Profiling WeChat Usage Behavior of Elderly Users Based on Mobile Device Logs (Postprint)

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Abstract

[Purpose/Significance] As China progressively enters an aging society, a growing number of elderly individuals are utilizing mobile social networks to enrich their daily lives. Survey data indicates that WeChat has emerged as the mobile social network platform with the largest elderly user base. Constructing user profiles for elderly WeChat user groups holds significant importance for promoting the enhancement of elderly individuals' social competencies in the mobile Internet era and improving their sense of well-being. [Method/Process] Usage log data of elderly WeChat users was obtained through mobile terminal log tracking software, and experimental environments were constructed with experimental tasks designed to acquire data on elderly users' usage capabilities. The k-means algorithm was employed to perform cluster analysis on the resulting data, followed by discussion and analysis of elderly user attributes and usage behavior data. [Results/Conclusions] Based on in-depth analysis of the clustering results of user attributes and behavior data within the elderly user profiling system, the behavioral characteristics of elderly WeChat users were examined. The findings reveal that, compared with other user groups, elderly WeChat users exhibit lower usage intensity, interaction intensity, and usage capability. Furthermore, the elderly WeChat user group demonstrates significant heterogeneity: elderly users with higher educational attainment show greater usage capability, interaction intensity, and usage intensity, indicating that active elderly WeChat users are predominantly highly educated. Developing relevant social guidance policies for elderly populations based on these behavioral characteristics holds both theoretical and practical significance for China's aging society development.

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Full Text

Research on WeChat Elderly User Behavior Profiling Based on Mobile Terminal Logs

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Abstract

[**Purpose/Significance**] As China gradually enters an aging society, an increasing number of elderly individuals are using mobile social networks to enrich their lives. Survey data indicates that WeChat has become the mobile social network with the largest number of elderly users. Constructing user portraits of elderly WeChat users is of great significance for promoting their social capabilities in the mobile Internet era and enhancing their life happiness. [**Method/Process**] This study obtained WeChat usage log data from elderly users through mobile terminal log tracking software, and collected elderly user capability data by constructing experimental environments and arranging experimental content. K-means algorithm was employed for clustering analysis of the data results, followed by discussion and analysis of elderly user attributes and usage behavior data. [**Result/Conclusion**] Based on the clustering results of user attributes and behavior data in the elderly user portrait system, this paper conducts an in-depth analysis of WeChat elderly user behavior characteristics. The findings reveal that compared with other user groups, elderly WeChat users exhibit lower usage intensity, interaction intensity, and usage capability. Moreover, the elderly WeChat user group demonstrates significant heterogeneity: elderly users with higher education levels show higher usage capability, interaction intensity, and usage intensity, indicating that active elderly WeChat users are predominantly highly educated. Formulating relevant social guidance policies for the elderly based on these behavioral characteristics holds both theoretical and practical significance for China’ s aging society development.

Keywords: mobile terminal log, WeChat elderly users, usage behavior, user portrait

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Introduction

Mobile social networks represented by WeChat have transformed traditional social interaction patterns. According to the *2018 WeChat Impact Report* [**?**], WeChat-driven information consumption reached 209.7 billion RMB, with user penetration rate among those over 60 years old reaching 46.7%. These figures demonstrate that WeChat has become the primary tool for daily mobile social interaction among the elderly. Profiling the characteristics of elderly WeChat user groups can better understand their behavioral patterns during usage, thereby facilitating the development of more usable mobile social products that truly meet elderly users' needs. This approach aims to expand the elderly user base and enhance their happiness in the mobile social context, promoting the construction of a harmonious society under the new era background.

User portrait research for mobile social network users has become a hot topic in academic circles both domestically and internationally. K. Ikeda et al. [?] mined Twitter users' text and interaction data, generating Twitter user portraits through clustering analysis to visually present characteristics of microblogging social network users. R. Grieve [?] profiled users of the image-based instant messaging tool Snapchat and found that its audience consists primarily of young people who prefer visual communication. Wang Lingxiao et al. [?] collected user activity indicators from the Zhihu Q&A community, analyzing user portrait characteristics from perspectives of user seniority, participation quality, and development trends. Ma Feicheng and Zhou Liqin [?] argued that knowledge management and services for smart health should emphasize user portrait analysis of smart health communities. Zhang Haitao et al. [?] crawled user needs, roles, and behavioral data from online health communities, established 细分 tags, and constructed user portraits for online health communities based on concept lattices.

