



# Cross-platform vs Within-platform: the Spillover Effect of Doctor's Knowledge Sharing on their Online Consultation Volume

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**Abstract.** Through the sharing of knowledge among doctors, patients can learn more about medicine and manage their own health. It's an important way for patients to form initial impressions of their doctors. Meanwhile, patient medical choice behavior is key for online consultation platforms' profitability. Doctors' knowledge sharing behaviors provide patients with a way to assess their doctors' competence. In previous research, scholars have delved into the profound effect that doctors sharing their medical expertise can have on patients' decision-making processes. This phenomenon has been extensively scrutinized as it pertains to healthcare decisions and outcomes, but mainly focused on the correlation within the platforms, ignoring the cross-platform perspective of the impact. Drawing on the theory of trust transfer, this study employs a panel regression model to examine how doctors' knowledge-sharing behaviors within and across platforms influence online consultations through spillover effects. We use data collected from the short-video platform Douyin and its consultation module Xiaohe Health, as well as the online consultation platform Haodf. The dataset comprises 468 doctors and 30,624 balanced panel observations. The results indicate that the knowledge sharing of doctors has a positive direct spillover effect on the in-platform online consultation, and a positive indirect spillover effect on cross-platform online consultation, leading to an increase in both within-platform and cross-platform online consultations. This reveals the doctors' knowledge sharing behaviors' spillovers within-platform and cross-platform, provides favorable evidence for the convenience of online healthcare access, and offers managerial insights for social and online consultation platform development policies.

**Keywords:** Online consultation; Health knowledge sharing; Spillover effect; Trust transfer

## 1 Introduction

The widespread adoption of the Internet and social media has profoundly influenced individuals' daily lives and routines, offering a more convenient and efficient channel for seeking medical care [1,2,3]. This convenience has led to a surge in online consultation platforms during the COVID-19 pandemic [4]. Meanwhile, the new generation of information technology has promoted the development of various digital platforms. The rapid development of social media enables doctors to share patient-concerned health information beyond medical platforms [5]. Viewers can also interact with doctors through these videos, such as liking, commenting, collecting, and forwarding. Based on the "Douyin Health Science Popularization Data Report" published in 2023, more than 35,000 certified physicians in Douyin created 4.43 million popular scientific content.

These social platforms where doctors disseminate medical knowledge constitute additional channels through which patients assess doctors' professional qualities [6]. By sharing professional knowledge, doctors can effectively boost their online reputation and professional image [7]. While sharing professional knowledge to build strong patient relationships, doctors can simultaneously bolster their online reputation and professional image. [8]. These social platforms provide multiple functions, including communication, social interaction, access to information, consumption, and shopping. Moreover, there also social media platforms that operate its own online health consultation modules over the platform (e.g. Douyin). Users on this type of social media platform can click the health science video, navigate to the posting doctor's page, and register for online health consultations. This is because that doctors' knowledge-sharing may raise viewers' awareness of potential health issues and prompt them to seek consultations either within the same platform or by following the doctor to other platforms (e.g. Haodf).

Therefore, there can be two types of spillover effects of the health science videos: one is the impact of health science videos on online consultation volume within-platform, and the other is the impact of social platforms on consultation volume over other platforms. Within-platform refers to the consultation activities completed by users within the same platform. For example, after obtaining knowledge sharing on Douyin, users can directly initiate consultations through the built-in "Xiaohe Health" consultation module of the platform. Cross-platform, by contrast, denotes consultation activities across different platforms. An instance is when Douyin users, after accessing knowledge sharing, jump to external platforms like Haodf online for consultation. Regarding spillover effects in the healthcare research, previous studies have primarily focused on spillovers from general knowledge-sharing behaviors within online health communities (OHCs) to online reputation and specific knowledge-sharing activities [9], spillovers from health insurance to food security [10], and spillovers from healthcare IT investments to healthcare costs [11], while less attention has been paid to the influencing factors of cross-platform spillover effect of online consultation.

Therefore, this study further explores the following research questions:

Q1: Does health knowledge sharing on social platforms have an impact on the online consultation function modules within-platform, that is, is there a direct spillover effect?

Q2: Does health knowledge sharing on social platforms have an impact on cross-platform online consultation, that is, is there an indirect spillover effect?

