Postprint: Study on Influencing Factors of Patient Physician Choice Behavior in Online Healthcare Communities

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Abstract

[Purpose/Significance] Online medical communities, as emerging platforms for doctor-patient interaction, leverage consultation services as a vital function to attract users, with paid consultation representing a key profit module for these communities. Understanding the information needs and influencing factors underlying patients' doctor-selection behavior in paid consultations can effectively improve physician services and enhance community vitality. [Method/Process] Grounded in consumer trust theory and consumer perception theory, and considering the research context of online communities, this study innovatively incorporates the effects of price and herd mentality to establish an influence model of patients' doctor-selection behavior in online medical communities. Using Haodf.com as a case study, website data was crawled for regression analysis to verify causal relationships among variables. [Results/Conclusion] Empirical analysis confirms the influence of physicians' offline reputation, online word-of-mouth, service quality, contribution value, popularity, and price on patients' doctor-selection behavior, while also revealing differences between online and traditional offline doctor-selection behaviors. The findings provide reference recommendations for physicians to improve services and for platform communities to boost activity and revenue.

Full Text

Study on Influencing Factors of Patients' Doctor-Selection Behavior in Online Healthcare Communities

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Abstract:

[**Purpose/Significance**] As an emerging platform for doctor-patient interaction, online healthcare communities rely heavily on consultation services to attract users, with paid consultations representing a key revenue module. Understanding the information needs and influencing factors behind patients' doctor-selection behavior during paid consultations can help improve physician services and enhance community vitality. [**Method/Process**] Based on consumer trust theory and consumer perception theory, and considering the unique context of online communities, this study innovatively incorporates price and herd psychology to construct an influence model of patient doctor-selection behavior in online healthcare communities. Using Haodf.com as a case study, website data was crawled and regression analysis was conducted to verify causal relationships between variables. [**Result/Conclusion**] The empirical analysis confirms that physicians' offline reputation, online word-of-mouth, service quality, contribution value, popularity, and price all influence patients' doctor-selection behavior, with notable differences from traditional offline doctor-selection. The findings provide reference suggestions for physicians to improve services and for platforms to enhance community engagement and revenue.

Keywords: online healthcare community; doctor-selection behavior; influencing factors; consumer trust; consumer perception

1. Introduction

The development of Internet technology has driven the maturation of online community models. As a thematic variant of network communities, online healthcare communities represent a typical "Internet + Healthcare" model that aggregates medical and health-related information. Various online healthcare services have emerged, including health information search, online consultation, and appointment scheduling. By overcoming spatial and temporal limitations, reducing costs and treatment expenses, and effectively protecting user privacy, Internet-based healthcare has cultivated a growing habit of seeking health consultations online. Users can select appropriate physicians for diagnosis while quickly understanding their conditions, facilitating early intervention and treatment planning. The primary participants are patients and physicians. In online healthcare communities, physician behaviors mainly include three types: regularly updating personal and appointment information, publishing articles periodically, and responding to patient consultations. Patients complete a medical consultation process through five behaviors: browsing information, searching and accessing content, selecting physicians, consulting doctors, and providing online evaluations. Figure 1 [Figure 1: see original paper] illustrates this process and the reference factors patients consider at each stage, which primarily include browsing/searching for information, selecting physicians for consultation, and providing feedback.

Online consultation services genuinely meet patient needs, attracting more users to the platform community, and these users' payments for consultation services constitute one of the platform's revenue sources. Therefore, studying doctor-selection behavior essentially means studying consumer behavior. Although the novel healthcare service model of online doctor-patient communication and patient interaction has significantly improved existing problems in the healthcare industry, questions remain about how patients identify target consultation physicians online, how physicians attract patients, and how to increase consultation order volume.

This study focuses on patients' doctor-selection behavior when choosing physicians for consultation. Based on theories influencing users' online consumption behavior, we explore the factors affecting patients' physician selection and the mechanisms through which these factors operate. The findings will provide clearer guidance for physicians in online healthcare communities to improve service quality, offer scientific basis and explanations to help patients quickly identify suitable physicians, provide suggestions for platform operators to enhance community engagement and transaction volume, and serve as a supplement to online healthcare community research.

