User Profile in Smart Elderly Care Community: Findings from Community in Western China

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Abstract: With the increase in the aging population, the need for elderly care services has diversified, and smart elderly care has become an effective measure to cope with this increasing aging population. Based on the data from the platform "Guan Hu Tong" of RQ Company in the community of Shaanxi Province in western China, this study mined the data of smart elderly care services through the recency, frequency and monetary value (RFM) model and the backpropagation (BP) neural network model, constructed the user profile of the elderly, and predicted users' practical demands. The following conclusions were drawn: The oldest users are important target users of smart elderly care service platforms; Elderly women living alone rely more on smart elderly care services; Meal delivery and health follow-up services are the most popular among elderly users.

Keywords: smart elderly care; user profile; backpropagation (BP) neural network

1 Introduction

Population aging is a significant demographic issue in the 21st century. According to the World Bank, in 2020, the world's population aged 65 and over exceeded 700 million. The figure from the National Health Commission (NHC) of the People's Republic of China (PRC) shows that the number of people aged 60 and over has reached 267 million, accounting for 18.9% of the total population, and the number of those aged 65 and over has exceeded 200 million, accounting for 14.2% of the total [1]. Before the 21st century, some developed countries had entered the aging process; consequently at the forefront of the aging phenomenon. At the outset of the 21st century, China has just become an aging society, but the aging process is progressing more rapidly than in other countries [2]. It is predicted that China will enter a phase of moderate aging between 2021 – 2025, and severe aging around 2035. With the ever-increasing and diversified needs of the elderly, the traditional eldercare model can no longer meet the rapidly growing and diversified eldercare needs. China is experiencing enormous pressure from its aging population [3]. The smart elderly care industry has embarked on a new model of digital, intelligent and precise elderly care services. In the new era of information and intelligence, it is essential to provide accurate and considerate elderly care services through information technology and data systems for elderly service management. Realize model optimization and technology upgrading of the intelligent smart elderly care industry. It also provides new methods for improving the service experience of the elderly and address the imbalance of supply and demand of services [4–6].

Smart elderly care was first proposed by the UK Life Trust. It refers to the use of modern sci-

ence and technology, such as information technology, to support the elderly in daily living, safety, medical care, entertainment, learning, and other aspects by helping them readily detect and deal with health-related issues. Smart elderly care aims to establish friendly, helpful, and personalized intelligent interactions between technology and the elderly so that they can live happier, more dignified, and valuable lives. Since China has become an aging society relatively late compared to other countries, the Chinese smart elderly care industry is in its infancy [7]. It is important to build a smart elderly care service platform in China [8]. As currently, the services are mostly limited to daily care and health care. Therefore, studying the specific needs of the elderly is key to providing adequate services for dealing with rapid aging and solving the supply-demand issues in caring for the elderly. Presently, China's research on the specific needs of the elderly primarily focuses on subjective needs, using questionnaires and interviews. For example, Zuo and Lei divided user needs into five different aspects, based on Maslow's hierarchy of needs, and then summarized the demand model of the services for the elderly and obtained information about the needs of different services through questionnaires [9]. Bai and Zhu analyzed the factors affecting the demand for smart elderly care services in Jianghan District, Wuhan, through questionnaires [10]. However, the subjective reports of elderly people often do not accurately reflect the demand for elderly care services. Therefore, demand for elderly care services cannot be analyzed only through subjective reports and should also be analyzed using objective data [11]. This study analyzed data on the use of elderly care services to obtain information on the needs of elderly people.

