly correlated variables, typical characteristics such as age, education, occupation, and income of different groups are extracted to construct specific user portraits for each elderly group's smartphone usage. Finally, existing models are continuously updated and optimized according to research needs.

3.1 Data Acquisition

Considering that some elderly have difficulties filling out questionnaires, this study obtains basic data through on-site surveys combined with in-depth interviews. The initially designed questionnaire is first tested on a small sample, and questions with unclear expressions or ambiguity are revised. Then trained college students conduct offline on-site surveys in selected Beijing communities. The questionnaire consists of 25 questions, as shown in Table 1, setting questions across three dimensions: elderly users' basic personal information, smartphone usage barriers, and usage of various functions. Considering comprehension difficulties for some elderly, a simple and intuitive three-level scale measures each specific indicator of smartphone function usage degree, requiring respondents to choose from "rarely use," "occasionally use," and "frequently use." Survey targets are Beijing permanent residents aged 55 and above. The questionnaire interview period was April to May 2023, with a total of [incomplete].

3.2 Descriptive Statistical Analysis

First, descriptive statistics were conducted on survey subjects' basic information. Results show females account for 52.9% and males 47.1%, indicating relatively balanced gender ratio. Age distribution shows 35.9% aged 55-60, 22.0% aged 61-70, 27.9% aged 71-80, and 14.2% over 80. Education distribution shows 29.0% with primary school or below, 23.4% with junior high school, 32.6% with high school to junior college, and 15.0% with undergraduate or above. Pre-retirement occupation distribution shows farming accounts for the largest proportion at 25.6%, followed by public institution personnel at 21.7%. Income distribution shows 47.9% of elderly have monthly income below 3,000 yuan, 26.5% have 3,000-5,000 yuan, and 25.6% have above 5,000 yuan. Main income sources are own pension (52.4%), own work or labor income (28.1%), and children or government welfare (19.5%). Health status is excellent for 44.6%, average for 45.7%, and poor for 9.7%.

Second, preliminary statistical distribution of respondents' smartphone usage was conducted. Smartphone usage duration distribution shows 22.3% of elderly users almost never use smartphones, 13.1% use less than 1 hour daily, 18.7% use 1-2 hours, 15.9% use 2-3 hours, and 30.1% use more than 3 hours. This indicates high smartphone penetration among the elderly, with a considerable portion forming relatively stable, long-term usage habits. Furthermore, Figure 2 [Figure 2: see original paper] presents a comparison of usage degrees across various smartphone functions. WeChat chatting, health code scanning, and news information are the three most commonly used functions, with frequent usage rates of 53%, 48%, and 44%, respectively. QR code payment (39%) and posting on Moments (38%) also show relatively high usage. In contrast, mobile music (33%), online shopping (30%), and Douyin videos (29%) show lower frequent usage rates, while practical functions such as online bill payment (25%) and online appointment registration (18%) also have low usage. Emerging applications such as mobile fitness, mobile karaoke, and online ride-hailing have even lower penetration, with over half of elderly rarely using these three functions, demonstrating elderly users' lag in adopting new technologies and applications.

3.3 Reliability and Validity Analysis

This study's user portrait labeling system for elderly smartphone usage includes 14 sub-indicators regarding usage degree of various functions, requiring reliability and validity analysis. SPSS 26 software's Cronbach's α coefficient test conducts internal consistency reliability analysis on the 14 sub-indicators. An α coefficient exceeding 0.8 indicates good reliability [27]. This paper's Cronbach's α coefficient is 0.941, indicating very high data reliability. SPSS 26 validity analysis shows the KMO value for 14 variables is 0.939, approaching 1, and Bartlett's sphericity test approximate chi-square is 3541.42 with $p < 0.001$, indicating high inter-variable correlation and suitability for factor analysis.

3.4 Extraction of Common Factors

Due to strong correlation among the 14 behavior variables, direct cluster analysis is inappropriate. This paper uses SPSS 26 for factor analysis to achieve data dimensionality reduction. The "principal component" method is selected for factor extraction, and "maximum variance method" performs factor rotation for better interpretation. Figure 3 [Figure 3: see original paper] presents a clear scree plot showing eigenvalue distribution, where the first three factors' eigenvalues reach or approach 1, with cumulative variance contribution of 73.05%, while other factors contribute less than 3%. Accordingly, this paper extracts the first three factors to comprehensively evaluate usage degree of 14 functions among the elderly.

Based on the rotated component matrix, each factor's primary behavioral variables are identified and named. Specific analysis is as follows:

WeChat chatting (0.858), health code scanning (0.834), news information (0.728), QR code payment (0.712), and posting on Moments (0.700) all have coefficients >0.7 on the first factor, significantly larger than on other factors. These five variables involve basic functions and services including social interaction, information acquisition, and mobile QR code scanning. Therefore, the first factor is named “Basic Application Services.”

Mobile karaoke (0.779), Douyin videos (0.757), mobile exercise (0.684), mobile reading (0.651), and mobile music (0.626) have significantly larger coefficients on the second factor. These five variables involve cultural and entertainment activities during leisure time, providing entertainment value and enriching spiritual life. Therefore, the second factor is “Leisure and Entertainment Services.”

