informs
https://pubsonline.informs.org/journal/isre

INFORMATION SYSTEMS RESEARCH
Articles in Advance, pp. 1–25
ISSN 1047-7047 (print), ISSN 1526-5536 (online)

On-Demand Healthcare Platforms: Impact of Question and Answer Service on Online Consultations and Offline Appointments

Yixuan Liu,[a] Ashish Agarwal,[b,*] Guoming Lai,[b] Weihua Zhou[c]

[a] China Europe International Business School, Shanghai 201206, China; [b] McCombs School of Business, University of Texas at Austin, Austin, Texas 78705; [c] School of Management, Zhejiang University, Hangzhou 310058, China
*Corresponding author

Contact: yixuanliu@ceibs.edu (YL); ashish.agarwal@mccombs.utexas.edu, https://orcid.org/0000-0001-9259-0113 (AA); guoming.lai@mccombs.utexas.edu (GL); larryzhou@zju.edu.cn (WZ)

Received: October 24, 2023
Revised: August 16, 2024; April 11, 2025
Accepted: May 18, 2025
Published Online in Articles in Advance: July 10, 2025

https://doi.org/10.1287/isre.2023.0644

Abstract. The emerging on-demand healthcare platforms connect patients with healthcare practitioners to provide quick access to primary care and consultation services. These platforms can offer a question and answer (Q&A) service to patients to seek more information before they seek care online or offline. Using rich panel data from an on-demand healthcare platform in China, we investigate the impact of such a Q&A service on demands for online consultations and offline appointments. Our findings indicate that the Q&A service has a complementary effect on the demand for both online consultations and offline appointments. Specifically, we estimate that the Q&A service can increase online consultation service purchases and offline appointments by 2% and 4.3%, respectively. Additionally, users' expenditures on the online consultation service can increase by 6.6%. We also find that the Q&A service leads to an increase in demand for the same doctor for online consultations while simultaneously increasing demand for other doctors across both channels. Furthermore, we demonstrate that the spillover effects of the Q&A service vary across different medical specialties and among providers of different professional titles. Patients tend to seek more specialized care in online and offline settings, suggesting better matching. Additionally, patients tend to seek care from doctors with higher titles. Finally, our results show that the use of the Q&A service reduces the need for future consultations and information-seeking behavior, suggesting improved health outcomes. In conclusion, our study highlights the effectiveness of Q&A-based information services in helping manage patients' needs in the on-demand healthcare industry.

History: Karthik Kannan, Senior Editor; Gordon Burtch, Associate Editor.
Funding: W. Zhou acknowledges financial support from the National Natural Science Foundation of China [Grant 72192823].
Supplemental Material: The online appendix is available at https://doi.org/10.1287/isre.2023.0644.

Keywords: on-demand healthcare platform • health IT • healthcare forum • multichannel

1. Introduction

On-demand healthcare platforms are designed to focus on providing primary care and consultation services. These platforms operate as two-sided setups, with healthcare practitioners[1] affiliated with clinics or hospitals on one side and patients seeking healthcare services, either online or offline, on the other side. Examples of such platforms include Teladoc, Amwell, and Doctor-on-Demand in the United States; the Babylon platform in the United Kingdom; and the ChunYuDoctor mobile platform in China. These platforms aim to address challenges in traditional healthcare, including high costs and long waiting times, by offering a large pool of doctors for patients to choose from (Petterson et al. 2012, Bodenheimer and Smith 2013). For example, Teladoc has 55,000 medical experts, and Amwell has 102,000 providers. However, the vast number of options can overwhelm patients (Swar et al. 2017), especially because many doctors are not local, and patients may lack prior interactions with them. This is compounded by an information gap, where patients often have limited knowledge about their ailments and the appropriate healthcare services. First-time users, in particular, may have significant uncertainties regarding the quality of service provided by the doctors on these platforms.

A recent innovation by many on-demand healthcare platforms is the introduction of subsidized question and answer (Q&A) services, enabling patients to access consultations at a very low cost with doctors.[2] These Q&A services offer enhanced accessibility in comparison with traditional appointments. The doctors are promptly notified of the requests and are expected to respond within a designated time frame. Following the utilization of the Q&A service, patients have the flexibility to decide whether to proceed with a premium online consultation with the same or a different doctor, schedule an offline appointment, or opt not to take any further action (Chen and Walker 2023).

At first glance, such Q&A services may seem akin to free trials for merchandise, aimed at reducing uncertainties about quality and encouraging subsequent purchases. However, the healthcare services provided by these platforms differ from typical merchandise offerings, which may lead to a variety of different outcomes. First, the demand for general healthcare is often infrequent. A single Q&A service may sufficiently resolve a health issue, eliminating the need for purchasing premium consultation services. In other words, there is a potential for cannibalization if notable portions of patients perceive the premium consultation service as redundant to the Q&A service. It might just shift the demand from the premium consultation service to the Q&A channel without generating any increase in demand for the platform. Second, the Q&A service, although possibly encouraging patients to purchase premium consultation services from the doctors who address their questions, may just be shifting the demand from other doctors and may not lead to net increase in demand for the healthcare platform. Alternatively, it may also lead to patients switching to other doctors within the same specialty or even different specialties. Several healthcare-specific reasons can contribute to this phenomenon. For instance, patients may discover that the doctors who provided the Q&A service are unable to adequately address their concerns, prompting them to seek premium consultation from another doctor. Alternatively, doctors may refer patients to specialists based on their Q&A interactions, or patients themselves may realize from the Q&A service that their condition requires the expertise of a different medical specialty. This highlights the potential for a spillover effect, where patients may opt to seek healthcare services from other providers beyond their initial Q&A interactions. Third, on-demand healthcare platforms also have an impact on offline clinic and hospital visits. Minor healthcare issues can be resolved through online consultations, reducing the necessity of in-person doctor visits. Therefore, the Q&A service, which familiarizes patients with the use of the online channel, may potentially have an adverse effect on the offline channel, creating a substitution effect. However, a counterargument can also be made. After obtaining information about their health issues or even receiving referrals from the online platform, some patients may promptly seek further diagnosis and treatment through the offline channel, thereby increasing the demand for clinics and hospitals. Consequently, the Q&A service, which familiarizes patients with the use of the online channel, may also benefit the offline channel, resulting in a complementary effect.

Despite the growing attention to online healthcare platforms in academic research, the potential impacts of the newly introduced Q&A service have yet to be thoroughly investigated. This study aims to fill this research gap by examining the following questions. How does the Q&A service introduced by the on-demand healthcare platforms affect the demand for their premium online consultations as well as offline appointments? How does this impact vary across doctors and specialties? To investigate these questions, we have partnered with an on-demand healthcare platform operating through a mobile app in China. The platform offers priced online consultation services provided by individual doctors and facilitates offline appointments in collaboration with hospitals. In order to encourage user engagement, the platform integrates a Q&A service where users can submit healthcare-related questions at a very low price and receive answers from doctors based on their specialty and availability. Leveraging a comprehensive panel data set obtained from the platform, which includes Q&A sessions, browsing data, records of online premium services, and offline appointment records for nearly 1 million users between March 2016 and April 2019, we employ a difference-in-differences (DID) approach on a matched sample to evaluate how the usage of the Q&A service impacts the demand for premium online services and offline appointments. We explore how this effect varies based on the quality levels and medical specialties of the doctors. Furthermore, we investigate healthcare outcomes associated with the service, including revisits and future healthcare information-seeking behavior.

Our analysis reveals that the introduction of the Q&A service results in an increase in subsequent purchases of consultation services, leading to a growth in revenue for the platform. Simultaneously, there is also an increase in offline appointments. Specifically, the Q&A service contributes to a 2% increase in demand for online consultations and a 4.3% increase in demand for offline appointments compared with the existing demand volumes. The platform's revenue from consultations shows an 6.6% increase. Additionally, we observe a slight increase in demand for online consultations from the same doctors who answer questions through the Q&A service. However, the Q&A service significantly boosts demand for both online consultations and offline appointments with other doctors in the same specialty. This indicates that the Q&A service helps alleviate uncertainty about specific doctors and also, introduces patients to other doctors within the same specialty, resulting in a spillover effect. Furthermore, we find that the Q&A service in one medical specialty generates increased demand for online consultations and offline appointments in other specialties, suggesting that it aids in matching patients with appropriate doctors across different specialties. Additionally, we establish that patients benefit from Q&A service as consultations and appointments through Q&A lead to fewer future visits and fewer browsing sessions.