As tools to realize accurate information, user profiles have been widely used in libraries, e-commerce, healthcare, tourism management, precision marketing, and other fields in recent years. For example, Li and Chen built user profiles by collecting user data on WeChat to help marketers improve product quality and user experience [12]. Yang built user profiles according to their web browsing behavior for user identification [13]. Han and Chen proposed a novel method for acquiring ontology-based user profiles to maintain representations of personal interests [14]. Li and Zhao identified the potential value of users through the frequency and monetary value (RFM) model and built user profiles to improve marketing accuracy [15]. Relevant studies have shown that building user profiles improves understanding of user needs and helps realize personalized and accurate information services [16]. User profiles are divided into different genres. Ontology-based user profiles are more effective for understanding specific meanings contained in information sources, semantic expression abilities, and logical reasoning [17]. Current user profiles method has been very mature, mainly by selecting the indicator system, then obtaining the data of each indicator and using clustering, neural network and other classification methods to obtain different categories of the indicator set. Although current studies on user profiles are extensive and scholars have built different user profiles for different user groups, there is less research on building user profiles for the elderly. As the smart elderly care platform collects basic user information and usage statistics data, this study tried to build a community elderly user profile using an ontology-based user profile. User value tags are determined by RFM models as well as backpropagation (BP) neural networks for classification, to help the platform accurately match the needs and recommendations of the smart elderly care service.

Combined with previous studies of smart elderly care and the extensive application of user profiles in service matching and recommendation, this study used data from the "Guan Hu Tong" platform of RQ company in Shaanxi to refine the category tags of user value based on the RFM model. Subsequently, a BP neural network model

was used to obtain users' real demand tags with high matching. Finally, user profiles were built in a smart elderly care community platform to improve the recommendation accuracy of elderly care services. The data collection area was the Nansha community service station of the RQ Company in Xi'an, Shaanxi Province. The Nansha community is located in the Beilin District. According to data from The Seventh National Population Census, the proportion of the population aged 60 and over in Shaanxi Province and Xi'an City was 19.20% and 16.02%, respectively [18]. The proportion of the population aged 60 years and over in the Beilin District was 20.19%, which exceeded the national average [19]. In addition, the elderly care industry in Beilin has developed rapidly and is leading the development of smart elderly care service platforms. Therefore, data from the Nansha community service station in Beilin District are highly representative.

The main contributions of this study are as follows. First, it builds user profiles for elderly users, which is crucial for understanding their real needs and accurately recommending appropriate services for them. Second, this study distinguishes itself from traditional surveys on elderly people and understands their real needs based on actual service usage. Third, this study trains the real demand classification model through a neural network algorithm, which can predict the real service needs of elderly users based on their basic information.

The structure of this paper is as follows. Section 1 introduces the study's research purpose. Section 2 describes the models and research procedures used in this study. Section 3 discusses the data obtained and the results of using the models and analyzes and discusses the results. Section 4 summarizes the main contents of this paper.

2 Methodology

This section introduces the RFM model used to build user value tags and the BP neural network model used for user-service matching. The RFM model is an evaluation tool that employs users' recent consumption information to evaluate user value; it can measure user value from multiple aspects. In this study, RFM models are used to obtain a simple value evaluation of elderly users, which is then used to build user value tags for user profiles. As a traditional neural network algorithm, the BP neural network model has a rich theoretical foundation and practical applications. In addition, it exhibits excellent adaptability to classification problems. In this study, the BP neural network model was used to match the actual service needs of elderly users. The research procedure of this study is introduced at the end of this section.

2.1 RFM Model

Users are important resources and lifelines of various enterprises with behavioral trajectories and consumption characteristics. User lifetime value refers to the value created by users for the enterprise throughout the process of contact with the enterprise. Typical user lifetime values include the investigation, formative, stable, and recession periods [20].

The first step in building user profiles is to choose a user tag. This study used the RFM model to build a user value tag as an important tag in the user profile. The first step involves the preliminary grouping of elderly users in terms of building a user classification system according to whether the indicator value is greater than the indicator mean value. Next, the user value tag of each user is visually displayed to provide a strategic reference for smart elderly care service platforms to target users. Recency refers to the latest consumption behavior of a user, that is, the user's latest purchase of a product or service. The more recent the last consumption time, the stronger the reaction to the instant goods or services provided with a relatively high value. Frequency refers to the number of times users consume within a certain period. The higher the

user's consumption frequency, the higher their satisfaction with the product and the higher their loyalty. Monetary value refers to the user's consumption amount, which is the most intuitive manifestation of the user's value; the higher the consumption amount, the higher the profit for the company [21]. Recency, frequency, and monetary value are divided into two categories, as shown in Tab. 1.

