Influencing Factors of Patients' Choice Behavior for Online Medical Team Services: A Case Study of Haodf.com Postprint

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Abstract

[Purpose/Significance] Medical team service is an emerging form of online medical service offered by online health communities. Investigating the factors influencing patients' choice of medical team services aims to provide practical recommendations for the development of online health communities and promote the advancement of online medical services. [Methods/Process] Based on 2,784 real doctor team data from the Haodf.com online medical platform, a research model was constructed to examine online medical users' medical team selection behavior. Regression analysis and bootstrap methods were employed to test the effects of team reputation, team size, team response speed, and team login behavior on patients' medical team selection behavior, as well as the mediating role of team price. [Results/Conclusions] The results indicate that team reputation, team size, team response speed, and team login behavior positively influence patients' selection behavior. Team price exhibits a masking effect between team reputation, team size and patients' medical team selection, and a mediating effect between team response speed and patients' medical team selection.

Full Text

Study on Influencing Factors of Patients' Selection Behavior of Online Medical Team Services—Taking Haodf.com as an Example

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Abstract: *[Purpose/Significance]* Medical team services represent an emerging form of online medical service offered by online health communities. This study investigates the factors influencing patients' selection of medical team services, aiming to provide practical recommendations for the development of online health communities and promote the advancement of online medical services. *[Method/Process]* Based on 2,784 real medical team datasets from the Haodf.com platform, we constructed a research model to examine factors affecting users' selection of team-based medical services. Using regression analysis and bootstrap methods, we tested the effects of team reputation, team size, team response speed, and team login behavior on patients' selection of medical team services, as well as the mediating role of team pricing. *[Result/Conclusion]* Results indicate that team reputation, team size, team response speed, and team login behavior all positively influence patients' selection behavior. Team price exhibits a suppressing effect between team reputation, team size and patients' selection, while showing a mediating effect between team response speed and patients' selection.

Keywords: online health community; online medical team; team price; patient selection; mediating effect

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With the increasing popularity of Web 2.0 technologies, online health communities (OHCs) have become an important channel for users to access medical information services, overcoming the temporal and spatial limitations of traditional healthcare. Through OHCs, patients can obtain medical-related information anytime and anywhere, communicate with doctors online, and receive treatment recommendations. OHCs have, to some extent, alleviated the imbalance between supply and demand of medical resources across different regions.

Since 2017, OHCs such as Haodf.com and Guahao.com have launched online medical team services. These medical teams consist of a leading expert and several medical personnel who may come from different medical departments, hospitals, and even cities. Compared to individual doctor services, team-based medical services offer several advantages: (1) doctors from different departments and hospitals can communicate and collaborate, enhancing internal information exchange and knowledge sharing; (2) patient waiting time is reduced, as any team member can respond to patient inquiries; and (3) patients can obtain treatment suggestions from different doctors within the team, reducing their doubts and increasing trust. Consequently, as a means to improve the quality of online medical services, online medical team services have attracted significant industry attention.

Medical service is a professional service characterized by severe information asymmetry between providers and patients. First, doctors possess more knowledge about patients' conditions and required treatments than patients themselves. Second, patients cannot accurately evaluate whether the services provided by doctors are appropriate. Therefore, patients face difficulties in selecting doctors based on service quality assessment. In OHCs, patients often rely on certain indicators provided by the platform to judge service quality, such as individual doctor reputation, organizational reputation, and patient voting counts. Existing literature has examined factors influencing patient selection of individual doctor services from various perspectives. For instance, Wu and Zhou studied how service provider characteristics, environmental background information, and other actors' behaviors affect patient choice, while Zhou et al. and Lu et al. investigated factors influencing doctor selection behavior in OHCs, and X. Cao et al. examined the impact of service quality and voting popularity on doctor revenue.

Patients selecting online medical teams face similar information asymmetry problems. Thus, studying the influencing factors of medical team selection is crucial for providing important insights and guidance for the development of online medical team services and promoting the healthy development of OHCs. However, only limited research exists on factors influencing online medical team selection. For example, H. Wu and Z. Deng explained knowledge collaboration among online medical teams from a transactive memory perspective, finding that team professionalism, credibility, and coordination significantly affect patient selection. J. Li et al. studied the impact of professional capital and team heterogeneity on online medical team demand.