We also examine the influence of doctors' seniority on the impact of the Q&A service. Our findings indicate that doctors with senior titles contribute to a stronger complementary effect of the Q&A service for both online and offline channels. This suggests that patients utilize the titles of participating doctors in the Q&A service to alleviate uncertainties associated with the platform's services. Additionally, we highlight the divergent consequences of the Q&A service for doctors with different titles and specialties. Specifically, we observe that users are inclined to "upgrade" their subsequent services by seeking consultations with doctors holding senior titles following their engagement with the Q&A service. Moreover, patients demonstrate a tendency to pursue more specialized and complex medical care after utilizing the Q&A service in the general specialty. These results remain consistent and robust across various tests and checks conducted in our study.

Our study offers valuable insights for on-demand healthcare platforms and participating doctors, emphasizing three key takeaways. First, the Q&A service drives higher demand and revenue for the platform by facilitating online consultations and offline appointments. Second, from a patient's perspective, the Q&A service aids in identifying the appropriate medical specialty and level of care, leading to suitable consultations or appointments and reducing future visits and browsing for medical issues. These effects vary across medical specialties and doctors' seniority levels. Lastly, we identify plausible underlying mechanisms, demonstrating that increased demand may result from resolving uncertainties about required medical consultations and patients becoming aware of the relevant medical specialties for their needs. Although our focus is primarily on the Q&A service, our analysis also indicates that online healthcare consultations can increase demand for traditional offline healthcare services, which holds significance for healthcare policymakers.

Our study makes significant contributions to the healthcare and information technology (IT) literature. It enhances the existing research on online healthcare forums. Previous studies have primarily focused on the impact of forums on patient outcomes (Wentzer and Bygholm 2013, Pagoto et al. 2014, Liu et al. 2020) and the effect of doctor participation in these forums on the recommendations that they receive (Khurana et al. 2019). We extend this work in two key ways. First, we examine the impact of forum-like Q&A capabilities on the demand for consultation and appointment services offered by healthcare platforms. Second, we demonstrate this effect not only for the same doctor but also, for other doctors within and across specialties. Additionally, we contribute to the literature on on-demand healthcare platforms. Previous research in this area has mainly investigated the complementary and substitution effects of telehealth channels (Zhou et al. 2007, North et al. 2014, Leveille et al. 2016, Bavafa et al. 2018, Shah et al. 2018, Fan et al. 2023) or online platforms (Uscher-Pines and Mehrotra 2014, Ashwood et al. 2017) on offline services. Our study adds to this body of work by focusing on the design aspects of online health platforms. Specifically, we evaluate the demand impact of Q&A services on other services provided by the platform and how these services help generate this demand through various information mechanisms, such as sampling, spillovers, and matching.

2. Literature Review

Research in the information systems and healthcare literature has examined the effects of different health IT implementations on factors such as costs (Atasoy et al. 2018), service quality (Menon and Kohli 2013), staffing decisions (Lu et al. 2018), and doctor productivity (Bhargava and Nath Mishra 2014). In the realm of health IT studies, our research aligns closely with the literature on online healthcare forums and digital healthcare platforms.

2.1. Online Healthcare Forums

The research on online healthcare forums primarily evaluates the involvement of patients in these forums and their impact. Various studies have investigated the factors that drive user participation in online healthcare forums, including information access (Rupert et al. 2014), emotional needs (Wentzer and Bygholm 2013), and social needs (Malik and Coulson 2010). Additionally, research has explored the outcomes associated with such participation, such as improvements in physical and psychological well-being (Wentzer and Bygholm 2013, Pagoto et al. 2014) and overall wellbeing (Liu et al. 2020). However, these studies primarily focus on the information acquired within the forums and the outcomes resulting from interactions within the forum environment. They do not extensively consider the impact of these forum-like interactions on the performance and outcomes of subsequent online and offline consultations. Khurana et al. (2019) investigate the impact of doctors' participation in online forums on the recommendations that they receive. However, they do not examine the effects of these responses on the demand for other doctors, specialties, and different channels. Chen and Walker (2023) evaluate the quality of responses provided by doctors on online health Q&A platforms and find that although the quality is generally high, patients may struggle to discern the quality of advice. Consequently, the influence of the information obtained through such interactions on subsequent consultations remains unclear.

2.2. On-Demand Healthcare Platforms

Some existing research on on-demand healthcare platforms focuses on their performance and implications in delivering medical care. Studies have examined the operational efficiency of accessing medical care through telemedicine, particularly in terms of resource allocation and coordination. For instance, Yeow and Goh (2015) demonstrate that telemedicine improves the efficiency of resource allocation in geriatric care. Similarly, Sun et al. (2020) find that the adoption of telemedicine enhances the efficiency of emergency room care, leading to reduced patient length of stay. The key driver for efficiency in these studies is the improved coordination across different services within the same medical setup and by the same doctor. Additionally, Hwang et al. (2022) evaluate the effectiveness of delivering healthcare to geographically distant patients through teleconsultations.

Another set of studies examines the impact of telemedicine on the utilization of other healthcare channels, but the findings from previous research on this topic are mixed. Some studies indicate a substitution effect of telehealth on office or telephone visits. For example, Zhou et al. (2007) find a negative correlation between access to secure patient-doctor messaging and primary care office visits and telephone contacts. Shah et al. (2018) demonstrate that virtual visits decrease in-person visits in accountable care organizations. However, North et al. (2014) report null effects, and Leveille et al. (2016) suggest a reverse impact, where office visits lead to subsequent use of a clinical portal. In contrast, Bavafa et al. (2018) observe a gateway effect, indicating that e-visits lead to an increase in office visits but with mixed impacts on telephone contacts and healthcare outcomes. They attribute this effect to the removal of gatekeepers. Ayabakan et al. (2024) also demonstrate a complementary effect in inpatient settings for nonchronic patients, but they also find a significant reduction in outpatient visits following a telehealth visit.

Several medical research studies have also examined the impact of emerging direct-to-consumer telehealth companies, including on-demand healthcare platforms, like Teladoc, American Well, and Doctor-on-Demand. Uscher-Pines and Mehrotra (2014) compare individuals who have adopted Teladoc with nonadopters and find that adopters were less likely to have prior connections with other providers and less likely to require follow-up visits with other providers. Ashwood et al. (2017) discover that these platforms offer convenient access to care, resulting in a small percentage of visits being substitutionary and a larger percentage representing new utilization. Fan et al. (2023) show that the number of offline appointments for doctors increases after opening an online consultation service. However, they evaluate this outcome from an individual doctor's perspective, and they do not consider the impact of such responses on the demand for other doctors within that specialty and other specialties. As a result, it is not known whether the demand gain by a doctor is at the cost of demand decrease for other doctors. They also do not consider different channels through which such demand could materialize.

Collectively, these studies suggest that online health platforms can generate new demand while also having a substitution effect on traditional providers. However, we are not aware of any studies that specifically evaluate the design of such healthcare platforms. To contribute to this field, our research focuses on assessing the impact of a Q&A service on the performance of online consultations and offline appointments facilitated through the platform. We also investigate how this impact varies across medical specialties and the professional titles of participating doctors.

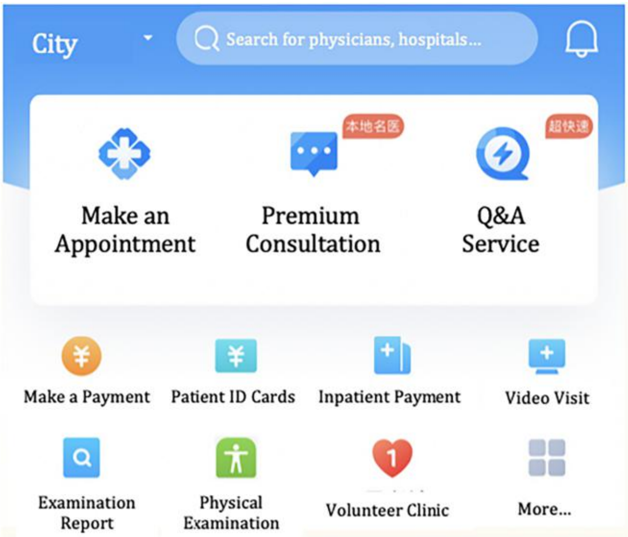
3. Empirical Setting

For this study, we collaborated with an on-demand healthcare platform that operates through a mobile app in China. The platform was established in 2015, and by 2018, it had expanded its services to over 70 cities across 17 provinces. It had established collaborations with approximately 500 hospitals. Over 50,000 healthcare service providers and nearly 10 million registered users had joined the platform.