Existing research covers user group characteristic analysis across various mobile social networks including microblogging, image sharing, online Q&A, and smart health, with samples primarily consisting of young and middle-aged groups. Few studies focus on mobile social network usage behavior characteristics of elderly user groups, and even fewer examine instant messaging mobile social network elderly user portraits. In terms of research methodologies, most employ surveys, web crawlers, and other data acquisition methods, with rare adoption of experimental and log analysis approaches.

This study addresses three research questions: (1) What behavioral data do elderly users generate when using WeChat? (2) How to construct a tag system for WeChat elderly user behavior portraits? (3) How to analyze relationships among WeChat elderly user behavior data based on mobile terminal logs and experimental data, and summarize elderly user behavior characteristics? To address these questions, this research combines mobile terminal logs with experimental methods, aiming to guide WeChat platform developers in creating more user-friendly functions tailored to this special group, thereby expanding the elderly user base and enhancing their sense of happiness during usage.

2 Related Research

2.1 Mobile Terminal Logs

Mobile communication terminals (hereinafter referred to as mobile terminals) include smartphones, iPads, etc. Since smartphone users account for a high proportion, mobile terminals typically refer to smartphones [?]. Users interact with information through mobile terminals, enabling the collection and mining of relevant behavioral data via mobile terminal logs. Mobile terminal log information includes query logs, browsing logs, and session logs, primarily functioning to record interactions between systems and users. For mobile terminal log mining, single logs cannot be considered in isolation, as process data is often dispersed across different logs, requiring the construction of multidimensional datasets to better analyze user behavior [?].

2.2 Data Fusion Theory

The massive user behavior data generated by mobile social networks can be effectively and reasonably processed based on data fusion theory. By applying fusion algorithms to cross-integrate data from different sources and structures, precise judgments of user behavior data can be made, potential value in massive user behavior data can be deeply mined, user group characteristics can be clearly delineated, and personalized services and standardized management can be provided according to user behavior characteristics [?]. The purpose of data fusion is to process data of different formats and dimensions through information technology, enabling effective integration of data from different sources into analyzable data. Currently, three widely applied data fusion methods exist: data-level fusion, feature-level fusion, and decision-level fusion.

Data-level fusion involves combining behavioral data from different individual users to form feature vectors, facilitating analysis and identification of user characteristics. Feature-level fusion extracts complementary features among data for integration. Decision-level fusion requires feature recognition of different data and obtains final results through integration strategies [?].

2.3 User Profiling Based on Mobile Terminal Log Mining

User profiling refers to the virtualization of real user information, where users are tagged based on their behavioral data, and behavior characteristics of certain user types are summarized and profiled according to behavioral data (social attributes and lifestyle habits, etc.) [?]. User profiling is widely applied across multiple fields, delivering not only commercial value to enterprises but also high academic value. Typically, user profiles are constructed based on user behavior characteristics, with user characteristic research forming the foundation of user profiling. For instance, N. Ljejava et al. [?] analyzed Facebook user characteristics, enabling differentiation between infrequent and frequent Facebook users based on characteristic data. P.M.A. Baker et al. [?] collected behavioral data from disabled individuals using Facebook and LinkedIn to analyze usage characteristics of disabled groups in mobile social networks, facilitating classification of disabled users in social networks and enabling governments to formulate targeted support measures based on their social network usage characteristics. Social network platforms can collect users' public information, construct profiles based on known attribute data, and employ machine learning algorithms to infer undisclosed personal attributes such as gender and marital status, thereby enabling personalized recommendations and precision marketing based on inferred attributes [?].

