Analysis on the influencing factors of users' usage intention and user behavior patterns in online medical community under COVID-19

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Abstract. With the spread of COVID-19, the shortage and uneven distribution of medical and health resources in the traditional medical industry, as well as the vulnerability to infection, have aroused concerns. As a new way of Internet medical treatment, online medical treatment greatly alleviates the pressure of difficulty in getting medical treatment. However, few studies have explored the factors that influence users' use of online medical communities and the patterns of users' behavior. Based on the theory of perceived value, social support, information asymmetry and information behavior of "Type Person", this paper constructs the influencing factor model of users' usage intention in online medical community. Questionnaires were distributed to users in the online medical community, multiple linear regression was conducted through SPSS to test the assumptions in the model, and then user groups were clustered to analyze user behavior patterns. The results showed that perceived benefit, social support, medical effect and user trust had positive effects on users' usage intention, while perceived risk had a negative effect on it. "Type A" users have a lower intention, "Type B" users are skeptical about medical effect, "Type C" users have a higher intention, and "Type D" users pay more attention to emotional support. Finally, this paper provides some suggestions for online medical community to improve the quality of medical information service.

Keywords: online medical community, usage intention, perceived value, social support; behavioral patterns.

1. Introduction
In January 2020, with the gradual spread of corona virus disease 2019 (COVID-19) epidemic information, the designation, transformation, and termination of treatment of fever clinics and designated hospitals for COVID-19 treatment put medical institutions all over China into an unconventional operation state, and the medical service system suddenly encountered a major test of emergency response capacity. In order to reduce the risk of infection, some patients have turned to the Internet for medical treatment. In this special period, "contactless" consultation of online medical community has become a more efficient and convenient option. According to statistics, during the epidemic, at least 10 Internet medical platforms in China launched online consultation pages, and more than 200 public hospitals provided free online diagnosis and treatment or online consultation for
COVID-19 (Zhang, 2020). On March 5, 2020, the Opinions of the CPC Central Committee and The State Council on Deepening the Reform of the Medical Security System was published. The document mentioned supporting the development of new service models such as "Internet + medical", and eligible "Internet +" follow-up services can be included in the payment scope of the medical insurance fund (The CPC Central Committee and The State Council, 2020).

The shortage of medical resources, per capita shortage, and the single medical mode are the fundamental reasons for the urgent reform of China's current medical system (Hu, 2017). The scarcity and dispersion of medical resources make large hospitals crowded with patients, while the medical resources of small hospitals are idle. Queues for access to health care and a growing shortage of hospital beds are raising questions about the coverage of quality health services. The mismatch between scarce medical service resources and growing user health awareness and medical needs is becoming more and more serious.

With the rapid development of the Internet and Web2.0 technology, the Internet has been changing the way people contact each other, search and use information resources in various fields. Under the influence of the Internet, the traditional industry continues to evolve and update, and its service mode and management concept become more and more information and intelligent. In 2018, The General Office of the State Council of China issued the Opinions on promoting the development of "Internet + medical health", and put forward the guiding opinions on improving the service system of "Internet + medical health", improving the supporting system of "Internet + medical health", and strengthening industry supervision and safety guarantee (General Office of the State Council of the People's Republic of China, 2018). With the rapid spread and spread of COVID-19, traditional medical models are confronted with the reality that medical resources are in short supply and unevenly distributed, and that contact consultation can easily lead to infection between patients and medical staff, which provides the real demand and motive power for the development of online medical communities.

The online medical community transforms the traditional medical treatment into a new smart medical model, eliminates the limitation of time and space, and enables the effective and reasonable allocation of medical resources. Online medical community can provide users with a series of medical information services such as online appointment and registration, online consultation with doctors, patient communication and interaction, and medical knowledge learning, which can help users understand their own health status, effectively manage and improve their health level. Online medical services bridge the thinking gap between doctors and patients and between patients, giving patients greater choice in medical and health services. Online medical utilization, with its convenience, high efficiency and massive medical information, eliminates the information asymmetry in the medical field to a certain extent, and alleviates the current situation of uneven distribution of medical resources and poor doctor-patient relationship. However, in the process of development and service, online medical community may face challenges such as user privacy security, significant medical effect, doctor-patient trust and so on. How to provide better online medical services and precise marketing is the fundamental problem of its development.