For users or patients, registering on the app is free of charge. Licensed doctors are also able to register and offer their services through the platform at no cost. In China, the majority of doctors are affiliated with hospitals or clinics. Therefore, the doctors providing services on the platform are not employed by the platform itself. Instead, they use the platform to offer online services as a means of supplementing their income. To connect with more healthcare providers, the platform has established partnerships with hospitals across various provinces and cities.[3]

In China, doctors are classified into four professional titles.[4] The platform ensures that the title of each doctor is clearly labeled whenever their information is presented to users. Furthermore, doctors with the top two senior titles are referred to as "experts," which is a common practice in Chinese hospitals. The platform follows this convention as well. For the sake of simplicity in our study, we refer to doctors holding

Figure 1. (Color online) Screenshot of the Home Page of the App with Translations



the top two senior titles as "top doctors," whereas those with other titles are referred to as "nontop doctors." Overall, in the specific province that we examined, there are 3,206 registered top doctors (accounting for 72.6% of the total) and 1,208 nontop doctors (accounting for 27.4% of the total).

The platform primarily offers three types of services to its users: premium consultation, offline appointment, and Q&A (refer to Figure 1). In the premium consultation service, users can engage in online conversations with doctors of their choice. Doctors determine their own service prices, with the average price set by top doctors being 21.2 yuan and by nontop doctors being 10.3 yuan in the specific province under study.[5] During the service period, users and doctors can exchange text messages, photos, and voice messages. The content of these conversations is visible only to the involved parties and is not accessible to others. The platform earns a commission from doctors' premium services.

Regarding the appointment service, the platform collaborates with hospitals and clinics to integrate with their appointment systems. This allows platform users to make offline office visit appointments with doctors affiliated with these medical institutions. The appointment schedules and fees are determined by the hospitals. The platform does not charge any fee for making an appointment and therefore, does not generate direct revenue from this service.

Lastly, the Q&A service was introduced in January 2018. Users can compose health-related questions within a word limit of 500 Chinese characters and attach photos if necessary. After categorizing the health concern using a pretrained model based on the keywords from user input, the platform presents the question to a group of doctors in the corresponding medical department. These doctors can view the question and decide whether to claim the question and then, respond. For each question, only one doctor can provide the answer. If no doctor in the most relevant medical department responds within a few minutes, the platform expands the announcement to more doctors. The Q&A service has a standardized price, which was one yuan in 2018, and it increased to five yuan in 2019. Once a question has been answered, it becomes publicly available for all users to browse at no cost. However, users cannot search for previously raised questions.[6] For a summary of the main services, refer to Table 1.

3.1. Data

The data set provided by the platform encompasses the time frame from March 2016 to April 2019. It comprises online activities of all registered users, totaling 924,719 individuals from six cities within a southern province of China. Our observations include the users' gender, age, registration time, and city. Furthermore, we have a comprehensive view of the entire journey associated with the three primary services.

Regarding the premium consultation service, the data set contains information such as the time of purchase, service fee, text content of the conversation, and provider details, including a unique doctor identification, affiliation, title, and gender. For appointments, we have data on the time that a user schedules an appointment and the accompanying doctor information. Additionally, for each Q&A browsed, we observe the content of the question and answer, the time of user access, and the provider's information. Similarly, for purchased Q&A sessions, we have data on the time that the question was posed and answered as well as the provider's information.

In summary, the data set comprises 43,987 premium consultation purchases, 1,048,567 appointments, 11,994 Q&A service purchases, and 639,034 browsing activities (refer to Table 2). Statistics about the services delivered by different levels of doctors are provided in the Online Appendix (refer to Table A.2 in the Online Appendix).

Table 1. Summary of Services

Attribute	Q&A	Consultation	Appointment
Price	Set by the platform	Set by providers	Set by hospitals
Provider	Users cannot choose providers	Users choose providers	Users choose providers

Table 2. Summary Statistics

Variables	μ	σ	Min	Max
Age (years)	37.63	14.17	16	86
Gender	Female: 55.7%; male: 38.9%			
City	XY: 41.9%; HS: 31.0%; JZ: 25.8%; ZJ: 0.5%; YC: 0.5%; SY: 0.3%			
Tenure (days)	284.92	217.73	0.13	1,141.04
# of Q&A browsed	0.691	6.764	0	2,593
# of Q&A purchased	0.013	0.170	0	42
# of Consultations purchased	0.048	0.594	0	361
# of Appointments made	1.134	2.836	0	164

Notes. For the age data, some users filled this field with numbers like zero or one. We treat those age data below 16 as missing values. For the distribution over gender, 5.5% is missing. For the distribution of users among six cities, we only include abbreviations of city names to ensure the anonymity of the platform. HS; JZ; SY; XY; YC; ZJ.

3.2. Variables

Because the use of medical services is infrequent, we construct variables at the user-month level. The variable $Consultation_{i,t}$ represents the number of premium consultations purchased by a specific user (i) in a given month (t). Similarly, the variable $Appointment_{i,t}$ denotes the number of offline visit appointments made by user i in month t,[7] and the variable $Browse_{i,t}$ represents the number of Q&A sessions browsed by user i in month t.

We also analyze users' interactions within specific medical specialties. The variables $Consultation_{i,d,t}$, $Appointment_{i,d,t}$, and $Browse_{i,d,t}$ indicate the number of consultations purchased, the number of appointments made, and the number of Q&A sessions browsed, respectively, from doctors specialized in the particular medical specialty (d). The platform adopts a standardized specialty classification system comprising 30 major categories. Figure 2 illustrates the overall demand for different services across various specialties, and Table A.1 in the Online Appendix provides summary statistics for each specialty.

Additionally, we examine consultations and appointments with doctors of different titles. To capture the impact of doctor seniority, we consider two sets of variables: $Consultation\_TopDoc_{i,d,t}$ and $Appointment\_TopDoc_{i,d,t}$. These variables represent the number of consultations purchased and appointments made by user i in month t with top-level doctors in medical specialty d, respectively.

Lastly, to assess the revenue generated from users, we calculate two expenditure variables. The first is the total monthly expenditure of each user on the consultation service ($Spend_{i,t}$), and the second is the expenditure on the consultation service within each medical category ($Spend_{i,d,t}$). These variables provide insights into users' spending patterns.

4. Model and Empirical Strategy

Our objective is to examine the impact of Q&A service adoption on the demand for online consultations and offline appointments. To achieve this, we employ a difference-in-differences model, where users who adopt the Q&A service constitute the treatment group and those who do not serve as the control group. In order to ensure comparability between the treatment and control groups, we utilize the propensity score approach. This approach has been widely employed in the information systems and operations management literature (Sun and Zhu 2013, Bell et al. 2018, Liu and Bharadwaj 2020).