This study draws on trust transfer theories to examine how doctors' health knowledge sharing on Douyin influences online consultations. Drawing on 30,624 balanced panel observations for 468 physicians culled from Douyin and Haodf videos and consultations (2017–2023), panel-regression estimates show that sharing professional knowledge generates both a positive direct spillover—boosting consultations within the same platform—and a positive indirect spillover—stimulating consultations across the other platform—while simultaneously strengthening physician–patient relationships.

## 2 Literature Review

Our work is closely related to the literature on doctors' health knowledge sharing behavior, trust transfer theory, and spillover effects.

### 2.1 Research on Doctors' Health Knowledge Sharing Behavior

Physicians' health-related knowledge sharing can be categorized as either general or specific. General sharing entails the free dissemination of broad health information via public channels such as articles and videos [12], whereas specific sharing involves personalized, private advice delivered in face-to-face visits or paid online consultations [13]. Prior studies in online health communities indicate that these behaviors shape consultation demand: the volume of published articles boosts both free and paid online consultations [14, 15], and the influence of general sharing further varies with the breadth and depth of physician–patient interactions [16].

### 2.2 Trust Transfer Theory

McKnight's trust theory [17] suggests that the two main dimensions of a doctor's personal quality and online reputation, including online reviews and online ratings, influence patient choice. Previous studies have shown that doctors' participation in social media can convey trust [18]. The process of trust transfer may occur when an individual or group perceives a strong connection between a trusted party and an unfamiliar third party. That is, if doctors and patients rely on each other in some form of messaging or interaction, then a high level of trust embedded in social platforms can encourage trust in unknown third parties (i.e., Internet online consultation).

Furthermore, trust transfer theory distinguishes two modalities: within-platform and cross-platform [19, 20]. Within-platform transfer occurs when trust vested in one entity—such as a location or institution—extends to another entity on the same platform. Cross-platform transfer, by contrast, arises when trust cultivated on one platform migrates to a separate, interacting platform [20]. Multiple studies have applied this theory to investigate its processes. For instance, Chinese online customers who trust the Internet payment system transfer their trust to the company's mobile payment (within-platform) [20,21]; respondents who trust offline public administration likely have high trust

in online public e-services (within-platform) [22]. Existing research on doctor–patient trust transfer has concentrated on how patients shift their trust between physicians’ online and offline settings [7], leaving the dynamics of trust transfer across distinct online platforms—or cross-platform trust migration—largely unexplored.

### 2.3 Spillover Effect

Spillover effects are the unintended effects of events in one environment on other individuals in a different, indirectly related environment [23]. The cross-platform spillover effects’ core idea is to interact with users through multiple platforms, enhancing economic or social benefits. Prior research on spillover effects pertaining to social interaction has been predominantly concentrated within the domains of politics, the economy, culture, and education. Concurrently, scholarly works have also explored user flow conversion within social media platforms. For example, Lee [24] linked social with politics and explored how social communication mitigated the spillover effects of political scandals. Iacono [25] explored whether the overall density of social links in a community promotes trusting behaviors, with strangers in terms of the role of social spillovers on trust. Current studies in the medical field focus on spillover effects within online health communities (OHCs) [9], medical insurance [10], and medical IT investment [11], while the spillover effects between online platforms or cross-platform are rarely involved.

## 3 Research Model

Grounded in trust-transfer theory, we posit that trust cultivated through physicians’ health-knowledge sharing on social platforms can migrate along two paths: (1) to the platform’s own consultation module (within-platform trust) and (2) to an external consultation platform (cross-platform trust). After encountering content from reputable doctors, patients may first engage via the platform’s social features, allowing interaction-based trust to flow directly into the in-platform consultation service (within-platform trust). Alternatively, patients can leverage tools such as Internet search to carry this trust to an off-platform consultation venue (cross-platform trust). In addition, based on the concept of within-platform trust, we believe that health knowledge sharing and interactive communication are conducive to enrichment of information exchange between doctors and patients, enabling patients to establish trust in that doctor, and it is possible to transfer this trust directly to the self-operated consultation within-platform. Thus, a positive direct spillover effect based on trust transfer is generated, which brings traffic and visits to the directly-operated consultation within-platform, and increases the volume of online consultation for doctors. Therefore, this paper proposes the following hypothesis:

*H1. When physicians disseminate health knowledge on social platforms, the resulting trust directly spills over within the same platform, driving up the number of online consultations.*