Based on data fusion theory, employing statistical modeling, association rules, and clustering analysis methods to fuse WeChat elderly users' mobile terminal log data and experimental data for constructing WeChat elderly user behavior tag systems [?] can better understand elderly users' behavior characteristics and preferences, providing foundations for application design improvement and personalized operation strategy formulation [?]. By collecting elderly user behavior data and constructing elderly user portraits based on mobile terminal logs and experimental data, WeChat elderly user needs can be deeply understood, thereby improving service strategies for this demographic [?].

3 Research Design

3.1 Data Collection

For fusing user behavior data from mobile social networks like WeChat, data-level fusion is primarily applied, specifically including three steps: collection of user behavior data, cleaning of user behavior data, and final fusion of processed user behavior data. WeChat user data mainly includes users' personal attribute data, user behavior characteristic data, and user GPS data [?]. Personal attribute data includes user profile information, which is relatively easy to collect, while user behavior characteristic data primarily relies on mobile terminal logs for collection. GPS data is used to analyze user movement trajectories, but such data is more difficult to obtain. After obtaining user behavior data, cleaning processes such as filtering duplicate data, correcting erroneous data, and removing invalid data must be performed to ensure data accuracy for subsequent fusion.

This experiment selected 103 elderly WeChat users from elderly universities and community elderly activity centers for a 20-day experiment. Experimental user selection criteria included: registered WeChat account for over one year, having more than 100 WeChat friends, possessing fixed chat groups, mastering main WeChat functions, and using WeChat as the primary daily social tool. Strict screening ensured that participating elderly users represented mature user groups among current elderly WeChat users, guaranteeing sample stability and representativeness.

To collect user behavior data through mobile terminal logs, log tracking software was installed on participants' phones to obtain daily WeChat usage logs, including daily login frequency, daily usage duration, and daily login times. During the experiment, users sent their daily phone logs obtained by the tracking software to the researchers after 10 PM each night. This process continued for 20 days. To protect participant privacy, users were informed in advance that collected data would be used for research purposes only and not for commercial use, with their consent obtained.

3.2 Experimental Design

Participants were sequentially numbered, and their behavior data was collected and organized accordingly. The experiment required elderly users to complete experimental tasks using provided devices, obtaining task completion numbers and completion time data based on their actual operations. The experimental tasks comprised six subtasks: (1) adding a designated person as a friend by scanning a QR code; (2) changing the designated person' s nickname to "Xiaoming" ; (3) sending a photo from the device album to the designated person; (4) sending a red packet to the designated person; (5) sending a specified news link from chat history to the designated person; (6) posting the news link to Moments.

Each subtask had a maximum completion time of 30 seconds; exceeding this limit was considered incomplete. If participants stated they could not complete a task, it was deemed beyond their capability, with completion time recorded as 30 seconds but not counted in the task completion number. Elderly user capability was assessed by tallying their completed task numbers and completion times.

3.3 Tag System Construction Process

After collecting elderly user usage behavior data (including mobile terminal logs and experimental data), correlation analysis was conducted based on data fusion theory to obtain correlations between data elements, and an elderly user behavior portrait tag system was constructed based on relevant usage behavior association data.

Correlation analysis revealed that usage duration and usage frequency showed significant correlation ($P < 0.01$), with the highest correlation coefficient of 0.827 among all behavioral data indicators. As these two datasets represent fundamental data generated during elderly users' WeChat usage, they compose the usage intensity tag in the elderly user behavior portrait.

Interaction frequency and interaction days also showed significant correlation ($P < 0.01$), with the strongest correlation of 0.631 among behavioral data indicators. These two datasets, representing interaction data generated during WeChat usage, compose the interaction intensity tag in the elderly user behavior portrait.

Task completion time and completed task quantity showed significant negative correlation ($p < 0.01$) with a correlation coefficient of -0.933. As these two datasets best represent elderly user capability levels, they compose the usage ability tag in the elderly user behavior portrait. Detailed correlation analysis results are shown in Table 2 .

After correlation analysis, WeChat elderly user behavior data was processed and summarized according to correlation degrees. The processed tag table includes: (1) usage intensity analyzed through usage frequency and duration obtained from mobile terminal logs; (2) interaction intensity analyzed through interaction frequency and days; (3) usage ability analyzed through completed task numbers and times obtained from experimental logs. A specific example is shown in Table 3 .