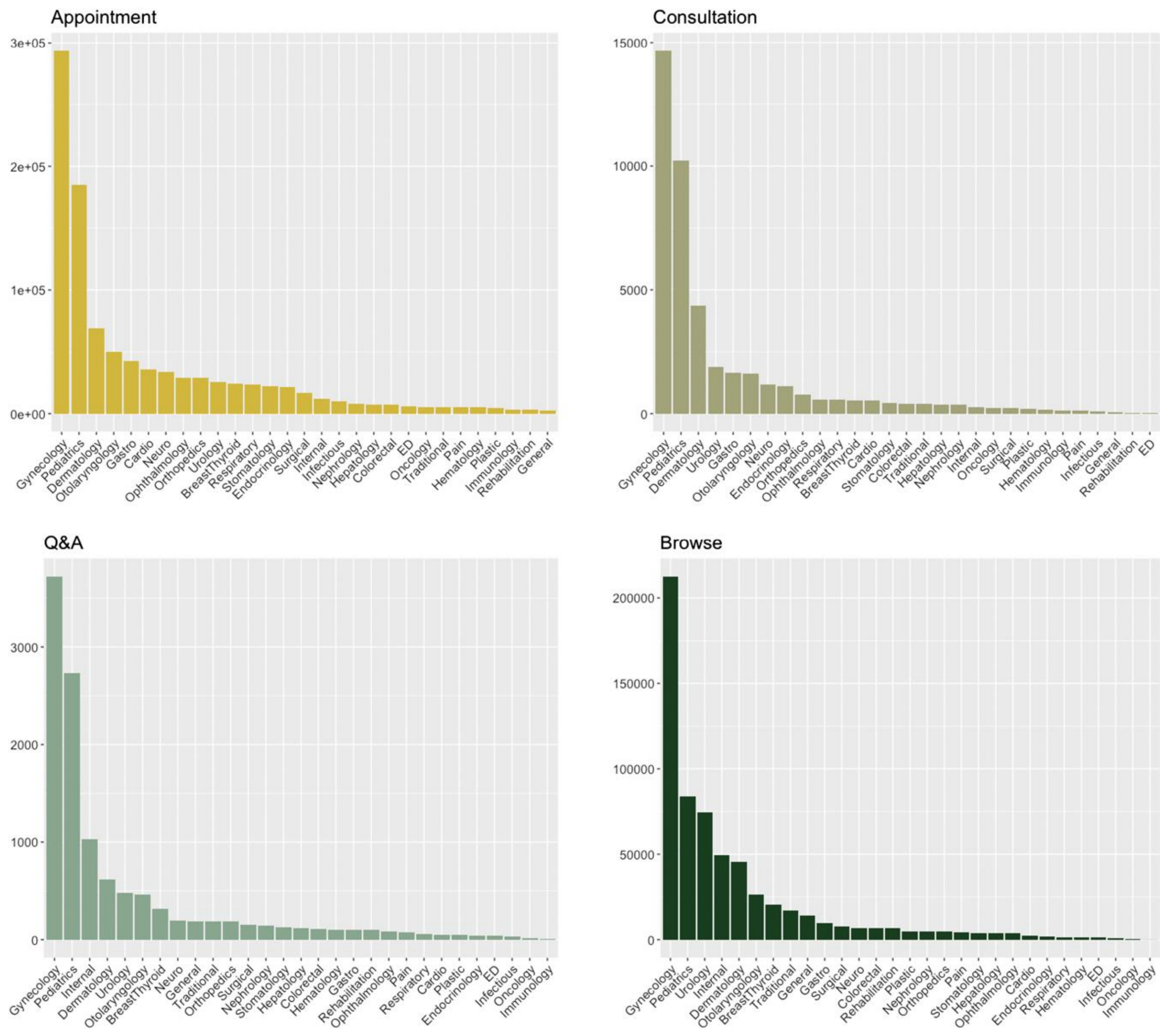
We measure the relative change in demand for online consultations or offline appointments among treated users compared with control users. However, it is important to note that users choose to use the Q&A service voluntarily, potentially influenced by factors such as their personal characteristics and health condition. This self-selection process could introduce biases in the analysis. To address this concern, we match users based on observed static and time-varying attributes. By doing so, we ensure that there is a parallel trend in demand before Q&A adoption between the treatment and control groups. Additionally, we validate the robustness of our main findings through other techniques, which we present in Section 6. In the following subsection, we provide a detailed description of the matching procedure and our model.

4.1. Propensity Score

We employ propensity score matching to match users based on their likelihood of adopting the Q&A service. We classify users who have utilized the Q&A service as "adopters" and those who have not as "nonadopters." For adopters, we assign a dummy variable $Q\&A_{i,t}$, which is coded as one for the month in which they first use the Q&A service and zero for all other periods. Nonadopters have $Q\&A_{i,t}$ coded as zero for all periods. To capture the propensity for Q&A adoption, we estimate the following model:

$$Q\&A_{i,t} = Prob(Y_{i,d,t-1}, Y_{i,d,t-2}, \bar{Y}_{i,d,t-1}, Gender_i, Age_i, City_i, Reg_i, t),$$

Figure 2. (Color online) Statistics of Consultation, Appointment, Q&A, and Browse in Each Medical Specialty



Note. ED, emergency department.

where $Prob(\cdot)$ denotes the probit model; the variables $Y_{i,d,t-1}$ and $Y_{i,d,t-2}$ are the one- and two-month lagged levels of $Appointment_{i,d,t}$, $Consultation_{i,d,t}$, $Browse_{i,d,t}$, $Appointment\_\,Top_{i,d,t}$, $Consultation\_Top_{i,d,t}$, and $Spend_{i,d,t}$; and $\bar{Y}_{i,d,t-1}$ is the one-month lagged cumulative levels of $Appointment_{i,d,t}$, $Consultation_{i,d,t}$, $Browse_{i,d,t}$, $Appointment\_\,Top_{i,d,t}$, $Consultation\_Top_{i,d,t}$, and $Spend_{i,d,t}$.

To account for demographic factors, we include controls for gender ($Gender_i$), age (Age_i), city ($City_i$), and registration time (Reg_i). We also incorporate time fixed effects to further capture variations over time. A summary of variables and their definitions is provided in Table A.3 in the Online Appendix.

When estimating the above model, we exclude adopters from the sample starting from the month of adoption. In other words, we do not estimate propensity scores for users who have already adopted the Q&A service. For the matching procedure, we employ the predicted probability of Q&A adoption derived from this selection model as the estimated propensity score.

4.2. Matching Strategy

We employ patient-level propensity score matching to create a comparable sample consisting of both adopters and nonadopters following the methodology used in previous healthcare-related studies (e.g., Li et al. 2022, Ayabakan et al. 2024). Given the extensive attributes of patients' online behaviors and the substantial size of the control group (9,165 adopters and

915,554 nonadopters), we go beyond propensity score matching and incorporate covariate matching. To achieve this, we combine propensity score matching with calipers on covariates, a technique also utilized in the literature (e.g., see Yang et al. 2020).

For an adopter who raised a question in month t, we identify a nonadopter who exhibits a similar probability of raising a question in month t' and possesses comparable time-invariant characteristics (gender, age, city, and registration time). Additionally, considering that users' health conditions evolve over time, we also match on time-varying behaviors, such as appointments made and questions browsed in month t' and prior periods. Furthermore, to account for the severity of users' conditions, we match users based on the topics that they have browsed before utilizing the Q&A service. Specifically, we combine consultation dialogues and Q&A sessions for each medical specialty and perform latent Dirichlet allocation analysis on the texts of each specialty individually to identify relevant topics. Subsequently, for each adopter, we identify nonadopters who exhibit similar attributes, have also browsed Q&A sessions within the same specialty, and demonstrate a similar topic distribution within each specialty as potential matching candidates.

A detailed description of the matching strategy is provided in Online Appendix A.2. To ensure that the matching result is not affected by the order of the data, we randomize the entire data set before conducting the matching. We employ a greedy matching algorithm and successfully match 5,442 pairs of adopters and nonadopters, accounting for 59.4% of all adopters. We conduct a balance check comparing adopters with nonadopters before and after matching (refer to Table A.4 in the Online Appendix).

4.3. DID Specification

To assess the causal impact of the Q&A service on both online and offline demands, we utilize the following DID regression model on the matched samples:

$$Y_{i,t} = \beta Adopt_{i,t} \times Post_{i,t} + \gamma Post_{i,t} + \alpha_i + \delta_t + \epsilon_{i,t},$$

where $Adopt_{i,t}$ is a dummy variable that takes the value of one for adopter i in all months and zero for corresponding nonadopter; $Post_{i,t}$ is a dummy variable coded as one for all months following the (or matched) adoption time for adopter (or nonadopter) and zero otherwise; and $Y_{i,t}$ represents the outcome variables in the subsequent month, such as the log of one plus $Consultation_{i,t}$, $Appointment_{i,t}$, $Spend_{i,t}$, and other relevant variables for different medical specialties and doctor titles. The dummy variable $Post_{i,t}$ captures temporal shifts in the outcome variable along with the Q&A service across both groups. It helps to isolate the effect of adopting the Q&A service (captured by $Adopt_{i,t} \times Post_{i,t}$) from dynamic effects (i.e., changes in health status) that could influence the outcome variable. The model is estimated using robust standard errors clustered at the individual user level. One key assumption in DID analysis is the parallel trend. This means that in the absence of treatment, the control and treatment groups should exhibit similar trends in the outcome variable. To verify this assumption, similar to Chen et al. (2024), we run the parallel-trend tests and visually present the estimated coefficients of the dynamic DID model in Figure A.1 in the Online Appendix.