Beyond triggering immediate within-platform bookings, physicians' health-knowledge posts can shape patients' broader medical choices, since users who consume such content are typically driven by health-management goals and the search for treatment alternatives [8]. Therefore, when the social platform improves the user's understanding of the doctor, and thus generates trust in the doctor, this trust has the potential to be transferred to other platforms where the doctor is located, such as cross-platform consultation [26]. This increasing the possibility of patients actively browsing and searching consultation across the social platform. Then brings new patient traffic for doctors, creates a positive indirect spillover effect based on trust transfer, drives traffic and visits to cross-platform consultations, and increases the volume of online consultations. Therefore, this paper proposes the following hypothesis:

*H2. By sharing health knowledge on social platforms, physicians create a positive, indirect spillover that drives up cross-platform consultation volumes.*

Figure 1 illustrates our conceptual framework, which examines how physicians' health-knowledge sharing simultaneously exerts a direct spillover on within-platform consultations (H1) and an indirect spillover on cross-platform consultations (H2).

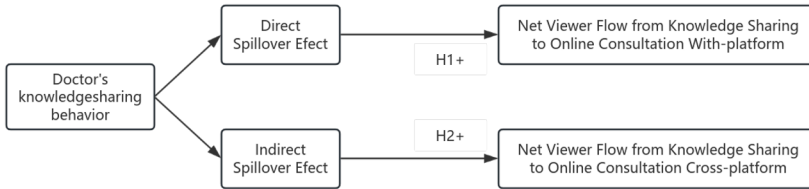


Fig. 1. Research model.

## 4 Research Methodology

### 4.1 Study Setting and Data Acquisition

Spanning 2017–2023, the dataset combines Douyin's short-video platform and its embedded consultation service, Xiaohe Health, with records from the independent online-consultation site Haodf. Douyin<sup>1</sup> is one of the most representative short video social platforms in China, boasting 680 million monthly active users—67.3% of China's entire mobile-Internet population. Xiaohe Health<sup>2</sup> is Douyin's within-platform self-operated consultation function. A doctor's personal information on Xiaohe Health includes name, hospital, department, job professional title, professional title, online consultation price, volume and time. Haodf online<sup>3</sup> is a leading online consultation platform in China. To ensure sample representativeness and universality, we collected information from 468 doctors across 39 departments, who are active on both Douyin and Haodf.

<sup>1</sup> <https://www.douyin.com/>

<sup>2</sup> <https://www.xiaohe.cn/>

<sup>3</sup> <https://www.haodf.com/>

Using Python-based web scrapers, we harvested all publicly available records from Douyin, Xiaohe Health, and Haodf between June 2017 and January 2023. After aligning, filtering and log-transforming the raw figures, we organized the information into a monthly balanced panel ready for analysis. Specifically, we first collected data on certified doctors from Douyin. We also crawled consultation data from the Xiaohe Health module and detailed doctor information from the Haodf online platform. Next, we cross-checked the three datasets to make sure that entries referred to the same doctor across platforms. To examine how physicians' knowledge-sharing activities spill over into consultation demand, we included only those who were certified on all three platforms. Logarithmic transformation was applied to reduce heteroscedasticity. The final dataset includes 468 doctors and 30,624 balanced panel observations.

## 4.2 Model Specification

For online consultation of Xiaohe Health module, the following regression model is used to analyze the impact of Douyin health videos on Xiaohe health module's consultation volume:

$$\begin{aligned} \text{XiaoheConsultation}_{it} = & \alpha_0 + \\ & \alpha_1 \text{releases}_{it} + \alpha_2 \text{likes}_{it} + \\ & \alpha_3 \text{collects}_{it} + \alpha_4 \text{comments}_{it} \\ & + \alpha_5 \text{forwardings}_{it} \\ & + \alpha_6 \text{controls}_{it} + \lambda_t + \\ & D_i + \varepsilon_{it} \end{aligned} \quad (1)$$

$$\begin{aligned} \text{XiaoheConsultation}_{it} = & \alpha_0 + \\ & \alpha_1 \text{releases}_{it} + \alpha_2 \text{likes}_{it} + \\ & \alpha_3 \text{collects}_{it} + \alpha_4 \text{comments}_{it} \\ & + \alpha_5 \text{forwardings}_{it} + \\ & \alpha_6 \text{controls}_{it} + \lambda_t + \\ & D_i + \varepsilon_{it} \end{aligned} \quad (2)$$