Each indicator is divided into two user categories, and all platform users can be divided into eight categories with different user values. The user classification system has a three-dimensional structure, as shown in Fig. 1.

Users can be divided into eight categories: important valuable, general valuable, important developable, general developable, important maintainable, general maintainable, important retained, and general retained [22].

Tab. 1   Initial user grouping

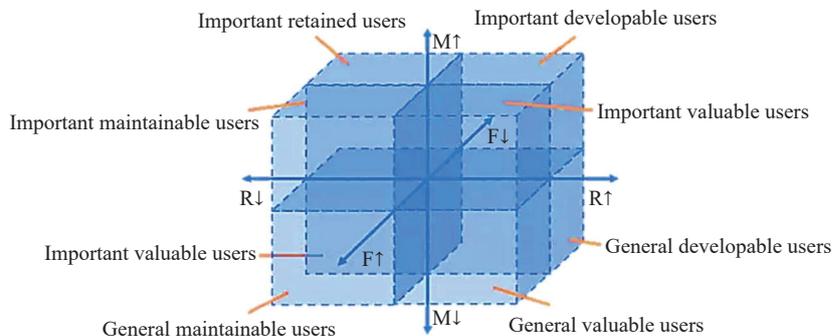| RFM model indicator	User grouping
R	Active user
	Silent user
F	Loyal user
	Developable user
M	High-contributing user
	Low-contributing user

Fig. 1   User classification system

2.2 BP Neural Network Model

The BP neural network model is based on the backpropagation training algorithm, which was first proposed by Paul Werbos of Harvard University in 1974 [23]. He proposed that artificial neural networks could be trained through the backpropagation of errors to solve the minimum error of the feedforward neural network between the actual output and the expected output. The BP neural network model uses error backpropagation to compensate for the error of the network training process to the neural network. The basic concept of the algorithm is gradient descent. Through error feedback, the threshold and weight are constantly adjusted to minimize the loss function. Finally, a neural network model is obtained whose output continuously approximates the real value [24, 25].

The specific structure of the BP neural net-work model consists of two parts: the forward propagation signal and the backward propagation error. In the forward propagation signal, the input layer in the training set is processed by the hidden layer to obtain the output layer. During propagation, the output value of the previous layer only affects the next layer. If the output result deviates from the expected result, the algorithm will automatically transfer to the back-propagation process [26], that is, adjust the thresholds and weights of each layer of the network according to the error, and propagate backward along the forward propagation path. The loss function of the BP neural network is minimized through two-way repeated propagation for sample training and parameter adjustment. Fig. 2 shows the three-layer BP neural network structure.

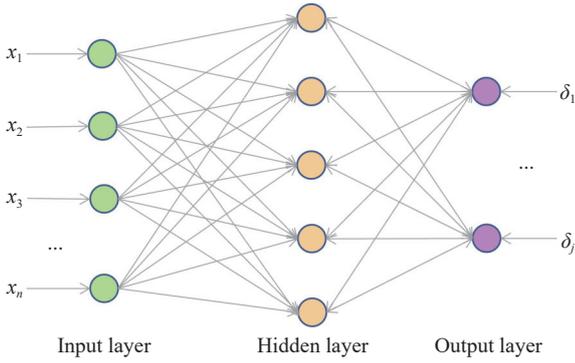This BP neural network is a nonlinear map-