Building on existing research, this study analyzes other potentially important factors affecting patients' online medical team selection behavior, further expanding our understanding of this phenomenon. First, based on signaling theory, reputation is an important factor influencing service selection. Response speed and login behavior reflect service quality and thus affect user choice. Second, larger team size better demonstrates the advantages of many-to-one service models. Third, existing research on doctor selection has found that service price mediates patient choice, but most studies focus on individual doctors; this research extends this to the medical team level. Therefore, this study examines online medical team services in OHCs, constructing a theoretical model to explore: (1) the relationships between team reputation, team size, team response speed, team login behavior and patients' online medical team selection; (2) the relationships between these factors and team price; and (3) whether team price mediates the relationships between these factors and patients' selection behavior.

2. Related Theories and Hypotheses

2.1 Signaling Theory

Signaling theory explains how participants with different information levels can minimize information asymmetry. When one party has more information than another, the information-advantaged party can send observable signals to the information-disadvantaged party to convey unobservable information, reduce information asymmetry, and help the latter make better decisions. In markets, sellers typically have more knowledge about product quality than consumers, creating information asymmetry. Sellers can send quality signals to help consumers distinguish between high- and low-quality products, thereby reducing information asymmetry. Many researchers have used signaling theory to explain information asymmetry in various contexts.

In OHCs, patients are information-disadvantaged compared to doctors and medical teams due to their lack of medical expertise. According to signaling theory, doctors as information-advantaged parties can send signals to patients. L. Chen et al. identified doctors' honesty and credibility as signals to patients, while X. Liu et al. and Q. Chen et al. identified individual reputation, organizational reputation, and doctor behavior as transmittable signals. Patients can use these observable cues to reduce information asymmetry and make appropriate choices.

2.2 Factors Influencing Patients' Online Medical Team Selection Behavior

Based on signaling theory and existing literature, signals that patients can reference when selecting medical teams in OHCs include team reputation, team size, team response speed, and team login behavior.

2.2.1 Team Reputation Existing research has found that reputation, as a signal of product quality, can reduce information asymmetry and lower consumers' perceived risk and uncertainty, helping them make rational decisions. In OHCs, constrained by their lack of professional knowledge, patients cannot discern service quality before selecting an online medical team and must rely on available signals to evaluate teams. This is similar to patients' online selection of individual doctors. For example, X. Liu et al. found that doctors' appointment counts in online medical communities correlate with their offline and online reputation. Q. Chen et al. found that reputation positively affects doctors' income. Compared to individual doctors, reputation's influence mechanism is more complex for medical teams. On one hand, online medical teams consist of two or more doctors, and patients must consider the team's overall reputation level. On the other hand, teams typically have a leading expert whose reputation may have a more prominent impact than other members.

Both overall team reputation and leading expert reputation can be measured from online and offline perspectives. Offline reputation refers to official evaluations of doctors' medical capabilities, while online reputation refers to comprehensive ratings calculated from patient evaluations on the platform. Team reputation signals can reduce information asymmetry between patients and online medical teams, facilitating selection. High-reputation medical teams are more likely to be trusted and selected by patients. Therefore, we propose:

H1a: Team reputation has a significant positive effect on medical team service consultation volume.

2.2.2 Team Size Team size refers to the number of team members and is a characteristic feature of teams. In OHCs, communication between patients and medical teams differs from consultations with individual doctors, shifting from one-to-one to many-to-one interactions. Each doctor in the team can understand the patient's condition and communicate according to their role, providing assistance. J. Li et al. noted that interacting with multiple doctors can reassure patients, who believe they can better understand their symptoms and receive more accurate diagnoses, making them more willing to select team services. Deng et al. pointed out that larger team size may increase patients' perceived social support, thereby promoting team service volume. Additionally, with more team members, the team can more reasonably allocate time and energy, improving service quality and attracting patient selection. Therefore, we propose:

H1b: Team size has a significant positive effect on medical team service consultation volume.