Online appointment registration (0.803), online bill payment (0.754), online ride-hailing (0.730), and online shopping (0.606) have coefficients >0.6 on the third factor. These four variables involve convenient life services through digital means, covering healthcare, finance, transportation, and shopping—important changes smartphones bring to digital life. Therefore, the third factor is named “Digital Life Services.”

4.1 Clustering Results of Elderly Smartphone Usage Behavior

Based on factor analysis, this paper applies K-Means clustering to divide elderly groups and explore inter-group differences. Clustering was performed four times with cluster numbers of 3, 4, 5, and 6. Table 2 shows that when the cluster number is 5, the difference between maximum and minimum sample sizes is smallest, and ANOVA F-values between different categories for each factor are largest, indicating most obvious between-category differences. Therefore, this paper ultimately selects 5 clusters.

Table 2 shows ANOVA values between different categories when cluster numbers are 3-6.

Table 3 presents final cluster center values and sample sizes for 5 clusters. Category characteristics are inferred based on cluster variable (three common factors) center values. Specific analysis is as follows:

Category 1 scores high on basic application services but low on leisure and entertainment services and digital life services. These elderly users mainly use smartphones for WeChat chatting and news checking, showing little interest in or familiarity with entertainment and advanced digital life functions. These are summarized as “Basic Application-Oriented Users,” accounting for 19.78% of the sample.

Category 2 scores high on both basic application services and leisure and entertainment services but very low on digital life services. These users value both basic functions and entertainment experiences but hold conservative or cautious attitudes toward mobile payment functions such as online shopping, bill payment, and ride-hailing. These are summarized as “Mobile Payment-Cautious Users,” accounting for 13.93% of the sample.

Category 3 scores highest on digital life services, also high on basic application services, but very low on leisure and entertainment services. These elderly users mainly use phones for social interaction and digital life services, focusing on practicality and efficiency rather than entertainment functions, emphasizing how smartphones improve quality of life. These are summarized as "Pragmatic Users," accounting for 11.70% of the sample.

Category 4 scores low on all three factors, indicating no particularly high preference or usage rate for various functions. They may be reluctant to use smartphones due to technical barriers, security concerns, or psychological factors, preferring traditional daily activity methods and holding reserved or resistant attitudes toward smartphones. These are summarized as "Traditional Lifestyle Users," accounting for 33.98% of the sample.

Category 5 scores high on both leisure and entertainment services and digital life services but relatively low on basic application services. These users actively participate in smartphone entertainment functions, enjoy technology experiences, and fully utilize digital life services, keeping pace with social development. Their relatively low basic application service usage may reflect accustomedness to more advanced or specialized applications for social needs. These are summarized as "Technology-Embracing Users," accounting for 20.61% of the sample.

4.2 User Portrait Feature Analysis and Strategy Recommendations

Chi-square tests from cross-tabulation tables calculate correlations between elderly users' basic attribute variables and group category variables. Table 4 presents correlation analysis results. Except for independence between gender and group category, seven other basic attribute variables are significantly correlated with group categories, meaning each attribute significantly impacts group category. Statistical analysis of significant personal attribute variable distributions across elderly groups, compared with overall distribution, extracts typical characteristics of different elderly group user portraits, as shown in Table 5 . Specific portrait characteristics and management strategy recommendations for each group follow.

Table 4 shows correlation analysis results between elderly users' basic attributes and group categories.

Table 5 shows feature analysis of user portraits for different elderly groups.

Note: ↑ indicates the proportion of the corresponding category in this group is significantly higher than the overall distribution; ↓ indicates significantly lower; "Same as overall distribution" indicates consistency with overall distribution.

(1) Basic Application-Oriented User Portrait Analysis and Strategy Recommendations

Main characteristics: Wide age and occupation distribution, mostly junior high school and high school education, monthly income mostly between 3,000-10,000 yuan, income mostly from own or spouse's pension, dispersed smartphone usage duration distribution (26.8% use less than 1 hour daily, 39.4% use more than 3 hours).

These users mainly employ smartphones for WeChat chatting and news checking, showing little interest in or familiarity with entertainment and advanced digital life functions. Long-formed lifestyle habits and low technology acceptance maintain their dependence on basic applications, with conservative attitudes toward emerging functions.

Strategy recommendations: **Simplified Interface**: Provide clean, clear operation interfaces with fewer complex functions to reduce learning costs; **Content Customization**: Push news and health information closely related to their lives to enhance stickiness; **Community Support**: Establish elderly user communities providing offline training and exchange activities to help them gradually understand and use more functions.

(2) Mobile Payment-Cautious User Portrait Analysis and Strategy Recommendations

Main characteristics: Mostly aged 60-80, primary school and junior high school education, mostly engaged in farming or private business, two-thirds with monthly income of 2,000-5,000 yuan, income mostly from pensions or labor income, 90% use smartphones more than 1 hour daily (42.0% more than 3 hours).