4.4. Identification

To address potential confounding factors and ensure the validity of our findings, we consider several factors in our analysis. First, we incorporate time-specific fixed effects to account for any time trends that may influence the overall usage of online services. Second, we incorporate user fixed effects to account for user-specific static unobservables that could be correlated with the decision to adopt the Q&A service and other services. The user fixed effects can also absorb any influence of doctors' attributes and the specific medical specialty given that we consider only a single occurrence of Q&A for each user. They also absorb the effect of any selection in the matching where a particular doctor is matched with a patient and may influence the outcome. Third, time-varying effects at the individual level could influence the choice to use the Q&A service and subsequently seek online consultations or offline appointments. To address this, we construct a matched sample of users using both static and dynamic variables for matching. This approach ensures that adopters and nonadopters of the Q&A service have parallel time trends as illustrated in Figure A.1 in the Online Appendix. We also verify that the platform did not implement any user-specific promotions that could serve as shocks to influence user behavior. Lastly, we conduct robustness analyses using the coarsened exact matching (CEM) approach, the look-ahead propensity score matching (LA-PSM) approach, the two-stage DID approach, and a randomized experiment that provide validation of our results (see Section 6 for more analyses and discussions).

We acknowledge that as with any observational study, our design cannot fully address dynamic confounding, such as changes in health status or other unobserved time-varying factors that may influence treatment assignment. Additionally, given our use of a matched sample combined with DID analysis, our estimates should be interpreted as local average treatment effects (LATEs) specific to the subpopulation matched on observed characteristics, which is consistent with the interpretation in similar designs (Babar and Burtch 2024). We further note that our experimental results, which rely on an instrumental variable (IV) design, also estimate LATEs—specifically, the causal effect for compliers whose treatment status is affected by the randomized encouragement. Across both the observational and experimental components of the study, we are careful to interpret the estimates as applying to selected subsets of users rather than to the general population.

5. Results and Mechanisms

5.1. Empirical Findings

We commence our analysis by examining the impact of the Q&A service on both online consultations and offline appointments. The coefficient of the interaction term, $Adopt_{i,t} \times Post_{i,t}$, is positive and statistically significant for consultations and appointments as shown in the first two columns of Table 3, which suggests that the Q&A service has a complementary effect on both online consultations and offline appointments. The estimates of the effects on the raw measures of consultations and appointments as outcome variables are shown in Table A.5 in the Online Appendix. Our results indicate that each Q&A is associated with an average increase of 2% (or 0.033 visits per month) in online consultations. Similarly, the adoption of the Q&A service is associated with an average increase of 4.3% (or 0.067 visits per month) in offline appointments. Furthermore, we investigate the effect of adopting the Q&A service on users' expenditures for online consultations or alternatively, the platform's revenue from the consultation service. The coefficient of the interaction term, $Adopt_{i,t} \times Post_{i,t}$, is positive and statistically significant for spending as shown in the last column of Table 3. Q&A adoption leads to an average increase of 6.6% (or 0.57 yuan per month) in revenue. These findings provide evidence of the positive impact of the Q&A service on both online and offline medical services as well as the financial benefits that it brings to the platform in terms of increased revenue from consultations. Lastly, Table 3 reports that the coefficients of $Post_{i,t}$ are significantly positive. This finding suggests that nonadopters also tend to seek additional medical services, although to a lesser extent than adopters.

Table 3. Estimates of Effects on Consultations, Appointments, and Expenditures

Variables	log*Consultation*	log*Appointment*	log*Spend*
$Adopt \times Post$	0.020***	0.043***	0.066***
	(0.0015)	(0.0058)	(0.0052)
$Post$	0.0098***	0.10***	0.032***
	(0.00093)	(0.0046)	(0.0032)
N	101,704	101,704	101,704
Adjusted R^2	0.114	0.173	0.104

Notes. Standard errors in parentheses are clustered at the user level. All regressions contain individual and time fixed effects.
$^{***}p < 0.01$.

The effect sizes observed for the number of consultations and appointments may appear small given that medical visits are relatively infrequent, and the estimates represent the long-term average effect over the entire panel. Furthermore, we also present the estimated effects for the period of 1–3 months following adoption in Table A.6 in the Online Appendix. In the first month after adopting the Q&A service, the number of consultations increases by 5.4%, resulting in an immediate 18% rise in user expenditure. Additionally, the number of appointments increases by 14% in the first month after Q&A adoption. These findings indicate a substantial and immediate surge in the demand for both online consultations and offline appointments following the use of the Q&A service. They also suggest that any potential indirect cannibalization of services, such as online consultations or offline appointments, through the Q&A service is overcome by the complementary gains from users who independently consider these services.

5.2. Plausible Mechanisms

The Q&A service serves as a channel for patients to quickly obtain healthcare in a cost-effective way. It also enables patients to access valuable knowledge regarding the online service format, become aware of potential additional care requirements, and receive guidance on the appropriate specialized care to seek. In the subsequent subsections, we perform various analyses to explore the possible underlying mechanisms driving these effects.

5.2.1. The Sampling Effect. The positive impact of the Q&A service on subsequent service purchases may be attributed to a sampling effect. In the case of online medical consultations, where most users have limited prior experience, the Q&A service was introduced as a simplified version, allowing consumers to familiarize themselves with this new format of medical care and verify the quality of the service provider. Drawing from the literature on digital product sampling for experience goods, previous studies have found that offering a free version of a mobile application stimulates demand for the paid version (Liu et al. 2014, Deng et al. 2018). As argued by Hong and Pavlou (2014) and Deng et al. (2018), customers often face uncertainties regarding product attributes and quality, which hinder their online market purchases. Introducing a free version of an app as a sample product helps alleviate these uncertainties and encourages customers to make full-version purchases of the focal app.

In the context of the healthcare services that we examine, if the sampling theory also applies, a light version of a service (i.e., the Q&A service) could help consumers confirm the attributes and quality of the service. Consequently, users may be more inclined to seek comprehensive services (such as consultations or appointments) from the same healthcare provider, leading to a positive effect on the number of subsequent services. To evaluate this potential mechanism, we utilize the number of subsequent consultations and appointments provided by the same doctor as outcome variables. Estimations shown in the first two columns of Table 4 illustrate a small but positive effect for the online channel, indicating that the sampling effect might induce users to follow-up with the same doctors online via the platform. For the offline channel, because we only see appointments made through the platform and not those made directly with hospitals, the effect on the offline channel might be underestimated. One potential concern is that the observed sampling effect may be confounded by browsing behavior. To address this, we include browsing activity as a control in our analysis of the sampling effect. As shown in Table A.7 in the Online Appendix, the positive effect of Q&A usage on follow-up consultations with the same doctor remains robust.

We further explore the sampling effect by examining the moderating role of uncertainties (Shoemaker and Shoaf 1975) surrounding the medical conditions that users face when adopting the Q&A service. If the sampling mechanism influences subsequent visits, we anticipate a stronger effect among users experiencing greater uncertainty regarding their medical condition. To quantify this uncertainty, we calculate the number of Q&A sessions that each user browsed within the same medical department during the month prior to their adoption of the service. A binary variable, *HighBrw*, is assigned a value of one for users who browsed a number of Q&As exceeding the median.[8] Drawing on the literature regarding buyer uncertainty and information search (Urbany 1986, Urbany et al. 1989, Ou and Ho 2022), we can expect users to engage in more health information-seeking behavior when uncertain about their condition. Consequently, if a user has browsed a higher number of Q&A sessions related to their health issue, it likely indicates a greater level of uncertainty. The results, presented in the last two columns of Table 4, demonstrate that online visits with the same doctor are primarily driven by users who had browsed a higher number of Q&As prior to adopting the service, thereby confirming the sampling effect.

Users face particularly strong uncertainties and information asymmetry when seeking medical services, which fall under the category of credence goods, where the quality of the service is challenging to verify even after consumption (Dulleck and Kerschbamer 2006, Gottschalk et al. 2020). Therefore, our analysis suggests that a sampling experience with a service could potentially alleviate uncertainties that users face before committing to the full service. This effect particularly leads to users seeking additional services from the same provider in online medical care.

The recommendation or service provided by one doctor may also prompt a patient to seek services from other doctors or alternative channels. In other words, in addition to the sampling effect, there may be other factors contributing to the increase in service purchases, which we will investigate further below.