2.2.3 Team Response Speed In OHCs, patient-team communication is not face-to-face instant interaction but online communication through platforms, which may create time lags. However, patients expect doctors in OHCs to diagnose as efficiently as offline doctors. Unlike individual doctor services, any member of an online medical team can respond to patients, making faster response speed a key advantage that may drive patient selection. Patients hope online medical teams can respond more quickly to their inquiries, saving time and improving service efficiency. Therefore, we propose:

H1c: Team response speed has a significant positive effect on medical team service consultation volume.

2.2.4 Team Login Behavior Most doctors in online medical teams work in clinics or hospitals in addition to providing online consultations, with some even serving multiple OHCs. L. Wang et al. found that doctors' time in OHCs is limited and variable, requiring them to use their spare time for online services. If doctors frequently log in to a platform, it demonstrates greater effort investment. H. Yang and X. Guo found that doctors' dynamic login behavior in OHCs is increasingly important for medical services. Unlike individual doctor services, any team member's login enables patient service. Therefore, team login behavior represents service timeliness to some extent, and patients prefer teams that frequently log in to OHCs for more timely services. Thus, we propose:

H1d: Team login behavior has a significant positive effect on medical team service consultation volume.

2.3 Factors Influencing Online Medical Team Prices and Their Mediating Effects

Online medical team consultation services are essentially internet-based service products. Compared to physical products, service products have characteristics of intangibility, inseparability, durability, and heterogeneity, making them more difficult to evaluate and resulting in more complex pricing structures. As a service product, online medical services face challenging pricing decisions. Therefore, studying factors influencing online medical team prices has important implications for platforms, medical teams, and patients.

First, high-reputation online medical teams tend to set higher prices. Existing literature shows that seller reputation positively affects prices for various product types. For example, W. Luo et al. studied the relationship between electronics sellers' reputation and pricing, finding that sellers with high online reputation charge higher prices. Research on reputation-price relationships has been extended to online medical services. Li Yingying found that doctors' "brand" characteristics such as professional title and hospital level positively affect online pricing. As discussed, this study measures online medical team reputation from both leading expert and overall team perspectives, and from online and offline dimensions. High-reputation teams need not attract patients with low prices but can set higher prices to signal high-quality services, while low-reputation teams must use lower prices to gain competitive advantage.

Second, larger team size indicates more doctors participating in patient treatment services, enabling more reasonable allocation of time and energy and more comprehensive handling of patient issues, thus commanding higher service quality and prices.

Additionally, Liu Xiaoxiao found that doctors who invest more effort on platforms set higher prices for corresponding returns. Faster team response speed and frequent login behavior indicate greater time and effort investment in the platform, justifying higher team service prices.

Based on the above, we propose:

H2a: Team reputation has a significant positive effect on team price.
H2b: Team size has a significant positive effect on team price.
H2c: Team response speed has a significant positive effect on team price.
H2d: Team login behavior has a significant positive effect on team price.

Price is a major factor influencing consumer purchasing behavior. First, as a service product in the market, online medical services follow supply-demand theory: demand decreases as price increases and increases as price decreases. Therefore, from supply-demand theory, higher online medical team prices lead to lower demand. On the other hand, existing literature shows that when facing uncertainty, consumers often use price as a quality signal to aid decision-making, with higher prices potentially indicating high-quality or high-cost services. Accordingly, higher medical team prices may also correspond to higher patient demand. Which theory dominates depends on which prevails in patients' online medical team selection. For testing convenience, we propose:

H3: Team price has a significant negative effect on medical team service consultation volume.

As discussed above, team reputation, team size, team response speed, and team login behavior may influence patients' online medical team selection behavior and also affect team price, which in turn influences selection behavior. Therefore, we propose that team reputation, team size, team response speed, and team login behavior partially affect patients' medical team selection through team price. Specifically:

H4a: Team price partially mediates the relationship between team reputation and medical team service consultation volume.
H4b: Team price partially mediates the relationship between team size and medical team service consultation volume.
H4c: Team price partially mediates the relationship between team response speed and medical team service consultation volume.
H4d: Team price partially mediates the relationship between team login behavior and medical team service consultation volume.