2. Related Theories and Hypothesis Model

The primary theories influencing patients' doctor-selection behavior in online healthcare communities include trust theory, perception theory, herd theory, and demand theory. Below, we derive six factors affecting patient doctor-selection behavior based on these four theories, combined with the online healthcare community context. For each factor, we select one to three research variables, resulting in twelve influencing variables for which model hypotheses are proposed, as shown in Table 1 .

Table 1: Correspondence Between Influence Theories, Factors, and Indicators with Research Foundations

Influence Theory	Influence Factor	Influence Indicators	Research Foundation
Trust Theory	Physician Offline Reputation	Physician Title, Hospital Level, City Level	Li Qi et al. [], Jiang Jinhu et al. [], K.S. Freeman et al. [], H. Fan et al. [], Wu Jiang et al. []
Trust Theory	Physician Online Word-of-Mouth	Short-time Feedback, Long-time Feedback, Paid Feedback	Li Qi et al. [], R.A. Bauer et al. [], E. Sillence et al. [], O. Ueland et al. [], K.B. Murray et al. [], L.J. Steyn et al. []

Influence Theory	Influence Factor	Influence Indicators	Research Foundation
Perception Theory	Physician Contribution Value	Knowledge Contribution Volume	Liu Jiang et al. []
Perception Theory	Physician Service Quality	Attitude Satisfaction, Effect Satisfaction, Timeliness Satisfaction	W. Luo et al. [], Wu Jiang et al. []
Herd Theory	Patient Herd Psychology	Comprehensive Popularity	
Demand Theory	Service Price Factor	Consultation Price	

2.1 Trust Theory Trust theory refers to community users' confidence in and willingness to depend on providers of online products (including tangible goods or intangible services) during opinion adoption and purchase processes. Existing research primarily explores online consumption influencing factors from perspectives such as product reputation, word-of-mouth, brand, and reliability. Consumer trust mainly relates to seller word-of-mouth, reputation, and consumer interest protection mechanisms []. Some researchers argue that product safety and reliability affect purchase intention by influencing customer trust [].

2.1.1 Influence of Physician Offline Reputation on Doctor-Selection Behavior

In online healthcare communities, all registered physicians undergo real-name authentication, with their titles, hospitals, and cities displayed. More economically developed regions with higher development levels have better overall medical conditions that attract outstanding medical talent. Different hospital levels represent the overall medical standards of institutions, with higher-level hospitals possessing superior medical infrastructure, technical capabilities, talent resources, and resource allocation. Different professional titles represent physicians' professional levels and authority, with higher-ranked physicians having accumulated extensive clinical experience through long-term practice and possessing greater expertise.

Therefore, in online medical consultation services, patients perceive physicians with higher titles, higher-level hospitals, and more developed locations as having stronger professionalism and authority, making them more likely to select these physicians' services. Based on this analysis, we propose the following hypotheses:

- **H1:** Physician title has a positive impact on online physicians' consultation volume

- **H2:** Hospital level has a positive impact on online physicians' consultation volume

- **H3:** City level has a positive impact on online physicians' consultation volume

2.1.2 Influence of Physician Online Word-of-Mouth on Doctor-Selection Behavior

In online healthcare communities, physician homepages display various forms of patient feedback, including thank-you letters, gift counts, and vote counts. After physicians complete consultation services, patients can provide feedback through quick voting or more time-consuming methods like writing premium reviews or thank-you letters, or by purchasing virtual gifts for physicians as expressions of gratitude. Patient feedback behavior both expresses gratitude and affirms physicians' professional competence and service quality. For subsequent patients, this information-sharing behavior provides additional physician information, reduces negative impacts from information asymmetry, and facilitates more suitable physician selection.