In the research of online medical community, Atanasova et al. (2018) found that the online medical community enables users to overcome the weaknesses encountered in face-to-face medical treatment and view the benefits of online patient interaction as providing information and emotional support for users' health needs. Sbaffi and Zhao (2019) found that online health search engine is the most commonly used information channel selection, and reputation, ease of use, style, practicality and recommendation are the key factors affecting users' judgment of information characteristics. Mpinganjira (2018) found that lack of trust negatively affects consumers' willingness to share and adopt information in virtual health communities, while information usefulness, community responsiveness, and shared vision have a significant impact on consumers' overall trust in healthy communities. Nigam et al. (2019) researched users' health theme preferences based on demographic attributes, time characteristics and community economic factors, and found that linking demographic characteristics with user information was more effective in explaining health preferences. Boonitt (2019) studied the quality of healthcare web sites and their impact on trust, perceived usefulness, and user intentions, and found that the quality of health web
sites had a positive impact on user perceived trust, and user trust could influence usage intentions. Wu and Li (2017) found that social support, sense of achievement and trust had significant positive effects on users' intentions. Dong et al. (2019) believed that information accuracy, source reliability and timeliness can improve user perception benefit. Zhang and Li (2017) believed that trust, social identity, self-efficacy and perceived usefulness have positive effects on users' medical sharing behaviors. Deng and Hong (2017) found that the credibility of hospitals, websites and doctors had a significant impact on users' trust.

With the development of online medical communities, overseas online health websites such as webMD, MyMedLab and Patientlike show a good development trend. By providing high-quality medical information services, patients can have a certain understanding of their own health level and make a wise choice in treatment. In China, the online medical community led by Good Doctor, Ping An Good Doctor and Famous Doctor Online has developed rapidly in recent years, providing patients with online medical information services, and patients can also realize effective control of diseases through online consultation and community interaction.

Previous studies mostly focused on social support, perceived benefit, trust and user information sharing in online medical communities, but seldom involved the analysis of user behavior characteristics and patterns. Therefore, this article will build users' usage intention influencing factor model in online medical community, the analysis of various factors on the relationship and degree of the influence of user intention to use, again according to the basic characteristics of the user for the user to carry on the clustering, mining of user behavior patterns, in the final analysis the medical behavior characteristics of different user groups and information needs. It is of great significance to study users' usage intention and users' medical behavior patterns to promote online medical community to grasp users' medical information preference and improve user satisfaction.

2. Theoretical bases and hypotheses

2.1. Theory of perceived value

Since the 1970s, the strategic model of enterprises at the customer level has been constantly developing and evolving, from product-centered to "customer-oriented", constantly striving for and winning customer satisfaction and recognition. In 1988, the perceptive value theory was first proposed by Zaithaml from the perspective of the customer, thinking that perceptive value is a kind of overall subjective evaluation of the user, who will weigh the perceived benefit and risk after receiving the product or service (Wu and Li, 2017). Perceived value consists of perceived benefit and perceived risk. Perceived benefit refers to the sum of the spiritual and material benefits actually perceived by users through transactions or consumption, and it is a post-subjective overall generalization. Perceived benefit of customers refers to the comprehensive satisfaction level including product, personnel, service and image value. Perceived risk is a sense of uncertainty caused by users' unpredictability of purchase results during consumption. Consumers' purchase strategies have hidden uncertain expectations of results, and some results may reduce consumers' satisfaction (Wang, 2018). Through the online medical community, users can check the qualifications of doctors, learn medical knowledge, and conduct self-health management. They can also get medical guidance and consultation services to improve the efficiency of consultation, so as to gain perceived benefits. However, the content of users' online interaction involves identity information, health condition, past medical history, etc., and users are concerned about the disclosure of personal privacy information. In and Zhang (2017) believe that the risk of privacy disclosure has a negative impact on the user's intention to provide information. Thus, we submit the following hypothesis:

H1: Perceived benefit has a positive impact on users' usage intention.
H2: Perceived risk has a negative impact on users' usage intention.
2.2. Theory of social support
Social support is the sum total of unrewarding social network behaviors that help vulnerable groups in society, involving a certain spirit or substance. Social support in online medical community mainly affects the health status of users from two aspects: information support and emotional support (Yang and Ju, 2017). Yan and Tan (2014) have shown that emotional support and information support can positively affect the health status of online medical community users. In the online medical community, high-quality medical information can not only improve the medical literacy of users, but also reduce the information weakness of patients in the process of doctor-patient communication and enable users to obtain information support, thus increasing the possibility of disease cure. Users can obtain emotional comfort by browsing other users' medical experience or communicating with community members, and receive care, greetings and spiritual encouragement from other online medical users, thus obtaining emotional support. We assume that:

H3: Information support has a positive impact on users' usage intention.