The panel model is specified as follows, where the subscript  $i$  indexes physicians and  $t$  indexes months. The dependent variable  $\text{XiaoheConsultation}_{it}$  records the number of consultations physician  $i$  receives through the Xiaohe Health module in month  $t$ . Key explanatory variables capture physician  $i$ 's Douyin activity in month  $t$ :  $\text{releases}_{it}$  is the count of newly posted health videos,  $\text{likes}_{it}$ ,  $\text{collects}_{it}$ ,  $\text{comments}_{it}$ , and  $\text{forwards}_{it}$  denote the aggregate likes, bookmarks, comments, and reposts those videos receive. A vector of control variables,  $\text{controls}_{it}$ , accounts for additional determinants of consultation volume—city tier, job title, professional rank, gender, merchandise-window status, online-consultation price, and service rating. Physician fixed effects  $D_i$  absorb time-invariant physician heterogeneity, year-month fixed effects  $\lambda_t$  capture common temporal shocks, and  $\varepsilon_{it}$  is the idiosyncratic error term, clustered by physician to yield robust standard errors;  $\alpha_0$  is the constant term.

To quantify the spillover from Douyin health videos to Haodf consultations, we retain model (1) but replace the outcome variable. Model (2) is specified as follows,

where  $i$  indexes physicians and  $t$  indexes months. The new dependent variable,  $\text{HaodfConsultation}_{it}$ , denotes physician  $i$ 's monthly online-consultation count on the Haodf platform.  $\text{releases}_{it}$ ,  $\text{likes}_{it}$ ,  $\text{collects}_{it}$ ,  $\text{comments}_{it}$  and  $\text{forwards}_{it}$  are the core explanatory variables included in baseline model (1).  $\text{controls}_{it}$  is the control variable included in the baseline model (1).  $D_i$ ,  $\lambda_t$ ,  $\varepsilon_{it}$  are doctor fixed effect, time fixed effect and random error terms, respectively.  $\beta_0$  is a constant term.

## 5 Results

We conducted panel regression analysis, as well as multi-period lagged regression for hypotheses testing. The following is the detailed process of multiple model testing and regression.

### 5.1 Stationarity Test

To prevent “pseudo-regression”, we conducted stationarity tests on each variable. We used two unit root test methods: LLC and Fisher-ADF. The tests were conducted with Stata. The results in Appendix 1 suggest that the original sequence is stable without difference.

### 5.2 Hausman Test, Sequence Correlation Test, Heteroscedasticity Test

To select appropriate type of panel regression analysis model (fixed effect model vs. random effect model), we conducted Hausman test. The results (Appendix 2) suggest fixed effects model for model 1 (Xiaohu health) and random effects model for model 2 (Haodf online). In addition, the random disturbance terms of the same individual may have sequence correlation in different periods. The sequence correlation test is to check if the random residual terms have their own correlation before and after. The original hypothesis is that no sequence correlation exists. The results of the sequence correlation test (see Appendix 2) reject the original hypothesis, indicating the existence of sequence correlation. Due to variance in random disturbance terms among individuals, heteroscedasticity can lead to the loss of the optimality of the estimator and reduced accuracy. Greene proposed a modified Wald statistic for testing this potential issue. Unlike standard Wald, LR, and LM statistics, the modified Wald test works even if residuals are not normal. The original hypothesis is homoskedasticity. The results (see Appendix 4) rejected the original hypothesis, indicating heteroscedasticity between groups.

### 5.3 Clustering Robust Standard Error Regression

The above estimation methods consider the influence of heteroscedasticity and sequence correlation on the variance-covariance matrix, but not together. We then adjusted standard errors for both simultaneously, obtaining robust standard errors in subsequent analysis.

**1)The clustering robust standard error regression of Xiaohe Health:** Table 1 reports the regression estimates for the effect of physicians' Douyin health-sharing on Xiaohe Health consultation volume. After controlling for city tier, job title, professional rank, gender, merchandise-window status, consultation price, and service rating, we find that both the number of newly posted videos ( $\beta = 0.194$ ,  $p < 0.01$ ) and the number of video bookmarks ( $\beta = 0.796$ ,  $p < 0.001$ ) significantly increase consultations, whereas video shares exert a negative influence ( $\beta = -0.552$ ,  $p < 0.001$ ). Likes and comments, however, show no significant association. These results confirm that physicians' knowledge-sharing activities generate a positive direct spillover to within-platform (Xiaohe Health) consultations, supporting Hypothesis 1.

**2)The clustering robust standard error regression of Haodf online:** Table 1 summarizes the effects of physicians' Douyin health videos on Haodf consultation volume, controlling for city tier, job title, professional rank, gender, merchandise-window status, consultation price, and service rating. Only the number of video bookmarks significantly boosts Haodf consultations ( $\beta = 0.110$ ,  $p < 0.05$ ); video releases, likes, comments, and shares show no significant impact. These findings indicate that physicians' knowledge-sharing activities create a positive indirect spillover to cross-platform (Haodf) consultations, supporting Hypothesis 2.