5.2.2. The Spillover Effect. In addition to confirming the quality, the Q&A service also plays a role in raising users' awareness of potential additional care required, whether through online or offline channels. The responses received through the Q&A service may be limited in terms of the amount of information provided, which can stimulate patients to seek more comprehensive information (Kumar and Telang 2012, Bavafa et al. 2018). If this is the case, users may seek further medical care from doctors within the same specialty following the Q&A sessions. However, instead of choosing the same doctor, some users may opt for services from a different doctor, creating a spillover effect. Previous studies have recognized that information channels, such as advertisements,

Table 4. The Effect for the Same Doctor

Variables	log*Con_SameDoc*	log*App_SameDoc*	log*Con_SameDoc*	log*App_SameDoc*
Adopt × *Post*	0.00078***	0.00035	0.00027	0.00038
	(0.00022)	(0.00026)	(0.00018)	(0.00061)
Post	0.00048***	−0.00012	0.00050***	−0.00011
	(0.00012)	(0.00016)	(0.00011)	(0.00018)
Adopt × *Post* × *HighBrw*			0.00072**	0.000034
			(0.00035)	(0.00076)
Post × *HighBrw*			−0.00012	−0.000077
			(0.00015)	(0.00051)
N	101,704	101,704	101,704	101,704
Adjusted R^2	0.057	0.074	0.057	0.074

Notes. Standard errors in parentheses are clustered at the user level. All regressions contain individual and time fixed effects.
$^{**}p < 0.05$; $^{***}p < 0.01$.

Table 5. The Effect for the Same Department Nontop Doctors and Top Doctors

	SameDepNonTopDoc		*SameDepTopDoc*	
Variables	log*Con*	log*App*	log*Con*	log*App*
Adopt × *Post*	0.0030***	0.013***	0.0080***	0.023***
	(0.00041)	(0.0025)	(0.00086)	(0.0029)
Post	0.0013***	0.021***	0.0042***	0.024***
	(0.00025)	(0.0020)	(0.00058)	(0.0023)
N	101,704	101,704	101,704	101,704
Adjusted R^2	0.083	0.174	0.112	0.146

Notes. Standard errors in parentheses are clustered at the user level. All regressions contain individual and time fixed effects.
***$p < 0.01$.

can create awareness of the products or services within the same category, leading to increased sales for these nonadvertised providers (Shapiro 2018). This effect may be more pronounced for higher-rated providers (Sahni 2016). Such demand spillovers have also been identified in the mobile app market, stimulated by recommendations or the emergence of popular complements (Liang et al. 2019, Lee et al. 2023). Similarly, as an information-provision channel, the Q&A service raises users' awareness of the need for additional medical care within the same specialty while also stimulating demand for services provided by other doctors. These effects could be more significant for doctors known for their higher quality.

To examine this effect, we utilize consultations and appointments with both nontop and top nonfocal doctors within the same medical department as the Q&A service as outcome variables.[9] Table 5 demonstrates the presence of positive effects on both nontop and top doctors across both online and offline channels. Although the coefficients are smaller compared with the main effect observed in Table 3, as we focus solely on visits within the same specialty (cross-specialty visits will be analyzed in subsequent sections), the results confirm the existence of a spillover mechanism to nonfocal doctors. Based on a seemingly unrelated estimation, for online consultations, the coefficient is significantly higher for same department top doctors as compared with nontop doctors ($\chi^2(1) = 7.24$, $p < 0.01$), suggesting a stronger spillover effect for highly regarded practitioners. However, for appointments, the difference is not statistically significant ($\chi^2(1) = 1.93$, $p = 0.16$). Our findings pertaining to spillover effects also suggest that exposure to even limited information channels can extend their benefits to a broader group of service providers within an online platform with a market-based setup.

5.2.3. The Matching Effect. Thus far, our focus has been on scenarios where patients' further medical needs are addressed within the same medical specialty as the Q&A service. However, it is also possible that the Q&A service guides users to consult or seek treatment from doctors in a different medical department. Considering this, we argue that the matching process or finding the appropriate type of medical care can also contribute to the positive impact of the Q&A service. Medical care is a highly specialized service with significant information asymmetry between providers and patients. Users of the medical platform may lack sufficient knowledge to choose from doctors with various specialties. This issue is even more pronounced in on-demand platforms where there is no coordination among doctors because of the marketplace setup.

If the Q&A service does facilitate matching users with the right type of medical care, the specialty of the medical care sought after the Q&A session may differ from the specialty of the Q&A service itself. Therefore, if the matching mechanism is effective, we should observe an increase in cross-specialty consultations or appointments following the Q&A service. To analyze this, we calculate the number of consultations and appointments within the same specialty as the Q&A service as well as those in different specialties, and we use these variables as outcome measures. As shown in Table 6, we find a significant increase in both same-specialty and different-specialty consultations and appointments because of the Q&A service. Specifically,

Table 6. The Effect for the Same and Different Medical Specialties

	log*Consultation*		log*Appointment*	
Variables	*SameSpecialty*	*DiffSpecialty*	*SameSpecialty*	*DiffSpecialty*
Adopt × *Post*	0.011***	0.0097***	0.034***	0.0090**
	(0.00098)	(0.0011)	(0.0039)	(0.0045)
Post	0.0054***	0.0046***	0.043***	0.062***
	(0.00065)	(0.00066)	(0.0030)	(0.0037)
N	101,704	101,704	101,704	101,704
Adjusted R^2	0.122	0.077	0.188	0.150

Notes. Standard errors in parentheses are clustered at the user level. All regressions contain individual and time fixed effects.
**$p < 0.05$; ***$p < 0.01$.

Table 7. The Moderating Role of Physician Recommendation for the Same and Different Medical Specialties

	log*Consultation*		log*Appointment*	
Variables	*SameSpecialty*	*DiffSpecialty*	*SameSpecialty*	*DiffSpecialty*
Adopt × *Post*	0.012***	0.0098***	0.038***	0.0085*
	(0.0011)	(0.0012)	(0.0044)	(0.0047)
Adopt × *Post* × *RecDiffDep*	−0.0088***	−0.00086	−0.027***	0.0039*
	(0.0021)	(0.0032)	(0.0075)	(0.0021)
Post	0.0053***	0.0046***	0.043***	0.063***
	(0.00066)	(0.00069)	(0.0033)	(0.0038)
Post × *RecDiffDep*	0.00086	−0.00017	−0.00059	−0.0050
	(0.00078)	(0.0013)	(0.0046)	(0.010)
N	101,704	101,704	101,704	101,704
Adjusted R^2	0.122	0.077	0.188	0.150

Notes. Standard errors in parentheses are clustered at the user level. All regressions contain individual and time fixed effects.
$^{*}p < 0.10$; $^{***}p < 0.01$.

the number of consultations within the same specialty increases by 1.1%, whereas the increase in different specialties is 0.97%. For appointments, the numbers increase by 3.4% and 0.9% in the same and different categories, respectively.

The increase in cross-specialty demand could potentially stem from a mismatch between the patient and the Q&A doctor. However, if there was a systematic mismatch problem with the Q&A process, we would not expect to see a corresponding rise in demand for same-specialty doctors.

We elucidate the matching effect by investigating whether the physician recommending specific medical specialties for follow-ups influences subsequent online or offline visits. We analyze the text of the Q&A session to identify the type of medical specialty recommended. In our study sample, during 1,331 Q&A sessions, doctors identified suitable medical departments for follow-up, and within these sessions, 917 instances mentioned a department different from the Q&A specialty. We extend the analysis outlined in Table 6 by introducing a three-way interaction term *Adopt* × *Post* × *RecDiffDep*, where the dummy variable *RecDiffDep* equals one if a different medical specialty was recommended for follow-up visits. As reported in Table 7, recommendations for a different medical department decrease visits to the same department but increase offline visits to different departments, potentially confirming the presence of a matching mechanism.

To further understand the potential matching mechanism, we conduct an additional text-based analysis. We create a subsample of adopters and matched nonadopters who have sought consultations from a different specialty in the month following the use of Q&A service by adopters. For adopters, we estimate the text similarity between the Q&A and the subsequent consultation dialogues, whereas for nonadopters, we estimate the text similarity between the Q&A that they browsed and the subsequent consultation dialogues. We then compare the difference in text similarity between adopters and nonadopters. The text similarity is calculated using SimHash (Charikar 2002), which identifies keywords from two inputs and computes the Hamming distance between them. A smaller SimHash value indicates stronger similarity between two text inputs. The comparison results are shown in Table 8. The average SimHash distance for adopters between the Q&A and post-Q&A consultations is 31.25, significantly smaller than that of nonadopters (average distance of 32.63) with $p < 0.05$. This result demonstrates that adopters, when seeking medical services from a different specialty, discuss information that is more closely related to the Q&A service compared with nonadopters, suggesting higher information similarity between Q&A and consultation. Higher information similarity implies that Q&A leads to a better match.