3.4 WeChat Elderly User Behavior Profiling Tag System

To investigate elderly user behavior portraits based on mobile terminal log mining, this study constructed a WeChat elderly user behavior profiling tag system. Based on collected user attributes and behavior data and correlation analysis, the system was built from four dimensions: elderly user basic attributes, usage intensity, interaction intensity, and usage ability. User attribute tags include age, gender, income, occupation, and education level. Usage intensity includes usage frequency and duration. Interaction intensity includes interaction frequency and days. Usage ability includes completed task numbers and completion time. The constructed tag system is illustrated in Figure 1 [Figure 1: see original paper].

4 Experimental Results

4.1 User Attributes

Among participating elderly users, 43 were male (41.7%) and 60 were female (58.3%). Age distribution showed that users aged 60-65 constituted the largest group with 59 participants (57.3%). Regarding education, those with high school and technical secondary school education were most numerous at 40 participants (38.8%). Occupationally, most elderly users worked in party/government agencies, state-owned enterprises, and public institutions, with individual business owners being the smallest group at only 14 participants (13.6%). Income-wise, the majority fell in the 2000-4000 RMB and 4001-6000 RMB monthly income ranges, accounting for 39.8% and 33.0% respectively. Descriptive statistics of experimental user attributes are shown in Table 4 .

4.2 User Usage Intensity

Based on correlation analysis, the usage intensity tag comprises usage frequency and duration. Participating elderly users showed concentrated usage frequency, with most opening WeChat 1-7 times daily, while only a few active users opened it more than 8 times daily. Usage duration exhibited a clear Gaussian distribution, with dense clustering in the [15, 30] minute daily usage range. Two distinct types emerged: highly active elderly users exceeded 60 minutes daily usage, while most users remained under 30 minutes. Usage duration and frequency showed significant positive correlation (Figure 2 [Figure 2: see original paper]), where increased usage duration corresponded with higher usage frequency.

A usage intensity calculation formula was constructed with normalized data in the [0, 1] interval:

$$UsageIntensity(UI) = a\frac{UsageFrequency_i}{MaxUsageFrequency} + b\frac{UsageTime_i}{MaxUsageTime} \quad \text{(Formula 1)}$$

Where a and b represent usage intensity impact factors. Assuming equal importance of usage frequency and duration, $a = b = 0.5$. $UsageFrequency$ represents user i' s daily WeChat opening frequency, $MaxUsageFrequency$ represents the highest usage frequency among experimental users, $UsageTime$ represents user i' s usage duration, and $MaxUsageTime$ represents the maximum usage duration among experimental users.

4.3 User Interaction Intensity

Based on correlation analysis, the interaction intensity tag comprises interaction frequency and interaction days. Interaction frequency refers to elderly users' daily message volume, counting each message as one interaction and each minute of video/voice chat as one interaction, reflecting user activity levels. Interaction days refer to the number of days within the 20-day experiment that elderly users interacted with others via WeChat, reflecting user stickiness.

Results showed interaction frequency followed a normal distribution, with most elderly users' daily message volume in the [8, 22] range, most densely clustered in [12, 18]. Interaction days concentrated at 18-20 days, indicating most participants used WeChat as a primary daily social tool. Interaction frequency and days showed positive correlation, suggesting higher interaction frequency leads to more frequent WeChat usage for information exchange and sharing, resulting in more interaction opportunities and higher stickiness (Figure 3 [Figure 3: see original paper]).

For clustering convenience, interaction intensity data was normalized based on user interaction logs. The interaction intensity tag comprises interaction frequency and interaction days [**?**]:

$$InteractionIntensity(II) = a\frac{InvolveDay_i}{MaxInvolveDay} + b\frac{Speech_i}{MaxSpeech} \quad \text{(Formula 2)}$$

Where a and b represent interaction intensity impact factors, set as $a = b = 0.5$ assuming equal importance. $Speech$ represents user i' s interaction frequency (daily message volume), $MaxSpeech$ represents the maximum interaction frequency among experimental users, and $InvolveDay$ represents user i' s interaction days (maximum being 20 days).