H4: Emotional support has a positive impact on users' usage intention.

2.3. Theory of information asymmetry
The theory of information asymmetry was first proposed in 1970 by George Akerlof, who studied the used-car market and found that sellers had more information about the car than buyers, leading to a decline. Information asymmetry refers to the situation where the information of both parties in a transaction is not equal, which will lead to the imbalance of interests, costs and risks of both parties (Zhou, 2010). In the online medical community, users are always at an information disadvantage due to their lack of knowledge about drug choices, treatments and medical costs. Whether the user trusts the service quality of the online medical community, whether the doctor's qualification and the expected result of diagnosis and treatment can be trusted are all factors affecting the user's intention. Trust between the medical service provider and the recipient is an important guarantee for achieving good medical results. Tang et al. (2018) believed that users' trust in online health communities positively affected the adoption intention of health information, we make the hypothesis:

H5: User trust has a positive impact on users' usage intention.

2.4. Influence of medical effect on user's use intention
No matter how eye-catching the service publicity is, it is not enough to get the point across. Besides, people will become loyal users due to the good effect of medical information service. The medical effect can greatly influence whether users continue to use online medical community. If the results of medical advice and diagnosis and treatment obtained by users are good, then users believe that the medical community is reliable and have a higher intention to use the online medical treatment acanthuses posit that:

H6: The medical effect has a positive impact on the users' usage intention.

2.5. Theory of information behavior of "Type Person"
Alan Cooper (2006) defines the theory of "Type Person" as: "Accurately describe user characteristics and what users want to accomplish, and clearly represent user categories and their nature". The "Type Person" model was initially used in the field of interaction and has played a huge role. The advantage of the research results is that it can clearly show several types of typical users and their attributes. Mulder and Yaar (2006) pointed out that the "Type Person" model has theoretical significance in studying user behavior patterns and practical significance in the process of system interaction design. Gu Liping (2010) applied this model to classify library users for the first time in library and information science, and established the search behavior model of users from the perspective of differentiation. Based on the information behavior theory of "Type Person", this paper analyzes and studies the behavior patterns of each type of users.

We extract the influencing factors of users' Usage intention according to perceived value, social support and information asymmetry. The theoretical model consists of six research variables, namely
perceived benefit, perceived risk, information support, emotional support, medical effect and user trust, and one dependent variable, usage intention, this paper proposes an users’ usage intention influencing factor model in online medical community (See Fig. 1).

![Figure 1. Users’ usage intention model in online medical community](image)

3. Methodology

3.1. Research measurements
In this study, data were collected by questionnaire survey. The questionnaire consists of two parts: the first part is the basic personal information questions designed to understand the characteristics of users' medical behavior; The second part is Likert five subtables of six independent variables of influence factors and dependent variables of intention, the score of 1-5 indicates complete disagreement, basic disagreement, general agreement, basic agreement, and complete agreement. There are a total of 7 variables in the online medical community user intention influencing factor model, namely perceived benefit (PB), perceived risk (PR), information support (IS), emotional support (ES), medical effect (ME), user trust (UT) and usage intention (UI). The scale design refers to the existing mature measurement standards and adjusts and improves the scale based on expert suggestions, the reliability of questionnaire quality is ensured. The measurement questions are measured by five-point Likert-type scales (1= totally disagree, 5=totally agree), and each latent variable contains at least three measurement questions, which ensures that the measurement questions can truly and effectively represent the meaning of latent variables. Before the large-scale survey, a preliminary survey was conducted on the questionnaire and its reliability and validity was tested. The Cronbach’s α was all greater than 0.7, indicating that the questionnaire had good credibility. At the same time, the questionnaire contents were adjusted according to expert feedback and factor analysis results to ensure the validity of the questionnaire.