Based on these hypotheses, this study constructs the research model shown in [Figure 1: see original paper].

3. Research Design

3.1 Variables and Data Collection

3.1.1 Dependent Variable The dependent variable is patients' selection of online medical team services, measured by the number of patients using the service. We used the increment in consultation volume for 2,784 teams between February 21, 2020 and March 21, 2020 as the dependent variable.

3.1.2 Independent Variables Independent variables include team reputation, team size, team response speed, and team login behavior.

(1) Team reputation. Team reputation comprises the leading expert's offline and online reputation and the medical team's offline and online reputation. The leading expert's offline reputation is measured by professional title, as designated by official institutions based on medical capability rather than the OHC platform. Team offline reputation is measured by the proportion of chief and deputy chief physicians in the team. Online reputation uses the platform's comprehensive ratings: after consultations, patients can rate doctors on a 1-5 scale, which the platform aggregates into overall scores. We use the leading expert's composite rating to measure their online reputation, and the proportion of team doctors with ratings above 4 to measure team online reputation.

(2) Team size, team response speed, and team login behavior. Team size is measured by the number of team members. Team response speed is the percentage of patient consultations receiving replies within 24 hours, with higher values indicating faster response. Team login behavior is measured by the proportion of team doctors who logged in within the past week, with higher proportions indicating greater team activity in the OHC.

3.1.3 Mediating Variable The mediating variable is team price, i.e., the price of medical team services.

3.1.4 Control Variables Control variables include the leading expert's price, city tier where the team is located, hospital tier, and department. These may affect medical team service volume. Existing literature shows that different cities' economic development and medical resource abundance may influence patient selection. We created a dummy variable: 1 for first-tier cities, 0 otherwise. Hospital tier may also affect selection behavior; Chinese hospitals are classified into three tiers, represented by 0-3 for ungraded, primary, secondary, and tertiary hospitals. To control for disease type effects, we integrated team departments into 27 categories, creating 26 dummy variables.

Table 1 provides detailed variable descriptions.

To eliminate effects of different team start times, we collected data from Haodf.com on two dates (February 21, 2020 and March 21, 2020) and calculated monthly increments. The data included information from both team and doctor homepages, such as professional titles, text consultation prices, doctor ratings, response speeds, and login times (see sample homepages in [Figure 2: see original paper] and [Figure 3: see original paper]). After data cleaning and retaining only teams existing at both collection points, we obtained complete information for 2,784 teams.

3.2 Descriptive Statistics and Correlation Analysis

Table 2 and **Table 3** present descriptive statistics and correlation analysis. Table 2 shows that the dependent variable (medical team consultation volume) has many zero values and large variance, so we applied logarithmic transformation: TSN = ln(TSN+1) before regression. Similar transformations were applied to the leading expert's price and team price due to large standard deviations. Correlation analysis shows that all seven main independent variables are significantly correlated with online medical team consultation volume, with correlation coefficients of 0.075, 0.032, 0.301, 0.217, 0.089, 0.374, and 0.232 respectively, all positive, providing preliminary support for the hypothesized model.

3.3 Model Construction

We constructed the following models to test hypotheses H1a-H1d:

Model 1:
$\ln(\text{TSN+1}) = \alpha_0 + \alpha_1\text{LP} + \alpha_2\text{CL} + \alpha_3\text{HL} + \alpha_4\text{DT} + \text{u}$

Model 2:
$\ln(\text{TSN+1}) = \alpha_0 + \alpha_1\text{LP} + \alpha_2\text{CL} + \alpha_3\text{HL} + \alpha_4\text{DT} + \alpha_5\text{LT} + \alpha_6\text{TT} + \alpha_7\text{LR} + \alpha_8\text{TR} + \alpha_9\text{CS} + \alpha_{10}\text{RS} + \alpha_{11}\text{TBi} + \text{u}$

Where LP represents leading expert price, CL represents city tier, HL represents hospital tier, DT represents department, LT represents leading expert offline reputation, TT represents team offline reputation, LR represents leading expert online reputation, TR represents team online reputation, CS represents team size, RS represents team response speed, TB represents team login behavior, α_0-α_{11} are regression coefficients, and u is the random error term.