**Table 1.** Empirical results.

	<b>Xiaohe</b>	<b>Haodf</b>
$\ln\text{releases}_{i,t}$	0.194** (0.038)	0.040 (0.053)
$\ln\text{likes}_{i,t}$	-0.243(0.026)	-0.098 (0.034)
$\ln\text{comments}_{i,t}$	0.121(0.029)	0.146 (0.043)
$\ln\text{collects}_{i,t}$	0.796***(0.031)	0.110*(0.042)
$\ln\text{forwards}_{i,t}$	-0.552***(0.028)	-0.030 (0.038)
city	-0.023	0.174
job title	-0.031	0.058
professional title	0.015	0.086
gender	0.033	-0.016
window	0.009	-0.038
price	-0.021	0.001
service score	0.042	0.165
R – square	0.1210	0.0408

Note: Robust standard errors are reported in the parentheses. \*\*\*  $p < 0.001$ ; \*\*  $p < 0.01$ ; \*  $p < 0.05$ .

## 6 Discussion

### 6.1 Key Findings

This study presents new findings and reveals important mechanisms that influence patients' choice of medical care. Robust evidence first confirms that physicians'

knowledge-sharing exerts a sizable, multi-period direct spillover on within-platform consultations. Each additional video posted lifts Xiaohe Health consultations by 19.4 % ( $p < 0.01$ ), while every extra bookmark elevates them by 79.6 % ( $p < 0.001$ ); thus, higher release and collection counts translate into proportionally greater on-platform demand. Surprisingly, broader dissemination through forwarding reverses this effect: every incremental share is associated with a 55.2 % decline in consultations ( $p < 0.001$ ), contradicting the expectation that wider circulation would always be beneficial. One plausible explanation is that, on the one hand, the viewer of the social platform forwards the video to others. After watching the video, the recipient does not directly seek within-platform consultation, but instead uses a common search engine out of the habit of knowledge search, and jumps to the cross-platform consultation accessible by the browser for medical treatment. By contrast, the self-operated consultation function module of Xiaohe Health only has within-platform entry channels and access rights, with no direct browser link, which results in video recipients going to cross-platform consultation through the search engine. On the other hand, since cross-platform consultation tend to have larger volume and popularity, video recipients usually choose common consultation platforms for medical treatment. Consequently, higher forwarding rates for health videos appear to depress within-platform consultation demand.

Second, physicians' knowledge-sharing also influences cross-platform consultations: each additional bookmark on Douyin is linked to an 11 % rise in Haodf consultation volume ( $p < 0.05$ ). Thus, the more patients save doctors' videos, the greater the subsequent cross-platform demand, evidencing a sustained, positive indirect spillover.

## 6.2 Practical Implications

For instance, if a particular platform provides a dedicated space for doctors who wish to share their expertise in a certain field, it could allow them to create a profile where they can curate the best content from various sources. This not only enhances the quality of knowledge but can also attract new audiences that may have been previously unexposed to such valuable information.

Another approach could involve creating a forum or chat room within the platform that allows doctors to interact with each other and discuss topics of mutual interest. Such forums could be moderated by experts in the field, ensuring that discussions remain constructive and relevant. Furthermore, if a platform is partnered with a medical journal or academic institution, it could facilitate the exchange of articles and research findings, further expanding the pool of knowledge available on the platform without compromising the integrity of the research itself.

In conclusion, as social media platforms continue to evolve, so too must their role in nurturing and distributing health and wellness information. By implementing the suggestions outlined above, platform operators can not only enhance the value of their services but also contribute significantly to the overall well-being of society.

## 7 Conclusion

Leveraging a balanced panel of 30,624 monthly observations from 468 physicians (2017–2023), we find that physicians' health-knowledge posts on Douyin generate an immediate 19.4 % lift in Xiaohe Health consults and an 11 % cross-platform bump on Haodf. These spillovers illuminate how patients navigate online care options and underscore the value of integrated traffic-to-consult funnels. Platform managers should therefore co-design incentive schemes—such as unified bookmarks or referral rewards—to convert viewers into paying patients and unlock new revenue. Future studies should probe how physician seniority, specialty, and patient demographics moderate these effects, refining personalized pathways to care.

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