Thus, in online medical consultation services, more patient feedback indicates higher trust and recognition from treated patients, conveying positive information to other patients who become more inclined to select that physician's services. Based on this analysis, we propose:

- **H4:** The number of paid patient feedback instances positively influences physicians' consultation volume in online healthcare communities
- **H5:** The number of short-time feedback instances positively influences physicians' consultation volume

- **H6:** The number of long-time feedback instances positively influences physicians' consultation volume

2.2 Perception Theory Perception theory encompasses perceived risk and perceived benefit. Perceived risk refers to users' sense of purchase risk regarding paid behaviors, used to analyze and explain purchasing behavior []. Six dimensions of perceived risk are identified: financial risk, product function risk, social risk, psychological risk, physical risk, and time risk []. Physical risk primarily concerns potential harm to health from purchased products or services; function risk concerns quality mismatches with expectations; financial and time risks concern mismatches between costs and benefits. Perceived benefit refers to advantages and gains consumers feel from products or services. Perceived risk and benefit jointly influence consumption intention and ultimately behavior []. In online health services, perceived benefit and risk significantly impact user consumption intention [].

2.2.1 Influence of Physician Contribution Value on Doctor-Selection Behavior

In online healthcare communities, physician homepages display their knowledge contribution to the platform. Beyond paid consultations, physicians publish popular medical articles to increase platform visibility, attract potential users, and contribute to the platform while demonstrating research capabilities and medical expertise. Greater knowledge contribution leads patients to perceive stronger medical competence and higher-quality consultation services. Based on this analysis, we propose:

- **H7:** Physicians' knowledge contribution volume positively influences their consultation volume

2.2.2 Influence of Physician Service Quality on Doctor-Selection Behavior

Physician homepages display patient evaluations of service quality across multiple dimensions, including attitude, effectiveness, and timeliness satisfaction. Effectiveness satisfaction represents satisfaction with treatment recommendations' validity, reflecting professional competence and medical technical level. Attitude satisfaction reflects overall service level and physician demeanor throughout consultations. Timeliness satisfaction primarily reflects online response speed—a crucial factor as patients expect rapid replies to resolve their concerns. Higher satisfaction from treated patients and faster response times create impressions of high-level, amiable service for subsequent patients.

Therefore, higher patient satisfaction indicates better service quality, making patients feel they face lower financial, physical, and psychological risks with greater perceived benefits, such as more professional service, more effective treatment recommendations, and good service attitudes. This attracts subsequent patients to preferentially select such physicians. Based on this analysis, we propose:

- **H8:** Attitude satisfaction positively influences online physicians' consultation volume
- **H9:** Service effect satisfaction positively influences online physicians' consultation volume

- **H10:** Service timeliness satisfaction positively influences online physicians' consultation volume

2.3 Herd Theory Herd behavior is a common phenomenon in social psychology, describing the process of adapting one's actions and beliefs to group or collective requirements. It refers to individuals abandoning personal opinions under group or media pressure to align with majority behavior. Existing research indicates that consumer attitudes and habits significantly influence herd behavior [], which in turn significantly impacts purchase intention.

Influence of Herd Psychology on Doctor-Selection Behavior

Patients selecting physicians in online healthcare communities are influenced by herd psychology, tending to choose physicians with high attention and large patient assistance numbers, believing such physicians offer better service quality and authority. This study defines physician comprehensive popularity as the herd psychology factor. Based on herd theory's influence on online consumption, we propose that herd psychology is a factor influencing patient doctor-selection behavior in online healthcare communities:

- **H11:** Physicians' comprehensive popularity positively influences their consultation volume in online healthcare communities

2.4 Demand Theory In economic principles, demand refers to the quantity of goods consumers are willing and able to purchase at each price level during a given period. The law of demand states an inverse relationship between price and quantity demanded. In online medical consultation services, patients' willingness to pay for consultations similarly depends on service price. Existing research has incorporated price factors into health information service purchase decision influences [].