Model 1 includes only control variables (LP, CL, HL, DT). Model 2 adds the independent variables (LT, TT, LR, TR, CS, RS, TB).

We further constructed Models 3, 4, and 5 to test whether team price mediates the relationship between independent variables and patients' online medical team selection:

Model 3:
$$\ln(TSN+1) = c_0 + c_1LP + c_2CL + c_3HL + c_4DT + c_5LT + c_6TT + c_7LR + c_8TR + c_9CS + c_{10}RS + c_{11}TBi + u$$

Model 4:
$$\ln(TP+1) = a_0 + a_1LP + a_2CL + a_3HL + a_4DT + a_5LT + a_6TT + a_7LR + a_8TR + a_9CS + a_{10}RS + a_{11}TBi + u$$

Model 5:
$$\ln(TSN+1) = c'_0 + c'_1LP + c'_2CL + c'_3HL + c'_4DT + c'_5LT + c'_6TT + c'_7LR + c'_8TR + c'_9CS + c'_{10}RS + c'_{11}TBi + bTP + u$$

In Model 3, c_1-c_4 represent control variable effects, and c_5-c_{11} represent total effects of independent variables. In Model 4, a_5-a_{11} represent effects of independent variables on the mediating variable (team price). In Model 5, b represents the effect of the mediating variable on the dependent variable after controlling for other variables, and c'_5-c'_{11} represent direct effects of independent variables after controlling for the mediator. According to mediation testing procedures, we first test whether c_5-c_{11} are significant; second, whether a_5-a_{11} and b are significant; and third, based on the significance of direct effects c'_5-c'_{11}, we determine whether team price mediates the relationships.

4. Research Results

4.1 Regression Analysis Results

White's test indicated heteroskedasticity (P=0.000<0.005). To address this, we used heteroskedasticity-robust standard errors. **Table 4** presents regression results for Models 1 and 2. The F-statistic (P=0.000<0.005) shows the regression models are statistically significant at the 5% level.

Table 5 shows multicollinearity test results. All VIF values are below 5, indicating no serious multicollinearity.

Hypothesis H1a proposed that team reputation affects patients' online medical team selection. Model 2 results show that among reputation variables, leading expert offline reputation, team doctor offline reputation, leading expert online reputation, and team online reputation have coefficients of 0.133 ($p<0.01$), -0.071 ($p>0.1$), 0.142 ($p<0.01$), and 0.190 ($p<0.01$) respectively. Team doctor offline reputation shows no significant effect, possibly because online teams require doctors of different ranks for different tasks (e.g., chief physicians for diagnosis, assistant physicians for data collection), making overall rank less relevant for patient selection. Thus, H1a is partially supported: patients prefer teams with high leading expert offline reputation, leading expert online reputation, and team online reputation.

Model 2 also shows team size, team response speed, and team login behavior have coefficients of 0.022 ($p<0.01$), 0.327 ($p<0.01$), and 0.129 ($p<0.01$) respectively, all significantly positively affecting patient selection. Patients prefer larger teams with faster response speeds and frequent login behavior for more comprehensive, efficient, and timely services. Therefore, H1b, H1c, and H1d are supported.

4.2 Mediation Effect Testing

Following mediation testing procedures, we first confirmed that team reputation, team size, team response speed, and team login behavior significantly affect patients' selection. Second, we tested whether these variables significantly affect team price. Using heteroskedasticity-robust standard errors, the F-statistic ($P=0.000<0.005$) indicates significant linear relationships. Residual normality tests for Models 4 and 5 show approximately normal distributions (see [Figure 4: see original paper]). Regression results are shown in **Table 6** (Model 4).

Model 4 results show that among reputation variables, only leading expert offline reputation has no significant effect on team price ($p>0.1$). Team doctor offline reputation, leading expert online reputation, and team online reputation all significantly positively affect team price ($a_6=0.203$ ($p<0.01$), $a_7=0.086$ ($p<0.01$), $a_8=0.294$ ($p<0.01$)). Thus, H2a is partially supported.