The above results indicate that the effect of the Q&A service extends to doctors in other medical specialties across both online and offline channels. Additionally, the Q&A service enhances information similarity in this cross-specialty effect, providing evidence for the matching mechanism. These findings align with the

Table 8. Comparing the Text Similarity Between Adopters and Nonadopters

Variables	Mean (adopters)	Mean (nonadopters)	*N*	*t*-value	*p*-value
SimHash	31.25	32.63	96	2.18	0.030

previous literature on the role of information provision in the matching process. Specifically, the Q&A service serves as an information-provision channel with limited capacity. Other types of information-provision channels, such as online search and live chat, have demonstrated that partially revealed information can facilitate the search process for consumers to find a suitable match (Gu and Wang 2022), and the information-provision function can reinforce sales (Tan et al. 2019). Our findings support this line of theory and extend it to the context of online healthcare services.

5.3. Ruling out Alternative Explanations

The analyses conducted thus far suggest that the positive impact of the Q&A service can be attributed to the sampling effect (confirming service and provider quality), the spillover effect (increased awareness of potential additional care needs), and the matching effect (guidance on seeking appropriate specialized care). However, it is important to consider other potential mechanisms that could help explain the impact of the Q&A service. In this subsection, we perform additional analyses to investigate and rule out two alternative explanations.

5.3.1. Role of the Doctor's Advice. In our sample, we have observed instances where doctors during the Q&A service may recommend scheduling an offline appointment.[10] This means that if a doctor is unable to fully address the patient's medical concern online, they are likely to advise the patient to schedule an offline appointment for further examination. It is plausible that the impact of the Q&A service is driven by these recommendations. It is important to note that as we consider only one Q&A interaction per patient, any such effects from specific doctors are accounted for and controlled by the patient-specific fixed effect. However, to explore this potential effect further, we examine how doctors' advice moderates the impact of the Q&A service. We introduce an interaction term, $Adopt \times Post \times AdvOffline$, where $AdvOffline$ is a binary variable coded as one when an offline office visit is clearly suggested by the responding doctor.[11] As shown in Table 9, we find that a doctor's advice regarding an offline appointment strengthens the effect on these appointments, whereas the main effect remains significant. However, we do not observe any effect of such advice on online consultations.

Table 9. The Effect of the Doctor's Advice

Variables	log*Consultation*	log*Appointment*
$Adopt \times Post$	0.019**	0.080***
	(0.0066)	(0.017)
$Adopt \times Post \times AdvOffline$	−0.0031	0.018**
	(0.0031)	(0.0080)
$Post$	0.022***	0.056***
	(0.0063)	(0.0162)
N	101,704	101,704
Adjusted R^2	0.119	0.188

Notes. Standard errors in parentheses are clustered at the user level. All regressions contain individual and time fixed effects.
$^{**}p < 0.05$; $^{***}p < 0.01$.

5.3.2. Effect of the App. Another potential explanation for the impact of the Q&A service on online consultations or offline appointments is that it familiarizes new users with the app. In other words, for users who have never utilized the online consultation or offline appointment service before, the Q&A service serves as an introduction to the app, increasing their likelihood of using these main services. If this is the case, then the observed effect can be attributed to app usage rather than the actual Q&A service. To explore the influence of this factor, we conduct a separate analysis using a subsample of old users who registered before the introduction of the Q&A service. These old users were already acquainted with the online platform and the app. The estimated results presented in Table 10 indicate that the Q&A service still has a significantly positive effect on both online consultations and offline appointments for these old users. Therefore, our findings suggest that the impact of the Q&A service is not solely a result of app familiarity.

5.4. Heterogeneous Effects Across Doctors and Specialties

Based on our analyses thus far, we have observed that the Q&A service has the following effects. (1) There is an increase in the utilization of subsequent medical services, both online and offline, and (2) these effects can be explained by the sampling, spillover, and matching mechanisms. However, it is important to consider that the Q&A service has limited capacity in terms of information provision, despite being an easy and on-demand communication platform. In terms of follow-up services, app users have the freedom to choose any doctor and medical specialty in both channels. This raises the question of whether the

Table 10. Estimation with the Old User Subsample

Variables	log*Consultation*	log*Appointment*
$Adopt \times Post$	0.017***	0.036**
	(0.0032)	(0.015)
$Post$	0.0072***	0.066***
	(0.0018)	(0.011)
N	22,428	22,428
Adjusted R^2	0.081	0.195

Notes. Standard errors in parentheses are clustered at the user level. All regressions contain individual and time fixed effects.
$^{**}p < 0.05$; $^{***}p < 0.01$.

Table 11. The Effect of Top Doctors Answering the Question

Variables	log*Consultation*	log*Appointment*
Adopt × *Post*	0.018***	0.036***
	(0.0019)	(0.0054)
Adopt × *Post* × *TopDoc*	0.0059**	0.016**
	(0.0028)	(0.0068)
Post	0.0098***	0.10***
	(0.00093)	(0.0037)
N	101,704	101,704
Adjusted R^2	0.114	0.174

Notes. Standard errors in parentheses are clustered at the user level. All regressions contain individual and time fixed effects.
$^{**}p < 0.05$; $^{***}p < 0.01$.

effectiveness of the Q&A service is consistent across all doctors or limited to certain individuals and whether it addresses all types of patient needs, regardless of the simplicity or complexity of their medical needs. In the following analysis, we explore the heterogeneous influences of the Q&A service on patients' choices of doctors and medical specialties.

5.4.1. Seniority of Doctors. First, we examine the moderating role of doctor titles in patients' choices of subsequent services. As previously mentioned, doctors are classified based on their experience and educational backgrounds. We hypothesize that top doctors, who are senior and more experienced, may provide more accurate and high-quality answers, thereby serving as a stronger signal for high-quality services. To investigate this effect, we introduce the interaction term *Adopt* × *Post* × *TopDoc*, where *TopDoc* is a binary variable indicating whether the responding doctor has a top-level title.

Table 11 shows the corresponding results. Our analysis reveals that for both online consultations and offline appointments, the coefficients of the interaction terms *Adopt* × *Post* × *TopDoc* and *Adopt* × *Post* are significantly positive. This finding suggests that Q&A responses from nontop doctors generate a positive demand in both online and offline channels. However, the effect is significantly higher for top doctors. This aligns with the results reported in Khurana et al. (2019) and reflects the significant information asymmetry in healthcare. A more experienced doctor is likely to have greater credibility in responses, leading to increased demand for additional medical services. It is important to note that although we previously demonstrated the effect of top doctors within the same specialty, Table 11 illustrates the effect across all specialties.

Next, we investigate how patients choose between doctors with different titles for online and offline medical services after using the Q&A service. We calculate the number of online consultations and offline appointments separately for top and nontop doctors to construct the outcome variables. We analyze a model that includes the interaction term *Adopt* × *Post* × *TopDoc* to understand the transitions across doctor titles (see Table 12 for the estimation results). Our findings indicate that for the online service, both types of doctors experience an increased demand after users adopt the Q&A service. However, responses from top doctors lead to a higher number of services being directed toward top doctors compared with nontop doctors. This effect of greater spillover among top doctors also extends to offline appointments. Interestingly, we observe that nontop doctors do not benefit from the Q&A service in the offline channel as it does not affect the number of offline appointments for this group. This disparate effect across the two channels suggests that patients have a stronger preference for high-value services in the offline channel. Despite more nontop doctors providing longer responses in the Q&A service (see Table A.2 in the Online Appendix), they benefit less across both channels. Our observations imply that exposure to the Q&A service influences a user's choice of doctors, leading to an uneven distribution of benefits. Therefore, the platform may need to consider compensating nontop doctors for their participation in the Q&A service.

Table 12. The Effect on Doctors with Different Titles

Variables	log*Con_TopDoc*	log*Con_NonTopDoc*	log*App_TopDoc*	log*App_NonTopDoc*
Adopt × *Post*	0.012***	0.0059***	0.020***	0.0014
	(0.0016)	(0.00084)	(0.0048)	(0.0012)
Adopt × *Post* × *TopDoc*	0.0053**	0.00069	0.026***	−0.00087
	(0.0023)	(0.0013)	(0.0066)	(0.0015)
Post	0.0077***	0.0024***	0.060***	0.0052***
	(0.00082)	(0.00041)	(0.0035)	(0.00081)
N	101,704	101,704	101,704	101,704
Adjusted R^2	0.100	0.072	0.138	0.115

Notes. Standard errors in parentheses are clustered at the user level. All regressions contain individual and time fixed effects.
$^{**}p < 0.05$; $^{***}p < 0.01$.