Fig. 2   Three-layer BP neural network structure

ing function $f : X \longrightarrow Y$, when we set an input layer $\{x_1, x_2, x_3, \cdots, x_n\}$ and corresponding output layer $\{\hat{y}_1, \hat{y}_2, \hat{y}_3, \hat{y}_4, \hat{y}_5, \hat{y}_6\}$ are given. The weights on input and hidden layers are given as $\boldsymbol{w_1} = \{w_1^1, w_1^2, \cdots, w_1^n\}$ and $\boldsymbol{w_2} = \{w_2^1, w_2^2, \cdots, w_2^k\}$. At the same time, the threshold values of the hidden layer and the output layer are also given as $\boldsymbol{\theta_1} = \{\theta_1^1, \theta_1^2, \cdots, \theta_1^k\}$ and $\boldsymbol{\theta_2} = \{\theta_2^1, \theta_2^2, \theta_2^3, \theta_2^4, \theta_2^5, \theta_2^6\}$. k is the number of nodes in the hidden layer. Determine whether to carry out the back propagation process by calculating the error δ between the output layer $\hat{y}$ and the expected output y. In hidden layer, the tansig function is selected as activation function.

$$\text{tansig}(x) = \frac{2}{1 + \mathrm{e}^{-2x}} - 1 \qquad (1)$$

Additionally, the mean square error（MSE）is selected as the loss function.

$$E_k = \frac{1}{2} \sum_{j=1}^{6} \left(\hat{y}_j^k - y_j^k \right)^2 \qquad (2)$$

For each training case (x_k, y_k), we obtained his mean square error, and then the accumulated mean square error on training set is given.

$$E = \frac{1}{m} \sum_{k=1}^{m} E_k \qquad (3)$$

3   Data Processing and Analysis

3.1   Data Description

Data were collected from the "Guan Hu Tong" smart elderly care service system developed by RQ Company in Shaanxi Province. The data col-

lection area was the Nansha community service station of the RQ Company in Xi'an, Shaanxi Province. In this study, data on 1 301 elderly service orders were collected; eventually, information from 590 users' personal files was summarized.

The data collected for the study contain no private information, such as users' names and phone numbers. The researchers and units have no conflicting interests. The researchers assure that this data will only be used for academic research. This study was approved by the Ethics Committee of the Institute of Statistics of the researchers' organization.

3.1.1   Data Content

The data collection subject of this study was smart elderly care service users in the Nansha community, Beilin District, Xi'an City. The data were collected from August 1, 2021, to October 31, 2021. The content includes:

1）Basic registration information given by elderly users in service centers;

2）Relevant basic information provided by elderly users when registering smart elderly care accounts on platforms;

3）Elderly care service order data.

3.1.2   Service Content

The service data contain the order information of six elderly care services, including bath aid, home cleaning, physiotherapy, medical consultation, health follow-up, and meal delivery services. The details of these services are as follows.

1）Bath aid service: Staff helps the elderly take a bath at home or at community service station. After the bath, staff dry their hair and give them a haircut（staff brings their own tools）.

2）Home cleaning service: Cleaners go to the homes of the elderly to clean floors, walls, furniture, and household appliances, organize household items, and perform other cleaning services.

3）Physiotherapy service: Physiotherapy personnel provide services for the elderly at home or at community service station. Physiotherapy programs include acupuncture, moxibustion, mas-

sage, and traditional manipulations.

4) Medical consultation service: Staff accompanies the elderly to hospitals for registration, drug collection, consultation, and other medical services.

5) Health follow-up service: Nurses visit the elderly to measure blood pressure, heart rate, blood sugar, and other health indicators and provide corresponding health management suggestions.

6) Meal delivery service: Staff delivers meals to the elderly at noon. The types of meals are regularly changed to meet the health needs of users (the staple food is rice on Mondays, Wednesdays, and Fridays, and pasta on Tuesdays, Thursdays, and Saturdays).

3.2 Descriptive Statistics

As shown in Tab. 2, the ratio of male to female users receiving smart care services was 1:1.09, which is relatively balanced.