Influence of Service Price on Doctor-Selection Behavior
In online medical consultation services, patients must pay for consultations, with fees varying by physician. Consultation fees can reflect service quality and authority to some extent while obeying demand theory. However, the influence of consultation fees on patient doctor-selection is also constrained by demand theory: higher prices reduce demand, while lower prices increase demand. As a service commodity, online medical consultation services do not meet exception conditions for Giffen goods, Veblen goods, or cultural/religious products, thus satisfying demand theory. Based on this analysis, we propose:

- **H12:** Physicians' service fees negatively influence their consultation volume in online healthcare communities

2.5 Hypothesis Model Public information in online healthcare communities forms the primary basis for patients' perception, trust, and herd psychology toward physicians. The online healthcare platform serves as a control variable, with platform differences excluded from consideration. Therefore, we establish the research model shown in Figure 2 [Figure 2: see original paper], where patient trust, patient perception, herd psychology, and price jointly influence doctor-selection behavior. This study analyzes how various community information types affect patient doctor-selection behavior, treating patients as an aggregated research group and thus excluding individual patient characteristics.

3. Data Collection and Cleaning

3.1 Data Collection and Variable Definition This study selected "Haodf.com" as the research subject. Since patients develop cognition of physicians through website browsing and select physicians based on this information, we crawled publicly available website data. Using Python, we developed a crawler program to capture physician data from March 2018, including real-name authenticated physicians with medical consultation records. We crawled basic information about physicians, hospitals, and regions from hospital and physician lists, and collected data on services provided, platform contributions, and patient feedback from individual physician homepages. After matching by physician ID, we obtained 17,011 raw data records. We selected corresponding data indicators from actual website data as variables for empirical research.

Independent variables were selected based on model hypotheses and corresponding empirical indicators from website data. Physician reputation factors used physician title, hospital level, and city level as empirical indicators representing real offline information. Physician knowledge contribution used article publication count as the empirical indicator, reflecting professional standards through article publication. For physician service quality factors, attitude satisfaction corresponded to attitude ratings, effect satisfaction to efficacy ratings, and timeliness satisfaction to response timeliness rates. For physician word-of-mouth factors, short-time feedback corresponded to vote counts, long-time feedback to thank-you letter counts, and paid feedback to gift counts. Patient herd psychology used patient recommendation popularity as the empirical indicator, representing other patients' endorsed physician popularity. Service price factors used consultation price as the empirical indicator.

The dependent variable represents the model's research objective. This study examines patient doctor-selection behavior—the act of choosing which physician to consult among many options. On Haodf.com, physician homepages display total patient consultation numbers, which we selected as the dependent variable to explore how various factors influence total consultation volume.

3.2 Data Preprocessing This section preprocesses raw data through cleaning to obtain data meeting descriptive statistical requirements and transformation to meet correlation and regression analysis requirements. Preprocessing steps include: valid field data matching, character field assignment conversion, missing value treatment, descriptive statistical analysis, and data transformation (normalization, standardization) followed by outlier removal.

3.2.1 Data Cleaning

Based on selected variables, we deleted irrelevant raw data and matched crawled data by physician ID. Character field assignment conversion rules are shown in Table 2 , with physician titles divided into 4 levels (low to high), hospital levels into 9 levels, and city levels into 4 levels (high to low). Physician titles were coded as: Resident=1, Attending=2, Associate Chief=3, Chief=4. Hospital levels were retrieved by hospital name and coded from Level 1C=1 to Level 3A=9. City levels were retrieved by hospital location and coded as: Tier-1=1, Tier-2=2, Tier-3=3, Tier-4=4.

Missing value treatment employed both filling and deletion. Since satisfaction and response rate data showed small variance, we used mean value imputation. Missing values in physician title, hospital level, city level, recommendation popularity, consultation price, and total consultation volume rendered entire records meaningless and were treated as anomalies for deletion. Missing values in vote counts, thank-you letters, gift counts, and article counts held practical significance and were replaced with 0, indicating no contribution or income. After processing, 13,114 cleaned data records remained.