Team size significantly affects team price ($a_9=0.040$ ($p<0.01$)): larger teams command higher prices. H2b is supported.

Team response speed significantly negatively affects team price ($a_{10}=-0.138$ ($p<0.01$)): faster response speed corresponds to lower team price, contrary to H2c. H2c is not supported.

Team login behavior has no significant effect on team price ($p>0.1$), so H2d is not supported.

Third, we examined whether team price mediates the relationships. Model 5 shows team price significantly negatively affects patients' selection ($b=-0.0005$ ($p<0.01$)), indicating that supply-demand theory rather than price signaling theory dominates, supporting H3.

Examining direct effects c_5-c_{11} in Model 5, all are significant except team doctor offline reputation (c_6, $p>0.1$). We used bootstrap analysis with 1,000 samples to test indirect effects, judging significance by whether 95% confidence intervals include zero (**Table 7**).

Results show team price does not mediate the relationship between leading expert offline reputation and selection (confidence interval includes zero). For team doctor offline reputation, both total and direct effects are non-significant, indicating no mediation.

For leading expert online reputation, the total effect is significant and the indirect effect confidence interval (-0.0105485, -0.0014657) excludes zero. After introducing team price, the coefficient increased from c_7=0.142 to c'_7=0.148, with indirect effect a_7b=-0.006 having opposite sign to direct effect c'_7. This indicates a "suppressing effect" rather than mediation—controlling for the suppressor variable strengthens the relationship.

Similarly, team online reputation shows a suppressing effect: indirect effect confidence interval (-0.0326088, -0.0065938) excludes zero, coefficient increased from c_8=0.190 to c'_8=0.203, with a_8b=-0.013 opposite in sign to c'_8. Thus, H4a is not supported.

For team size, the indirect effect confidence interval (-0.0038067, -0.00008936) excludes zero. After introducing team price, the coefficient increased from c_9=0.022 to c'_9=0.026, with a_9b=-0.004 opposite in sign to c'_9, indicating a suppressing effect rather than mediation. H4b is not supported.

For team response speed, the indirect effect confidence interval (0.0026941, 0.0144576) excludes zero. The coefficient decreased from c_{10}=0.327 to c'_{10}=0.320, with $a_{10}b$=0.007 having the same sign as c'_{10}, indicating partial mediation. The mediation effect accounts for 2.14% of the total effect (ab/c). H4c is supported.

For team login behavior, the indirect effect confidence interval (-0.0102776, 0.0015401) includes zero, indicating no mediation. H4d is not supported.

5. Discussion

5.1 Research Findings

This study constructed a model of team reputation, team size, team response speed, team login behavior → team price → patients' online medical team selection, testing hypotheses using medical teams from Haodf.com. Results show:

(1) Team reputation, team size, team response speed, and team login behavior significantly positively affect patients' online medical team selection. Good team reputation reflects past service quality, while larger teams, faster response, and frequent login behavior indicate capacity to provide comprehensive, efficient, and timely services—all preferred by patients.

(2) Team reputation and team size significantly positively affect team price. High-reputation teams can command higher prices, while low-reputation teams use lower prices to attract patients. Team response speed significantly negatively affects team price—possibly because teams with fewer offline patients respond faster and need lower prices to attract online patients.

(3) Mediation tests show team price partially mediates the relationship between team response speed and patient selection. A one-unit change in response speed changes selection by 0.327 units, with 0.007 units operating through price (2.14% mediation). Team price shows suppressing effects between team reputation, team size and selection—controlling for price strengthens the positive effects of reputation and size on selection.

5.2 Implications

This study has important theoretical significance: (1) It enriches OHC literature, which has focused on individual doctor-patient interactions, by examining the newer team-based service model. (2) Based on signaling theory, it verifies significant positive effects of team reputation, size, response speed, and login behavior on selection, deepening understanding of patient team selection mechanisms. (3) It tests team price's mediating role, finding suppressing effects for reputation and size but mediation for response speed, expanding understanding of pricing mechanisms.