Tab. 2   Gender situation of elderly users

Gender	User grouping	Percent (%)
Male	282	47.8
Female	308	52.2

In terms of age, 10 years was used as the interval. The proportion of elderly users aged 70 to 79 accounted for 50.6%, followed by elderly users aged 80–89, accounting for 32.4%. In contrast, the elderly under the age of 60 and over 90, accounted for only 2.5% of the total smart elderly care service users, as shown in Tab. 3.

Tab. 3   Age of elderly users

Age	Percent (%)
50–59	2.4
60–69	14.5
70-79	50.6
80–89	32.4
Over 90	0.1

This study divided the living conditions of elderly users into living alone, spouses living together, and living with children. As shown in Tab. 4, 31.9% of elderly users are reported living

alone. There was little difference between the number of elderly people living with their children and those living alone, while the proportion of elderly users living with spouses was 37.9%.

Tab. 4   Residence of elderly users

Residence	Number	Percent (%)
Living alone	188	31.9
Spouses living together	224	37.9
Living with children	178	30.2

In terms of the physical condition of elderly users, as shown in Tab. 5, 28.3% of elderly users could take care of themselves, while 71.7% could not. Considering that the physical condition of elderly users is closely related to the effectiveness of elderly care services, this study divided the physical condition of elderly users into self-care, need for care, partial disability, and disability.

Tab. 5   Physical condition of elderly users

Physical condition	Number	Percent (%)
Disability	71	12.0
Partial disability	126	21.4
Need of care	226	38.3
Self-care	167	28.2

During the data collection period from August 2021 to October 2021, the system recorded 1 301 orders of information from 590 users, covering six smart elderly care services, such as bath aid services, home cleaning services, and physiotherapy services. Specific service types and order quantities are shown in Fig. 3. Combined with the user's personal files, it is found that meal delivery services and health follow-up services are the two most used elderly services, accounting for 35.6% and 34.8%, respectively.

The number of elderly service users is listed in Tab. 6. Health follow-up service is the most popular service, with 49.1% of elderly users choosing this service. Although the proportion of users who chose the meal delivery service is relatively small, the average number of service orders per user is higher.
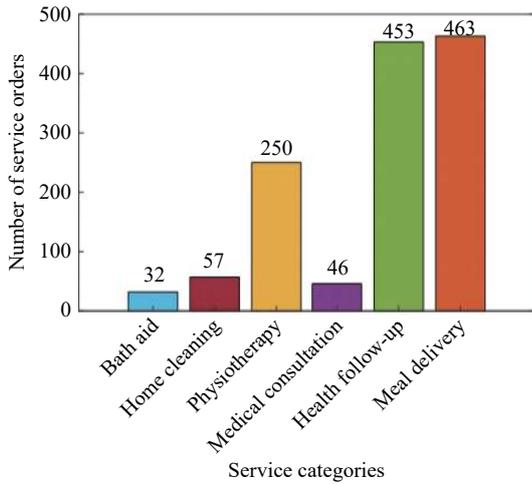
Fig. 3　Frequency of various care service orderse

Tab. 6　Physical condition of elderly users

Type of service	Number	Percent (%)
Bath aid	23	3.9
Home cleaning	34	5.8
Physiotherapy	178	30.2
Medical consultation	37	6.3
Health follow-up	290	49.1
Meal delivery	132	22.4

From the perspective of each user receiving the service, elderly users with the most orders received a total of 51 services during the data collection period, while the overall average number of uses per service was 2.2.

3.3　User Value Tags

Based on the characteristics of the data in this study, the definitions of the indicators of the RFM model are as follows:

R: The deadline for data collection is October 31, 2021, so the value of recency is the number of days until November 1, 2021, from the last elderly care service.

F: Number of elderly care services received from August 1, 2021, to October 31, 2021.

M: Spending on elderly care services from August 1, 2021, to October 31, 2021.