3.2.2 Descriptive Statistics
Descriptive statistical analysis examined overall variable distributions in the cleaned dataset. Since variables were not strictly normally distributed, we used mean, standard deviation, quartiles, and skewness to describe data distributions (see Table 2). Results show: (1) Physician offline reputation factors (title and hospital level) had relatively high means, indicating high overall medical resource quality in the community; (2) Physician online word-of-mouth factors showed large standard deviations, indicating significant differences; gift count data showed the highest dispersion; (3) In physician contribution value factors, article publication count showed high dispersion, reflecting varying attitudes toward article publishing; (4) Consultation price showed considerable dispersion, indicating pricing differences; (5) The dependent variable (consultation volume) showed significant variation and dispersion, making the study of influencing factors valuable for service improvement.

3.2.3 Data Transformation
Given large magnitude differences between variables and obvious skewed distributions (except for physician title, hospital level, city level, and recommendation popularity), we applied square transformation for left-skewed data (vote counts, thank-you letters, gift counts, article counts) and logarithmic transformation for right-skewed data (attitude satisfaction, efficacy satisfaction, response timeliness rate, consultation price, consultation volume) to scale data uniformly and reduce skewness. We removed outliers beyond confidence intervals to reduce noise. Using confidence intervals bounded by mean $\pm$ sampling error, we obtained 9,145 final records suitable for correlation and regression analysis.

4. Empirical Research

4.1 Spearman Correlation Analysis To avoid multicollinearity in multiple regression models, we conducted correlation analysis of all independent variables. Spearman correlation was applied to the final cleaned data as it better suits datasets with non-continuous variables than Pearson correlation. Table 3 shows strong correlations between vote counts and thank-you letters (r=0.916), and between efficacy satisfaction and attitude satisfaction (r=1.00). Consultation price and physician title also showed strong correlation (r=1.00). Other variable correlations remained within normal ranges.

4.2 Regression Analysis Based on correlation analysis, we established two control groups for strongly correlated indicators to eliminate collinearity. Group A retained consultation price, attitude satisfaction, and thank-you letter count; Group B retained physician title, efficacy satisfaction, and vote count. Using SPSS for regression analysis on normalized datasets, results appear in Table 4

. Both groups showed consistent performance, indicating reliable model conclusions. R^2 values exceeded 0.59, indicating independent variables explained over 59% of dependent variable variance, demonstrating good model fit. ANOVA F-statistics (sig=0.000<0.005) confirmed significant linear relationships at the 5% level, validating model interpretability.

Variables with non-significant effects (physician title, city level, recommendation popularity, consultation price) were excluded. The final multiple regression models are:

$$CQ_A = 0.246Gift + 0.081Letter + 0.121Arti + 0.513Re - 0.015HR - 0.918Att$$

$$CQ_B = 0.262Gift + 0.060Vote + 0.121Arti + 0.587Re - 0.016HR - 0.785Eff$$

4.3 Empirical Results From Trust Theory Perspective:
"Physician title" and "city level" showed no significant impact on consultation volume, while "hospital level" had minimal impact. Thus, H1 and H3 are rejected, H2 is accepted, indicating physician offline reputation essentially does not influence patient selection. "Thank-you letters" and "vote counts" positively influenced consultation volume but with small coefficients; "gift count" showed significant positive influence with a large coefficient. Therefore, H4, H5, and H6 are accepted, demonstrating that online word-of-mouth affects physician selection, with paid feedback being more persuasive and receiving greater patient attention.

From Perception Theory Perspective:
"Article publication count" significantly and positively influenced consultation volume, supporting H7. This shows patients reference physicians' knowledge contribution to the platform, favoring physicians with greater contributions. "Attitude satisfaction" and "efficacy satisfaction" significantly and negatively influenced consultation volume with large coefficients, while "response timeliness rate" significantly and positively influenced consultation volume with substantial effect. Thus, H8 and H9 are rejected, H10 is accepted, indicating patients do not blindly choose highly-rated physicians but focus on response timeliness.