3.2. Procedure
This study is a survey of users in the online medical community. Questionnaires are distributed on the "Sojump" platform, the randomness of respondents is high and not subject to geographical restrictions, which reflects a certain degree of random sampling. 265 online questionnaires were collected from users of China's "Good doctor online" website from March to April 2020. The data were screened and cleaned, 25 invalid questionnaires were deleted, 240 valid questionnaires were retained, and the questionnaire recovery efficiency was 90.6%. The reasons for the invalid questionnaire were mainly that the respondents filled in the questionnaire for a short time or filled in the same scale options.
3.3. Respondents

Four different demographic variables, including gender, age, education level, and monthly income, were considered to determine the profile of the participants. In terms of gender, male users (51.7%) are slightly more than female users (48.3%). In terms of age, users are mainly 18-25 years old (20%), 26-30 years old (38.8%), and 31-40 years old (27.1%), indicating that online medical users belong to the youth and middle age stage. In terms of educational level, the majority are junior colleges (19.2%), bachelor's degree (63.3%), and master's degree or above (10.4%). In terms of monthly income, the average monthly income of users is mainly below 4,000 yuan (47.9%), and 4,000-8,000 yuan (40.4%). The above results show that the online medical community users are young and middle-aged (26-40 years old), middle and higher education (junior college, bachelor's degree), middle and low income (less than 8000 yuan) people. These users conform to the characteristics of Internet active population, which makes this study of certain significance.

| Variable (Category) | Frequency (n) | Percentage (%) |
|---------------------|---------------|----------------|
| Gender              |               |                |
| Male                | 124           | 51.7%          |
| Female              | 116           | 48.3%          |
| <18                 | 2             | 0.8%           |
| 18-25               | 48            | 20.0%          |
| 26-30               | 93            | 38.8%          |
| 31-40               | 65            | 27.1%          |
| 41-50               | 23            | 9.6%           |
| >50                 | 9             | 3.8%           |
| Primary school      | 1             | 0.4%           |
| Junior high school  | 4             | 1.7%           |
| Education level     |               |                |
| High school         | 12            | 5.0%           |
| Junior college      | 46            | 19.2%          |
| Bachelor's degree   | 152           | 63.3%          |
| Master degree or above | 25       | 10.4%          |
| <4000               | 115           | 47.9%          |
| >8000               | 28            | 11.7%          |

Note: CNY, China Yuan. 1 CNY ≈ 0.145 USD.

4. Results and discussion

4.1. Reliability and validity of measures

Cronbach’s α reliability test was used for reliability analysis. The higher the reliability, the better the stability of the scale. In this paper, SPSS was used to test the reliability and validity of the scale data. The Cronbach’s α coefficient of each variable was above 0.6, indicating that the scale has good consistency and reliability, and the reliability level is acceptable (as shown in Table 2). Validity test is mainly evaluated according to content validity and structure validity. Content validity tests the rationality and comprehensiveness of the items in the scale. The questionnaire in this paper draws on the mature scale system and is revised by experts, so it has good content validity. Structural validity is used to verify how accurately the measurement question interprets each variable. In this paper, SPSS was used to conduct factor analysis on the sample data to test its validity, Kaiser-Meyer-Olkin (KMO) value was used to test the simple correlation coefficient and partial correlation coefficient between variables, and Bartlett’s test was used to test the correlation between variables in the correlation matrix. If KMO value is less than 0.6, it means that it is very unsuitable for factor analysis. If KMO value is greater than 0.9, it is very suitable for factor analysis. In between, it can be accepted for factor analysis.
If the factor load is less than 0.45, the validity is not good; if the factor load is greater than 0.5, the validity is normal. As shown in Table 2, it can be seen that the KMO values of the 7 variables are all greater than 0.6, and the Bartlett’s P values are all less than 0.001, so the sample data is suitable for factor analysis. In addition, the factor loading of each observed variable was also greater than 0.6, indicating that the measurement question could well explain the variable. Therefore, the measurement scale has good reliability and validity.