Users whose recency indicator is greater than the sample mean are identified as active users; otherwise, they are silent users; users whose frequency indicator is greater than the sample mean are loyal users; otherwise, they are developable users; users whose monetary indicator is greater than the sample mean are identified as high-contributing users; and otherwise, they are low-contributing users. Therefore, each user can be defined according to eight types of user value tags: important valuable, general valuable, important developable, general developable, important maintainable, general maintainable, important retained, and general retained user. That is, important valuable users are those whose RFM values are all higher than the sample mean. General valuable users are users with higher recency and frequency and lower monetary value than the sample mean; important developable users are users whose recency and monetary value are higher than the sample mean and whose frequency is lower than the sample mean; general developable users have higher recency and lower frequency and monetary value than the sample mean; important maintainable users refer to those whose frequency and monetary value are higher than the sample mean but whose recency is lower than the sample mean; general maintainable users are those whose frequency is higher than the sample mean and recency and monetary value are lower than the sample mean; important retained users have higher monetary value and lower recency and frequency than the sample mean; general retained users' recency, frequency, and monetary value are all lower than the sample mean.

Among these groups, valuable users are key to the continual maintenance of the platform. They use services most frequently and are the most loyal to the platform. General valuable and important developable users are key development targets for the platform. Although general valuable users spend less, they use services more frequently. Important developable users are highly likely to become important valuable users. The platform must focus on the above three users.

3.4 Real Demand Forecast

This study takes the gender, age, residence, and health status of elderly users as the input layer, and the output layer represents the real needs tags of users. A three-layer BP neural network model was built to predict the actual needs of elderly users for several services. The specific forecasting processes are as follows.

1) Define the input layer: The input layer consists of four nodes: gender, age, residence, and health status. All indicators except age were quantified as numeric data and expressed as vectors. For example, the vector of residence is expressed as—living alone, spouse living together, or living with children; therefore, the vector of the user living with their spouse is expressed as $(0, 1, 0)$.

2) Define the output layer: The output layer should be the type of service that elderly users really need, and it is also expressed as a vector (bath aid, home cleaning, physiotherapy, medical consultation, health follow-up, and meal delivery services). For example, if a user receives a total of five bath aid services, one medical consultation service, and eighteen meal delivery services during the data collection period, the real demand is expressed as $(5, 0, 0, 1, 0, 18)$.

3) Clarify the number of nodes in the hidden layer: There were a total of 590 elderly users in this study. To avoid overfitting, based on the empirical formula in the BP neural network model [27], we determined that the optimal value range of the hidden layer nodes is $[1, 5]$

$$h = \sqrt{m + n} + a \qquad (4)$$

In the empirical formula, m is the number of input layer nodes, n is the number of output layer nodes, and a is the regulation constant. According to the data characteristics of this study, take the number of input nodes $m = 4$; the number of output nodes $n = 1$, a to take $[-1, 3]$.

4) Neural network parameters: choose "trainlm" as the training function, "tansig" as

the node transfer function, and set the maximum training times "epochs" to 1000. Taking acceptable error as 1% and the learning rate as 0.1. The "epochs" and acceptable error are manually set hyperparameters. For the hyperparameters of learning rate, we use cross validation method for selection, randomly divided the 490 user data in the training set into 10 equal parts for cross validation, and brought different learning rates into it to observe the average accuracy of prediction. We selected the learning rate with the highest accuracy as the parameter value. So, the learning rate is selected as 0.1. The initial values of the weights w_1 in the input layer and w_2 in the hidden layer in the neural network are both taken the random number on $(-0.5, 0.5)$. Similarly, the threshold initial values θ_1 in the hidden layer and θ_2 in the output layer are taken the random number on $(0, 1)$. These parameters are model parameters, and the parameters of the optimal model are obtained through training.