The study also offers practical recommendations:

(1) For medical teams: (a) Focus on reputation building. Both offline professional titles and online patient ratings matter—teams should select leading experts with senior titles and maintain high service quality for good online reviews. (b) Improve response speed and login frequency through better internal division of labor to provide efficient, timely diagnoses. (c) When setting prices, consider these mechanisms carefully to establish reasonable service prices.

(2) For patients: (a) Pay attention to team reputation, size, response speed, and login behavior. (b) Focus particularly on response speed, other patients' ratings, and login frequency/activity level, as these best reflect actual service conditions. (c) Be aware of price's indirect effects to avoid choosing low-quality teams due to price influences.

(3) For OHC platforms: (a) Establish robust online reputation feedback mechanisms allowing patient ratings and reviews to help others select teams and enable excellent teams to thrive. (b) Create information display platforms showing team response speed, login behavior, etc., to aid decision-making. (c) Since price plays an important role, establish comparison systems for similarly priced teams to maximize the influence of reputation and size factors, helping patients choose optimal teams.

5.3 Limitations and Future Directions

This study has limitations: (1) Data came only from Haodf.com; different platforms may have different characteristics, limiting generalizability. Future research should collect data from multiple OHCs to verify findings. (2) This study used cross-sectional data lacking dynamic information. Future research could collect panel data to analyze dynamic effects of different factors.

References

[1] Wu Jiang, Li Shanshan. Research on users' willingness to use information services in online health communities[J]. Information Science, 2017, 35(4): 119-125.

[2] LI J, WU H, DENG Z, et al. How professional capital and team heterogeneity affect the demands of online team-based medical service[J]. BMC medical informatics and decision making, 2019, 19(1): 119.

[3] WU H, DENG Z. Knowledge collaboration among physicians in online health communities: a transactive memory perspective[J]. International journal of information management, 2019, 49: 13-33.

[4] DULLECK U, KERSCHBAMER R. On doctors, mechanics, and computer specialists: the economics of credence goods[J]. Journal of economic literature, 2006, 44(1): 5-42.

[5] ARROW K J. Uncertainty and the welfare economics of medical care[J]. American economic review, 1963, 53(5): 941-973.

[6] LU N, HONG W. Exploring the impact of word-of-mouth about physicians' service quality on patient choice based on online health communities[J]. BMC medical informatics & decision making, 2016, 16(1): 151.

[7] Wu Jiang, Zhou Lusha. Research on influencing factors of users' purchasing decisions in online health information services[J]. Journal of the China Society for Scientific and Technical Information, 2017, 36(10): 1058-1065.

[8] Zhou Tao, Wang Yingying, Deng Shengli. Research on user participation behavior in online health communities based on social capital theory[J]. Journal of Information Resources Management, 2020, 10(2): 59-67, 95.

[9] Lu Quan, Li Yishi, Chen Jing, et al. Research on influencing factors of patient doctor selection behavior in online medical communities[J]. Library and Information Service, 2019, 63(8): 87-95.

[10] CAO X, LIU Y, ZHU Z, et al. Online selection of a physician by patients: empirical study from elaboration likelihood perspective[J]. Computers in human behavior, 2017, 73(8): 403-412.

[11] LIU X, GUO X, WU H, et al. The impact of individual and organizational reputation on physicians' appointments online[J]. International journal of elec-

tronic commerce, 2016, 20(4): 551-577.

[12] CHEN Q, YAN X, ZHANG T. The impact of physician's login behavior on patients' online search, evaluation and decision[C]//CHEN H, ZENG D, YAN X, et al. Smart health. Switzerland: Springer, 2015: 192-203.

[13] Liu Xiaoxiao. Research on the impact of online doctor reputation and doctor effort on consultation volume[D]. Harbin: Harbin Institute of Technology, 2014.

[14] Xue Shufeng. Research on pricing influencing factors of internet healthcare[D]. Nanjing: Nanjing University, 2016.

[15] SPENCE M. Signaling in retrospect and the informational structure of markets[J]. American economic review, 2002, 92(3): 434-459.