**Table 2. Results of reliability and validity (N = 240)**

| Constructs         | Items  | Loadings | KMO  | Bartlett’s test | Cronbach’s α |
|--------------------|--------|----------|------|-----------------|--------------|
| Perceived Benefit  | PB1    | 0.792    |      | 0.720           | 0.696        |
|                    | PB2    | 0.865    |      |                 |              |
|                    | PB3    | 0.694    |      |                 |              |
|                    | PB4    | 0.871    |      |                 |              |
|                    | PR1    | 0.748    |      |                 |              |
| Perceived Risk     | PR2    | 0.737    | 0.658| 0.000           | 0.765        |
|                    | PR3    | 0.757    |      |                 |              |
|                    | IS1    | 0.847    |      |                 |              |
|                    | IS2    | 0.743    |      |                 |              |
|                    | IS3    | 0.692    |      |                 |              |
|                    | IS4    | 0.836    |      |                 |              |
|                    | ES1    | 0.672    |      |                 |              |
| Information Support| IS2    | 0.697    | 0.775| 0.000           | 0.741        |
|                    | ES3    | 0.869    |      |                 |              |
|                    | ME1    | 0.732    |      |                 |              |
| Emotional Support  | ES2    | 0.697    | 0.775| 0.000           | 0.741        |
|                    | ES3    | 0.869    |      |                 |              |
|                    | ME2    | 0.851    | 0.806| 0.000           | 0.776        |
|                    | ME3    | 0.729    |      |                 |              |
|                    | UT1    | 0.836    |      |                 |              |
| Medical Effect     | ME2    | 0.851    | 0.806| 0.000           | 0.776        |
|                    | ME3    | 0.729    |      |                 |              |
|                    | UT1    | 0.792    | 0.793| 0.000           | 0.807        |
| User Trust         | UT2    | 0.661    |      |                 |              |
|                    | UT3    | 0.661    |      |                 |              |
|                    | UT4    | 0.696    |      |                 |              |
|                    | UI1    | 0.852    |      |                 |              |
| Usage Intention    | UI2    | 0.739    | 0.694| 0.000           | 0.792        |
|                    | UI3    | 0.671    |      |                 |              |

4.2. *Correlation analysis*

Correlation analysis studies the degree of correlation between two variables. As the data is not continuous and is classified variable data, no normality test is conducted in advance. Therefore, Spearman correlation coefficient is selected for correlation analysis of variables. As shown in Table 3, the correlation coefficients were all between 0.6 and 0.8, and the significance level of the correlation was all less than 0.01, indicating that there was a significant linear correlation between each influencing factor variable and the user's use intention.

**Table 3. Spearman correlation coefficient between each variable and usage intention**

| Path      | Sample size | Item number | Coefficient | Sig.(2-tailed) |
|-----------|-------------|-------------|-------------|----------------|
| PB→UW     | 240         | 4           | 0.669***    | .000           |
| PR→UW     | 240         | 3           | 0.612**     | .003           |
| IS→UW     | 240         | 4           | 0.600**     | .008           |
| ES→UW     | 240         | 3           | 0.663***    | .000           |
| ME→UW     | 240         | 3           | 0.793***    | .000           |
| UT→UW     | 240         | 4           | 0.757**     | .004           |

*Note: p < 0.05, **p < 0.01, ***p < 0.001.*
4.3. Regression analysis on usage intention

Regression analysis is a statistical analysis method to determine the interdependence between two or more variables. We use multiple regression analysis method to test the hypothesis. PSS was used for multiple regression analysis, and it was found that the adjusted determination coefficient $R^2$ was 0.76, indicating that each variable as a whole could explain the 76% change of users' usage intention, and the model had a good goodness of fit. The overall test F value of the regression model is 38.435, and the corresponding significance level is less than 0.001, indicating that at least one of all independent variables will influence the usage intention. Therefore, it can be considered that the regression model has a significant linear relationship.

The hypothesis testing results of this model are shown in Table 4. The $B$ value represents the non-standardized regression coefficient. It can be seen that the perceived risk (-0.226***) has a significant negative impact on the users' usage intention, while other factors have a positive impact on the users' usage intention, and the model hypothesis has been verified. According to the standardized regression coefficient $\beta$ value, among the six influencing factors, the medical effect is the most influential, followed by user trust, perceived benefit and perceived risk, and finally, emotional support and information support. The significance level corresponding to the T value of the six variables is less than 0.05, that is, each influencing factor can effectively predict the change of users' use intention with at least 95% assurance. Tolerance is greater than 0.1 and variance inflation factor (VIF) is less than 10, indicating that there is no multicollinearity problem between independent variables. Fig. 2 shows the regression analysis results of the usage intention influencing factor model.

| Path      | B  | $\beta$ | T   | Sig. | Tolerance | VIF  |
|-----------|----|---------|-----|------|-----------|------|
| constant  | .120 | .376   | .708 |      |           |      |
| PB→UI     | .330 | .263   | 3.089 | .003 | .468      | 2.137|
| PR→UI     | -.226 | -.230 | -3.671 | .000 | .865      | 1.156|
| IS→UI     | .165 | .140   | 1.329 | .019 | .303      | 3.302|
| ES→UI     | .168 | .160   | 1.610 | .012 | .344      | 2.911|
| ME→UI     | .539 | .461   | 4.325 | .000 | .298      | 3.359|
| UT→UI     | .343 | .294   | 2.781 | .007 | .303      | 3.295|

Note: $B$, unstandardized coefficients; $\beta$, standardized coefficients.