4.4 User Usage Ability

Based on correlation analysis, the usage ability tag comprises completed task numbers and completion time. Before the experiment, 10 active WeChat users tested the tasks to establish scoring standards. Using six common WeChat functions as experimental tasks, these 10 active users completed all tasks effortlessly within approximately 60 seconds.

Results showed most elderly users completed 4-6 tasks, but the proportion completing all tasks was not high, with some completing fewer than 3 tasks, indicating unfamiliarity with common WeChat functions. Even those completing all tasks took significantly longer than active users, primarily due to age-related physical and cognitive decline. Completed task numbers and completion time showed negative correlation (Figure 4 [Figure 4: see original paper]), where more completed tasks corresponded with shorter completion times, indicating greater familiarity and proficiency.

After obtaining experimental log data, usage ability was normalized. The usage ability tag comprises completed task numbers and completion time:

$$UsageAbility(UA) = a\frac{PerformTask_i}{StandardTask} + b\frac{FinishTime_i}{StandardTime} \quad \text{(Formula 3)}$$

Where a and b represent usage ability impact factors, set as $a = b = 0.5$ assuming equal importance. $Perform$ represents user i' s completed task number (standard being 6 tasks), $FinishTime$ represents user i' s completion time (standard active user completion time being 60 seconds).

5 Discussion Analysis

5.1 Correlation Analysis Between User Attributes and Usage Behavior Tags

After preprocessing and normalizing user attribute data, correlation analysis with user behavior data revealed no significant relationships between gender, income and behavior data. However, educational background showed significant correlation with behavior data. Educational background was normalized as: primary school and below = 0.2, junior high = 0.4, senior high = 0.6, technical secondary school = 0.8, university and above = 1.0.

Correlation analysis between usage ability and attribute data showed significant relationships between usage intensity, interaction intensity, usage ability and educational background. Usage intensity and interaction intensity showed the strongest correlation (coefficient = 0.729), indicating mutual influence. Educational background and usage ability showed the strongest correlation (coefficient = 0.737), suggesting elderly users' usage ability is most influenced by education level. Correlation results between behavior tags and attribute tags are shown in Table 5 .

5.2 Clustering Analysis of Educational Background and Usage Behavior Tags

K-means clustering of educational background and usage behavior data produced three clusters (Figure 5 [Figure 5: see original paper]), representing low-education, medium-education, and high-education elderly user groups. Higher education corresponded to higher usage intensity, interaction intensity, and usage ability, with significant gaps between low/medium and high-education groups. Well-educated elderly users typically have larger, more complex social circles, more daily interaction opportunities, and consequently higher usage and interaction intensity. Higher education also correlates with stronger learning ability, openness to new things, better memory, and deeper understanding of WeChat functions, enabling faster task completion.

Two-by-two clustering of usage intensity, interaction intensity, and usage ability revealed significant internal differentiation among elderly users, following the "80/20 rule" where high-intensity/high-ability users constitute a minority. Usage intensity vs. interaction intensity and usage intensity vs. usage ability showed clear clustering effects, while interaction intensity vs. usage ability showed moderate effects.

5.3 Clustering Analysis of User Usage Behavior Tags

WeChat elderly user behavior data tags include three sub-tags: usage intensity, interaction intensity, and usage ability. Overall clustering of these tags classifies elderly users into three categories: highly active, moderately active, and low-active elderly users. K-means clustering results based on behavior data (Table 6) show severe internal differentiation. Clusters 1 and 2, representing medium-low activity users, account for 77% of participants, while Cluster 3's high-activity users represent only 23%.

According to WeChat' s 2018 official data report, with 900 million daily active users sending 38 billion messages daily, the average is 40 messages per user per day. Using interaction intensity as an example, the highest daily message volume among experimental elderly users was 41, merely reaching the average level. This indicates that even highly active elderly users only match average WeChat user levels, with the elderly group lagging behind overall.

In 2018, WeChat statistics showed 50% of users spent 90 minutes daily on the platform, while experimental elderly users concentrated in the [20, 30] minute range, indicating significantly lower usage intensity. Elderly users' usage intensity, interaction intensity, and usage ability currently rank in the lower-middle range, suggesting substantial room for improvement across all behavioral metrics (Figure 6 [Figure 6: see original paper]).