In total, 590 users were randomly divided into the train or test sets; the test set comprised the smart elderly service data of 490 users, and the test set comprised the smart elderly service data of the remaining 100 users. The experimental tool used MATLAB software to set the number of hidden layer nodes from one to five. In MATLAB neural network tools, the optimal model output is based on the minimum test error, rather than the minimum training error. This also avoids overfitting. There is almost no difference between the verification error of cross validation in the training set and the test error in the final test set. Therefore, it is correct to select the output results on the test set as the prediction accuracy of the model. The data of the training set were input into the neural network to take the most numerical demand category in the output vector as the prediction results, and the real results were compared with the prediction results. The prediction accuracy rates are presented in Tab. 7.

Tab. 7　Physical condition of elderly users

Number of nodes of hidden layer	1	2	3	4	5
Number of epochs	113	206	175	192	183
Prediction accuracy rate(%)	51	83	75	72	79

3.5　User Profile

The user profile results were based on the value category tag and real demand tag, with age, residence status, and health status as auxiliary tags. The main tag of the user profile, that is, the real demand tag of services can be determined by entering users' basic information. Real demand tags and auxiliary tags are then used to build ontology-based user profiles, as shown in Fig. 4.
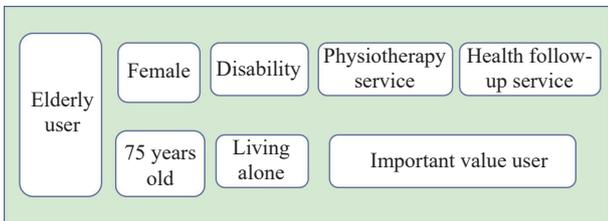

Fig. 4　Display of user profile

According to the results of the BP neural network model, when a 75-year-old female elderly user is living alone and has an age-related disease that renders them disabled, we can predict that they need physiotherapy and health follow-up services. According to this order information, this user is an important valuable user of the smart elderly care service platform. To better meet the users' real care needs and improve the service efficiency of the platform, the platform can recommend physiotherapy services and health follow-up services accordingly.

3.6　Results

3.6.1　BP Neural Network Prediction Results

According to the prediction of BP neural network, the training model of 490 users was selected, and 100 users showed an accuracy rate of more than 80% on the test set. For each test user, we select the two services with the largest prediction value as the recommended services. The prediction results on the test set are shown below. The label of bath aid service does not appear among female users. Only the disabled elderly who live alone have the label of bath aid service. The predicted home cleaning service tag has a higher proportion of elderly livinging alone, but the total predicted number of bath service tag and household cleaning service tag is less. More than 42% of the users are recommended for physiotherapy services, and the proportion of elderly living alone is less. There are also few service tags for medical consultation service. Most of the them are the oldest old who live alone and need to be cared for. The prediction results show that there are no younger elderly and disabled elderly among the users of medical consultation service. More than 76% of the users of the health follow-up service tag are recommended, but there are no disabled elderly among all the recommended users. 59% of the users of the food delivery service were recommended, with a high proportion of those who live alone, but few the oldest old were recommended for the service. Therefore, the service prediction of BP neural network for all types of users is relatively clear, which is more consistent with the service actually used by 100 elderly users in the actual test set.

3.6.2　User Profile Results

1) The oldest users are important target users of the smart elderly care service platform.

Based on the results of the data pre-processing, more than 80% of the users were over 70 years old, which placed them in the highest age category. Among them, the elderly aged between 70 and 79, who accounted for 50.6% of total users, used the service 578 times. Those aged over 80 years, who accounted for 32.5% of the users, used the service 458 times. Therefore, the age of the most frequent users of the smart elderly care service platform was relatively high. Older adults who use care services more frequently are more likely to become loyal, high-value users.

2) Elderly women living alone rely more on the smart elderly care service.