These users have relatively low education and income, can skillfully use basic applications and entertainment functions, but lack learning of more complex digital life service applications involving mobile payment. Fixed but low income provides financial security but also makes them particularly cautious about fund security. They value basic functions and entertainment but hold conservative or cautious attitudes toward mobile payment-related digital life services.

Strategy recommendations: **Security Promotion**: Strengthen payment security knowledge popularization to enhance trust; **Small-amount Guidance**: Gradually guide mobile payment usage through small transactions or promotional activities; **Dedicated Support**: Provide exclusive payment services and customer support for elderly users to solve their concerns.

(3) Pragmatic User Portrait Analysis and Strategy Recommendations

Main characteristics: Relatively young (mostly 55-60), mostly working in public institutions or private enterprises, relatively high education (mostly college level or above), income mostly 3,000-10,000 yuan with higher proportion from work income, good health status, smartphone usage mainly controlled within 1-3 hours daily.

These relatively young, highly educated users have good learning and adaptation abilities, are generally willing to try and adapt to new technologies, and have high self-motivation and life quality pursuit, making them focus on practical functions such as digital life services and social interaction. Additionally, being busy with work or personal affairs may lead them to view smartphones as tools for improving life efficiency and convenience rather than entertainment.

Strategy recommendations: **Efficient Applications**: Provide efficient, convenient digital life service applications meeting actual needs; **Learning Resources**: Provide online learning resources or courses to help continuously improve digital skills; **User Feedback**: Actively collect feedback to continuously optimize products and services.

(4) Traditional Lifestyle User Portrait Analysis and Strategy Recommendations

Main characteristics: Generally advanced age (mostly over 70), about half previously engaged in agricultural labor, primary school or below education, monthly income below 2,000 yuan, relatively high proportion relying on children's support or government welfare, generally average or poor health status, mostly not using smartphones or using less than 1 hour.

This group is generally older with low education and income, previously engaged in physical labor. Long-formed lifestyle habits and emotional attachment to traditional lifestyles make them relatively conservative and resistant when facing smartphone technological innovations. Technical barriers may be main obstacles, while unfamiliarity with new technologies may trigger security concerns, leading them to prefer traditional daily activity methods with low smartphone usage rates.

Strategy recommendations: **Intergenerational Support**: Family members can help gradually overcome technical and psychological barriers to improve acceptance and usage of basic functions; **Assistance Tools**: Provide simple, easy-to-use assistance tools or devices to help solve practical life problems; **Community Care**: Respect their traditional lifestyles, strengthen community elderly care service systems, and provide face-to-face care and help.

(5) Technology-Embracing User Portrait Analysis and Strategy Recommendations

Main characteristics: Relatively young age, mostly college level or above education, mostly civil servants or public institution staff, relatively high income (over half with monthly income above 5,000 yuan), mostly excellent health status, many using smartphones more than 3 hours daily.

These relatively young, highly educated users have high learning ability and keen insight into new technologies. They are brave in trying and willing to accept various new smartphone functions, whether for leisure entertainment or digital life services, quickly integrating and enjoying them, fully experiencing technology convenience and fun. High income also makes them pay more attention to life quality and spiritual satisfaction, enjoying smartphone entertainment and convenience and using digital services to improve life efficiency.

Strategy recommendations: **Cutting-edge Experience**: Provide latest technology products and application experiences to satisfy curiosity and exploratory desire; **Personalized Services**: Provide personalized products and services according to interests and needs; **Exchange Platform**: Establish high-end user exchange platforms, inviting them to share experiences and insights to enhance brand image and promote user interaction.

5 Conclusion

This paper deeply explores elderly smartphone usage user portrait construction from the digital divide perspective. Through questionnaire surveys and in-depth interviews, we construct a user portrait labeling system covering smartphone social interaction, leisure entertainment, and digital life functional usage capabilities. Using factor analysis and K-Means clustering, we divide elderly smartphone users into five segments: traditional lifestyle, basic application-oriented, consumption-cautious, pragmatic, and technology-embracing. This research enriches theoretical achievements in the elderly digital divide field and provides important references for precision services and product design.

Results show elderly users exhibit diverse smartphone usage characteristics. Traditional lifestyle and basic application-oriented elderly are relatively conservative, focusing on basic communication and daily needs; consumption-cautious elderly hold cautious attitudes toward advanced functions like online shopping and mobile payment; pragmatic elderly prefer using smartphones to improve life convenience and efficiency; while technology-embracing elderly show high acceptance and frequent usage of new functions. These segment identifications help us deeply understand elderly digital divide status and causes. Based on this analysis, we propose highly targeted and operable service strategy recommendations.

Through personalized recommendations and refined services, we can help the elderly better integrate into digital society, improving quality of life and happiness. This also provides foundational support for policymakers to formulate more scientific and objective measures, promoting resolution of the elderly digital divide.

Future research on elderly smartphone usage user portraits requires further deepening. With continuous technological progress and increasingly rich elderly digital life, we need to continuously monitor new trends and characteristics, continuously improving the user portrait labeling system. In conclusion, bridging the elderly smartphone usage digital divide requires joint efforts from government, enterprises, communities, and families to jointly improve elderly usage experience, help them integrate into the digital era, and share technological convenience.

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