5.4 Elderly User Behavior Portrait

Analysis of user attribute tags and behavior tags in the elderly user portrait system reveals unique behavioral characteristics. Most participants demonstrated weak usage ability, with experimental tasks based on common WeChat functions proving challenging. Even successful participants required significantly more time than active users, indicating substantial gaps in function familiarity and understanding.

Overall, elderly users show low usage and interaction intensity, primarily due to simpler social circles after retirement and fewer daily interaction opportunities. However, internal differentiation is pronounced: users with high usage intensity also show high interaction intensity, and well-educated elderly users demonstrate outstanding usage ability within the group.

At the experiment' s conclusion, with participants' consent, their WeChat personal signatures were collected. Personal signatures typically reflect life attitudes. A word cloud generated from elderly users' signatures revealed positive life attitudes, with frequent appearance of uplifting words such as progress, effort, revitalization, freedom, and striving (Figure 7 [Figure 7: see original paper]). Despite lagging behind active WeChat users in all three behavioral metrics, elderly users generally maintain positive and optimistic life and learning attitudes, indicating significant potential for capability improvement.

5.5 Service Response Strategies Based on User Profiling

Data analysis reveals unique usage behavior characteristics among elderly WeChat users. Corresponding service strategies are proposed from government and WeChat platform perspectives.

Government Level: Governments should prioritize cultivating elderly information literacy, establishing evaluation standards for Chinese elderly information literacy referencing US models. Systematic information literacy training curricula should be developed for the elderly, with increased policy and financial support for information literacy courses, while mobilizing social capital to continuously improve the elderly information literacy education system [**?**]. Grassroots government agencies should actively conduct information literacy training lectures for elderly WeChat users within their jurisdictions, helping them enhance information awareness, capability, and ethics. Trained elderly users can then promote dissemination to other seniors, conserving government human resources.

Platform Level: WeChat should establish dedicated data analysis departments to collect elderly user behavior data within legal limits, conduct big data analysis on elderly group behavior, and provide targeted guidance based on analytical results. The platform should implement login rewards to encourage elderly users to increase daily opening frequency, thereby enhancing usage intensity. Mimicking QQ' s friendship indicators (e.g., chat frequency symbols like "ship" or "spark"), WeChat could motivate elderly users to increase interaction intensity with friends and relatives. Furthermore, WeChat should simplify functional operation steps, adjust mobile social network functions according to elderly users' cognitive levels and physical characteristics, and reduce learning pressure through simplified operations, enabling elderly users to master more advanced functions and enjoy convenient mobile social services.

Theoretical and Practical Contributions

Theoretically, this study analyzes elderly user behavior characteristics from real user attribute and behavior data, explores correlations between attribute and behavior data, and constructs a WeChat elderly user behavior portrait tag system based on data fusion theory. This framework can be applied to portrait research on other WeChat user groups and other mobile social network platforms, establishing a research framework for deepening mobile social user portrait studies.

Practically, by obtaining WeChat elderly user behavior data through mobile terminal logs and experimental logs, and through data 归纳 and clustering analysis based on user portrait attribute and behavior tags, this study employs experimental methods to analyze elderly user behavior characteristics. This helps government departments, the WeChat platform, and elderly users themselves deeply understand elderly group behavior characteristics, improve software functions targeting these characteristics, enhance elderly user group activity, and provide foundations for subsequent mobile social network developers to create products for elderly users.

Limitations and Future Research

This study' s limitation lies in the relatively small sample size, primarily due to unopened WeChat user data interfaces, log tracking software limitations on phone models, and incomplete collection of phone system logs, making it difficult to obtain large-sample, multidimensional WeChat user behavior data. Future research will expand sample size and data dimensions to achieve more precise profiling of elderly WeChat user behavior.

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Author Contributions

Li Jiaxing: Paper writing, revision, data collection, and final version editing.
Wang Xiwei: Research proposition and framework design.
Chang Ying: Paper proofreading.
Zhang Changliang: Literature collection and abstract translation.