The proportion of elderly users whose physical condition was "need of care" is the highest,

followed by "self-care" users and "partial disability" users, while that of users whose physical condition was "disability" was the lowest. Based on the service categories and data provided by the platform, elderly female users who live alone and require professional care are overrepresented. Some of the diseases that they suffer from are acute and critical. Moreover, there is a need for mental comfort. Elderly women look forward to the specialized and humanized service content and thus are more likely to choose community smart elderly care services. In particular, the vast majority of female users favor medical consultation services; thus, male users are less frequently labeled with such services on their user profiles.

3) Meal delivery and health follow-up service are the most popular with elderly users.

Based on the service order data of all users in terms of order quantity, the top three elderly services are meal delivery, health follow-up, and physiotherapy services. In terms of the number of users in the same period, the three services with the largest number of users are health follow-up, physiotherapy, and meal delivery services. Based on the results of the user profiles, meal delivery and health follow-up services are the most popular service types at present, and their degree of reuse is also high, meaning that they will become crucial to upgrading and developing smart elderly care services in the future. Among them, meal delivery services are reordered the most; during the three-month study period, the highest number of meal delivery service reuses was 49. The health follow-up service showed the characteristics of periodic use; although this service accounts for the largest number of service orders, the frequency of reuse for this service is lower than for meal delivery services. In addition, the health follow-up service is provided cyclically, and users tend to self-monitor their health at intervals.

3.7 Discussion

Based on the service use data and labeling of the real needs of elderly users in this study, all users who ordered bath aid services were male. Therefore, female users are not covered in the labels of the bath aid service on the generated user profiles and cannot be recommended for this service, which inevitably leads to less understanding and de-feminization of the bath aid service. The main reason female users do not choose the bath aid service may be that they perceive it as violative of traditional norms. The bath aid service is more private than other services; therefore, the design of the service can be improved by, for example, training more professional female bath assistants and providing two different forms of bath assistance: door-to-door and in-store. More attention should also be paid to cleaning bath facilities and providing humanized bath aid services for the elderly who are disabled or without mobility. These measures can further meet the needs of female users and help resolve their resistance to bath-aid services.

This study has the following shortcomings. First, the data obtained in this study are limited. Data were gathered from only 1 301 orders from 590 users. The amount of data is relatively small; therefore, the accuracy of the trained model is not sufficiently high. There are fewer indicators in the data dimension. For example, the data in the income column are missing and cannot be applied to the model, while the income situation is the most important indicator for measuring the affordability and acceptability of smart elderly care services for the elderly. Therefore, more comprehensive user information is required to further increase the number of nodes in the input layer of the BP neural network and to improve the accuracy of the prediction model. With regard to the subsequent prediction of users' real demands, intensive learning is also crucial to continuously train the prediction model with newly generated order data and further improve the accuracy of prediction. Second, this study only adds user value tags and real user demand labels to the user profiles. In subsequent studies, more

labels can be considered to generate more comprehensive profiles for elderly users. Third, for checking the accuracy of the user's demand label, user evaluation and feedback on the recommended services can be obtained based on the service recommendation of the Application.

4 Conclusion

Supported by the data from the community smart elderly care service platform, this study builds user profiles using the RFM and BP neural network models, analyzes elderly users' applications, and eventually obtains a neural network model with a high matching of elderly care services. Based on research on the use of elderly care services, the main findings of this study are as follows.

First, the elderly are important users of smart care services in Xi'an. Therefore, in the face of the dynamic demands of the most aged population for smart elderly care services, service design should be more favorable for the elderly, and their service experience should be improved.

Second, elderly female users in Xi'an, especially those who live alone, are more dependent on smart elderly care services, particularly medical consultation services. Therefore, the platform should pay more attention to the comfort of elderly female users, increase mental health services, and recommend such services to female users.

Finally, the main services in this platform are health follow-up and meal delivery services. The meal delivery service is frequently reordered, and the health follow-up service is cyclical. Therefore, the platform should highlight these two services and add the cyclical element to the recommendation of the health follow-up service to improve recommendations.

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