From Herd Theory Perspective:
"Patient recommendation popularity" showed no significant influence on consultation volume. Therefore, H11 is rejected, failing to demonstrate herd psychology's effect on doctor-selection.

From Price Perspective:
"Consultation fee" and "physician title" were highly correlated, with neither significantly influencing selection. Thus, H12 is rejected, indicating traditional demand theory cannot explain medical consultation service purchases.

5. Research Summary

Amid complex information in online healthcare communities, this study examined patient doctor-selection behavior, constructing an influence model from trust, perception, herd, and demand perspectives, and empirically tested it using Haodf.com data. Findings reveal that patients' consultation behavior in health communities represents information seeking and consumption behavior, not entirely equivalent to offline medical visits. After receiving multi-faceted information, patients' selections are minimally influenced by offline physician characteristics but primarily by online performance, especially service timeliness and other patients' paid feedback. Additionally, patient doctor-selection behavior cannot be directly explained by herd theory or demand theory.

Key conclusions from actual website conditions:

1. **Offline information has no significant effect on online selection behavior.** Two reasons explain this: First, average physician titles in the community reach associate chief physician level, with 91.31% of platform-certified hospitals being tier-3 grade-A institutions, showing no significant professional differences. Undifferentiated information does not significantly influence selection. Second, unlike offline medical visits aimed at diagnosis and treatment with limited information (primarily titles and specialties) and geographical constraints, online consultations aim to obtain disease information with access to multi-dimensional service metrics and no geographical limitations, making offline characteristics less prominent. Online consultation pricing directly correlates with physician titles, thus also failing to significantly influence selection.

2. **Online performance is key to influencing patient selection.** While demand theory and herd theory correlate with selection, patients are more sensitive to information directly related to physician service when multiple information types coexist. Service efficiency, paid gifts received, and knowledge contribution more intuitively reflect physician performance in the community and hold greater reference value. Patients value knowledge contribution because it reflects physician platform activity and provides perception of online service levels; selecting active physicians with high publication rates increases likelihood of receiving enthusiastic, patient service.

3. **Patients focus on key information when selecting physicians, particularly high-cost, objective information:** (a) In online word-of-mouth factors, paid feedback strongly persuades doctor-selection, while time-consuming feedback holds little reference value. Patients perceive paid feedback as more deliberate and better reflecting genuine intentions. (b) In service quality factors, physician response timeliness greatly influences selection, while other patients' ratings of attitude and effectiveness do not effectively motivate choice. Response timeliness represents objective platform statistics, and users prioritize online consultation timeliness,

aligning with online activities' short, flat, and fast characteristics. Existing e-commerce research confirms that positive reviews influence purchase intention less than negative reviews influence rejection [], and that review quality and quantity jointly affect purchase intention, with quality mattering more when quantity is insufficient []. Physician satisfaction rating data averages 98%—extremely high. Further variance analysis reveals consultation volume means across satisfaction intervals follow an approximate normal distribution: volumes peak at 888.08 for 40%-60% satisfaction, drop to 723.6 for 60%-80%, and further decline to 477.15 for 80%-100%. This suggests the platform's satisfaction rating mechanism is imperfect, reducing credibility and negatively impacting doctor-selection.

Practical implications for service improvement:
- For physicians: Ensure consultation reply quality while improving efficiency and increasing platform activity.
- For platforms: Optimize feedback mechanisms by highlighting other patients' paid feedback in interface design (as patients pay more attention to gift counts while increasing platform revenue).
- Platforms should also strengthen satisfaction rating controls to reduce fraudulent activities like fake reviews, ensuring information quality and improving platform reputation.

Optimizing factors influencing patient doctor-selection enhances patient experience, promotes healthy online healthcare community development, and helps address healthcare industry challenges like resource shortages and information asymmetry. Future research could further segment physicians and patients to better explain findings.

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Lu Quan: Proposed research topic and outline structure
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Chen Jing: Theoretical analysis and paper revision
Li Baoping: Data collection and processing

Note: Figure translations are in progress. See original paper for figures.