Figure 2. Results of the users’ usage intention influencing factor model
Note: Unstandardized coefficients; *p<.05, **p<.01, ***p<.001
4.4. Analysis of user behavior patterns

4.4.1. Basic statistics. The success of business through the Internet model is based on user engagement. In the past, the research often regarded the user as a whole and seldom studied the regular relationship between the user participation behavior pattern and different behaviors. In order to further understand users' online medical information behavior, we conducted descriptive analysis of users' medical behavior data. In terms of whether they have used online paid medical consultation, 98 online medical users (40.8%) have used paid medical consultation, indicating that paid medical consultation has good user recognition and conversion rate. In terms of the ways for users to pay for consultation, graphic consultation (56.7%), telephone consultation (27.1%) and voice consultation (15.4%) account for the majority, indicating that the most acceptable communication mode for users is online graphic chat, so as to avoid direct communication with doctors. In terms of the average monthly consultation times of users, 80.4% chose 0 to 2 times, indicating that the user stickiness of online medical community is insufficient. In terms of disease types, internal medicine (55%), paediatrics (12.1%) and surgery (10.4%) accounted for the majority, indicating that the medical information consulted by users online was dominated by internal medicine, pediatrics and surgery.

4.4.2. Classification of user behavior patterns. According to the information behavior theory of "Type Person", we use the Two-Step clustering method of SPSS to cluster each categorical variable and analyze and study the behavior pattern of each type of user on six influencing factors. After constant testing, the clustering effect of age, income and educational level was better. According to the three-basic information of users, the online medical user group is divided into four categories, category A accounts for 20.8% of the sample, Category B accounts for 19.5%, category C accounts for 23.6% and Category D accounts for 36.1%. The classification scale does not appear too large or too small, and the overall classification degree is good. After the end of clustering, the category of each user can be seen in the SPSS original data. After research and analysis, the user type definition is shown in Table 5.

| User Type | Details |
|-----------|---------|
| "Type A" users | Young people with medium education level and income |
| "Type B" users | Middle-aged people with lower education level and lower income |
| "Type C" users | Middle-aged people with medium education level and higher income |
| "Type D" users | Young people with higher education and lower income |

Depending on the different number of users in each category, we use the mean value to analyze the behavior patterns of the four categories of users. The average score of factors influencing users' usage intention is shown in Table 6. It can be seen that "Type A" users have the lowest satisfaction on perceived benefit and information support, while perceived risk is higher. At the same time, the recognition degree of other indicators is also low, indicating that such users have low intention to use online medical community. Combined with the characteristics of such users, they are young, generally have little or no diseases, and pay attention to privacy risks, they will not think that online medical community will be of great help to them, so their usage intention is low. “Type B” users have the lowest recognition degree in terms of medical effect and perceived risk, and moderate recognition degree in other indicators, indicating that such users are not worried about the risks of online medical treatment, but also do not recognize its medical effect, and are mainly skeptical about the medical effect. Combined with the characteristics of these users, they are middle-aged people with lower education and lower income. Their personal characteristics determine that they are greatly affected by the medical effect, while their lack of profound understanding of the Internet makes them underestimate the risks of online medical treatment. “Type C” users have the highest satisfaction in all indicators, but the lowest in terms of emotional support. Combined with the characteristics of users, they have higher income and generally...
have less emotional needs for online community interaction. “Type D” users have the highest perceived risk and emotional support, but the lowest trust. Combined with the characteristics of users, these users hope to obtain higher emotional support when faced with the mismatch between high education and low income, but they believe that online medical treatment is full of risks, so they distrust the online medical community.