[16] CONNELLY BRIAN L, CERTO S, et al. Signaling theory: a review and assessment[J]. Journal of management, 2011, 37(1): 39-67.

[17] GIOVANNI M, FRANCO P, ALEKSEY T. Price as a signal of product quality: some experimental evidence[J]. Journal of wine economics, 2014, 9(2): 135-152.

[18] BENLIAN A, HESS T. The signaling role of IT features in influencing trust and participation in online communities[J]. International journal of electronic commerce, 2011, 15(4): 7-56.

[19] Wang Hao, Liu Shan, Gao Baojun. Research on the impact of doctors opening personal websites on patient review volume[J]. Chinese Journal of Management, 2018, 15(6): 901-907.

[20] CHEN L, RAI A, GUO X. Physicians' online popularity and price premiums for online health consultations: a combined signaling theory and online feedback mechanism explanation[C]//8th international conferences on information systems. Madeira: IADIS, 2015.

[21] CHEN Y, XIE J. Online consumer review: word-of-mouth as a new element of marketing communication mix[J]. Management science, 2008, 54(3): 477-491.

[22] Li Jiaying, Deng Chaohua, Wu Hong. Empirical research on virtual team applications in medical services[J]. Chinese Journal of Management, 2020, 17(8): 1238-1244.

[23] YANG H, GUO X. Exploring the effects of patient-generated and system-generated information on patients' online search, evaluation and decision[J]. Electronic commerce research and applications, 2015, 14(3): 192-203.

[24] WANG L, YAN L, TONG Z, et al. Understanding physicians' online-offline behavior dynamics: an empirical study[J]. Information systems research, 2020, 31(2): 537-555.

[25] LAGU T, HANNON S N, ROTHBERG B M, et al. Patients' evaluations of health care providers in the era of social networking: an analysis of physician-rating websites[J]. Journal of general internal medicine, 2010, 25(9): 942-946.

[26] GALEBAKHTIARI S, POURYASOURI T H. A hermeneutic phenomenological study of online community participation applications of fuzzy cognitive maps[J]. Computers in human behavior, 2015, 48: 637-643.

[27] LUO W, CHUNG Q B. Retailer reputation and online pricing strategy[J]. Journal of computer information systems, 2010, 50(4): 50-56.

[28] Li Yingying. Research on influencing factors of doctor service prices in online medical communities[D]. Harbin: Harbin Institute of Technology, 2016.

[29] MICHEL C. What does this discount tell you? investigating the impact of pre-promotion price effects[EB/OL]. [2021-03-21]. https://ssrn.com/abstract=2938363.

[30] GERSTNER E. Do higher prices signal higher quality?[J]. Journal of marketing research, 1985, 22(2): 209-215.

[31] Wen Zhonglin, Ye Baojuan. Mediation effect analysis: methods and model development[J]. Advances in Psychological Science, 2014, 22(5): 731-745.

[32] Zhao Desen, Dou Chai, Zhang Jianmin. Business environment and green economic growth—mediating and suppressing effects of entrepreneurship[J]. Inquiry into Economic Issues, 2021(2): 66-77.

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Study on Influencing Factors of Patients' Selection of Online Medical Team Services—Taking Haodf.com as an Example

Abstract: *[Purpose/Significance]* Medical team services are an emerging form of online medical service provided by online health communities, which have greatly improved the development of online medical services. This paper attempts to explore factors affecting the sales of medical team services in online health communities, aiming to put forward practical suggestions for the development of online health communities and promote the development of online medical services. *[Method/Process]* Based on a dataset including 2,784 teams drawn from a leading online health community in China, we built models to examine the influencing factors that affect patients' choice of online medical team services. In particular, we studied how factors including team reputation, team size, team response speed and team login behavior affect patients' choices of online medical team services using regression analysis and bootstrap. In addition, we explored the mediating role of prices. *[Result/Conclusion]* Results show that team reputation, team size, team response speed and team login behavior had positive effects on patients' choices. Team price had a suppressing effect between team reputation, team size acts and patients' choices, but acted as a partial mediator between team response speed and patients' choice of online medical team services.

Keywords: online health community; online medical team; team prices; patient selection; mediating effect

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