Table 6. Results of user behavior patterns classification

| User Type   | Perceived Benefit | Perceived Risk | Information Support | Emotional Support | Medical Effect | User Trust |
|------------|-------------------|----------------|---------------------|-------------------|----------------|-------------|
| "Type A" users | 3.47              | 3.58           | 3.45                | 3.42              | 3.60           | 3.38        |
| "Type B" users | 3.50              | 3.16           | 3.54                | 3.51              | 3.54           | 3.63        |
| "Type C" users | 4.11              | 3.18           | 4.01                | 3.32              | 3.91           | 3.93        |
| "Type D" users | 3.52              | 3.69           | 3.64                | 3.94              | 3.58           | 3.32        |

5. Conclusions and implications

By collecting data through questionnaire survey, we explored the influencing factors of online medical users’ usage intention and their influencing relationship. On this basis, the influence of various factors on different user behavior patterns is studied, hoping to provide research reference for online medical community to improve the quality of medical information service.

5.1. Conclusions

The users of the online medical community are mainly young and middle-aged (26-40 years old), middle and higher education (junior college, bachelor's degree), middle and low income (below 8000 CNY). Paid consultation is supported by users with good user recognition and conversion rate. However, the user stickiness is not enough, on average, the users visit the website 0 to 2 times per month, and the diseases they consult are mainly internal medicine, which reflects the objective limitations of the disease consultation in the online medical community. Finally, through cluster analysis, users are divided into four categories, and it is found that "Type A" users have a lower usage intention, "Type B" users are skeptical about medical effect, "Type C" users have a higher intention, and "Type D" users pay more attention to emotional support.

By building users’ usage intention influencing factor model in online medical community, we put forward six theoretical hypotheses, using multiple linear regression to verify these hypotheses. The results showed that users’ usage intention was positively affected by perceived benefit, information support, emotional support, medical effect and user trust, while perceived risk could negatively affect users’ usage intention. Medical effect had the greatest effect on usage intention, with a standardized coefficient of 0.461 (Sig.<0.001), while the standardized regression coefficient of information support was 0.140 (Sig.<0.05), which has a low impact on the usage intention. It can be seen that the quality and effectiveness of online medical community medical information is what users are most concerned about.

5.2. Implications for the online medical community

This paper constructs the users' usage intention influencing factors model in online medical community. By analyzing the users' usage intention influencing factors and the medical behavior patterns of each type of user, we believe that online medical community should make corresponding improvement from the following three aspects: Accurate information service should be adopted for the target customer group; User perceived risk should be reduced; The quality of medical information service needs to be improved. Therefore, three suggestions are proposed for the online medical community:
(1) In terms of users: Targeted at the target user groups of young and middle-aged (26-40 years old), middle and higher education level (junior college, bachelor's degree), middle and low income (below 8000 CNY), precise recommendation of medical information service should be adopted when recommending medical information and communicating with each other, so as to reduce costs and improve service efficiency. To solve the problem of insufficient user stickiness, more community activity modules should be carried out to attract users to contribute flow. For "Type A" users should provide more preferential measures to improve their intention. In view of the "Type B" users should recommend more medical treatment and health care knowledge, increase users' trust in the medical effect. For "Type C" users, new modules should be carried out constantly to maintain user loyalty, and for "Type D" users, more discussion communities should be carried out to increase emotional support and user trust.

(2) In terms of privacy protection: the perceived risk of users in the online medical community mainly come from the risk of users' medical privacy. On the one hand, online medical community should strengthen the protection and supervision measures of users' health information, and improve the data security performance of the information system; On the other hand, publicity measures should be adopted to enhance users' self-protection awareness of personal privacy information.

(3) In terms of deepening information services: Users pay more attention to the quality and value of medical information services when using online medical services. Meanwhile, the research results of this paper show that the medical effect is the biggest factor affecting users' usage intention. The online medical community should accurately analyze the users' medical information needs and preferences, maximize the quality of medical information and improve user satisfaction, so as to effectively solve the users' medical information needs and actual needs for interaction and communication, and finally improve the users' intention to use the online medical community.

5.3. Limitations of the study and further research
In the context of COVID-19, the analysis of factors influencing users' usage intention and user behavior patterns in online medical communities has certain reference value for future research in online medical community. Meanwhile, the suggestions proposed in this paper can help online medical communities provide better medical services. However, there are still two deficiencies in this study. Firstly, the questionnaire design only considers the user side and only a few questions explore the user behavior patterns. The questionnaire design has not been evaluated by online doctors, and its comprehensiveness and persuasion have not been further improved. Secondly, the questionnaire sample size of target users is relatively small, so more should be collected to obtain more accurate research conclusions. To sum up, in the future research process, we should ensure the quality of the previous research, and put forward more constructive research conclusions on the basis of previous studies, so as to provide more reliable research support for the development of online medical community.

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