Table 13. The Effect of Q&A in Simple Specialties

	log*Consultation*		log*Appointment*	
Variables	*Complex*	*General*	*Complex*	*General*
Adopt × *Post*	−0.00031	−0.00050	−0.0057	−0.0014
	(0.0021)	(0.00091)	(0.013)	(0.0031)
Post	−0.00044	0.00053	0.023*	0.0069**
	(0.0016)	(0.00040)	(0.012)	(0.0030)
N	5,209	5,209	5,209	5,209
Adjusted R^2	−0.021	0.009	0.045	0.039

Notes. Standard errors in parentheses are clustered at the user level. All regressions contain individual and time fixed effects.
*$p < 0.10$; **$p < 0.05$.

Table 15. The Effect of Q&A in Complex Specialties

	log*Consultation*		log*Appointment*	
Variables	*General*	*Simple*	*General*	*Simple*
Adopt × *Post*	0.00049	0.0014	0.00078	0.00025
	(0.00036)	(0.00086)	(0.0020)	(0.0030)
Post	−0.000020	0.0012*	0.0038**	0.012***
	(0.00018)	(0.00064)	(0.0016)	(0.0029)
N	19,009	19,009	19,009	19,009
Adjusted R^2	0.004	0.030	0.062	0.095

Notes. Standard errors in parentheses are clustered at the user level. All regressions contain individual and time fixed effects.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

5.4.2. Medical Specialties. As we have illustrated, the matching effect of the Q&A service can extend the demand for further medical services to various medical specialties. To explore this heterogeneous effect across different specialties, we classify them into distinct categories. First, we create a category for general medical issues, encompassing general practice, internal medicine, and general surgery. Doctors in this category do not specialize in diseases related to specific organs. In China, where an official referral practice is not established, doctors have a responsibility to guide patients toward specialized doctors. Second, we classify dermatology and endocrinology as simple specialties. According to Tonelli et al. (2018), dermatologists and endocrinologists often treat patients with the least complexity as measured by the number of comorbidities, prescribed medications, and other criteria. Lastly, all other medical specialties, except pediatrics and gynecology, are classified as complex specialties.[12]

We investigate how patients' Q&A interactions in one category influence their online and offline medical services in a different category. Building upon the analysis of cross-specialty effects for the matching mechanism in Section 5.2.3, we specifically focus on the crosscategory effects and present the results in Tables 13–15. For both simple and complex specialties, we do not observe a significant effect on subsequent services in either channel. However, intriguingly, when it comes to the Q&A interactions in the general category, users tend to seek more specialized and complex medical care both online and offline. Note that cross-specialty demand increases from general to complex specialties (Table 14) but not the other way around (Table 15), suggesting that the increase in demand is not because of mismatch during the Q&A phase. This pattern aligns with our expectation that generalist recommendations may prompt patients to seek advice from specialists.

Table 14. The Effect of Q&A in General Specialties

	log*Consultation*		log*Appointment*	
Variables	*Complex*	*Simple*	*Complex*	*Simple*
Adopt × *Post*	0.010***	0.0029	0.029***	0.0033
	(0.0021)	(0.0019)	(0.0090)	(0.0035)
Post	0.0051***	−0.00028	0.045***	0.0052*
	(0.0014)	(0.00085)	(0.0068)	(0.0030)
N	13,794	13,794	13,794	13,794
Adjusted R^2	0.081	0.144	0.097	0.049

Notes. Standard errors in parentheses are clustered at the user level. All regressions contain individual and time fixed effects.
*$p < 0.10$; ***$p < 0.01$.

These findings suggest that the Q&A service, as an information channel, can guide patients in obtaining specialized care, particularly for complex medical specialties. Healthcare services, being credence goods, impose significant search costs on patients when trying to find the right type of care (Dulleck and Kerschbamer 2006). This cost can be even higher for patients with complex medical needs because of asymmetric information. As our observations indicate, when transitioning from general specialties to complex specialties, the Q&A service acts as a channel facilitating information exchange between the two sides of the healthcare market and aiding in better matching patients with healthcare providers. Consequently, in line with previous literature (Van Den Bulte et al. 2018), our findings demonstrate that the benefits of the matching effect may be more pronounced for customers with complex needs.

5.5. Effect on Healthcare Outcomes

We further analyze the impact of the Q&A service on healthcare outcomes. Although we do not have direct access to patients' health records to measure health outcomes, we can utilize platform data to evaluate revisits following a consultation or appointment. Revisits have been widely employed as a metric for health-related outcomes and patient welfare in management and healthcare studies (e.g., van der Linden et al. 2011, Guo et al. 2019). As previously demonstrated, the Q&A service has the potential to assist users in finding the appropriate doctors and addressing issues related

Table 16. The Effect on Revisits for Consultations and Appointments

	$\kappa = 1$: 1 Month after Q&A		$\kappa = 2$: 2 Months after Q&A		$\kappa = 3$: 3 Months after Q&A	
Variables	log*Con*	log*App*	log*Con*	log*App*	log*Con*	log*App*
$Adopt \times Post_{\kappa-}$	−0.035***	−0.044	−0.020***	−0.079***	−0.016***	−0.069***
	(0.011)	(0.032)	(0.0057)	(0.017)	(0.0044)	(0.013)
$Post_{\kappa-}$	−0.020	−0.20***	0.018***	0.049***	0.018***	0.10***
	(0.017)	(0.046)	(0.0055)	(0.016)	(0.0037)	(0.012)
N	3,585	3,585	7,904	7,904	11,709	11,709
Adjusted R^2	0.254	0.446	0.222	0.357	0.204	0.331

Notes. Standard errors in parentheses are clustered at the user level. All regressions contain individual and time fixed effects.
***$p < 0.01$.

to provider-patient mismatch. In line with this, we would expect to observe a reduction in revisits among users who adopted the Q&A service prior to their consultation or appointment.

To examine this effect, we select a subset of matched pairs comprising adopters and nonadopters who underwent a consultation or appointment within one, two, or three months after adopters engaged in the Q&A service. We then estimate the impact of Q&A adoption on revisits occurring at one, two, and three months after the actual online consultation or offline appointment.[13] Specifically, for the subsample within 2κ months post-Q&A, we employ the following specification:

$$Y_{i,t} = \beta Adopt_{i,t} \times Post_{\kappa-,i,t} + \gamma Post_{\kappa-,i,t} + \alpha_i + \delta_t + \epsilon_{i,t},$$

where $Post_{\kappa-}$ is coded as one for the period after κ (equal to one, two, or three) months post-Q&A. As depicted in Table 16, patients who utilized the Q&A service tend to have fewer revisits, both online and offline. Related to the mechanisms discussed in Section 5.2.3, the reduction in revisits could be explained by the matching effect in that the Q&A service facilitates appropriate matching between users and service providers. To test this channel, we repeat the above analysis using same- and different-specialty revisits as outcome variables. As shown in Table 17, we see a consistent effect of Q&A reducing revisits among Q&A users. This pattern aligns with our interpretation of the Q&A service improving patient-provider matching across specialties.

Additionally, we examine users' browsing behaviors following interactions with doctors, whether online or offline. Following the same logic as described earlier, we anticipate that users who adopted the Q&A service prior to a consultation or appointment would engage

Table 17. The Effect on Revisits for the Same and Different Medical Specialties

	$\kappa = 1$: 1 Month after Q&A		$\kappa = 2$: 2 Months after Q&A		$\kappa = 3$: 3 Months after Q&A	
Variables	log*Con_Same*	log*App_Same*	log*Con_Same*	log*App_Same*	log*Con_Same*	log*App_Same*
$Adopt \times Post_{\kappa-}$	−0.016**	−0.0083	−0.0073**	−0.018	−0.0047**	−0.020**
	(0.0066)	(0.022)	(0.0032)	(0.011)	(0.0023)	(0.0081)
$Post_{\kappa-}$	−0.0035	−0.057	0.0076**	0.022**	0.0054**	0.027***
	(0.0096)	(0.036)	(0.0033)	(0.011)	(0.0022)	(0.0078)
N	3,585	3,585	7,904	7,904	11,709	11,709
Adjusted R^2	0.011	0.170	0.030	0.140	0.024	0.143
	$\kappa = 1$: 1 month after Q&A		$\kappa = 2$: 2 months after Q&A		$\kappa = 3$: 3 months after Q&A	
Variables	log*Con_Diff*	log*App_Diff*	log*Con_Diff*	log*App_Diff*	log*Con_Diff*	log*App_Diff*
$Adopt \times Post_{\kappa-}$	−0.021**	−0.029	−0.013***	−0.064***	−0.011***	−0.051***
	(0.0092)	(0.031)	(0.0048)	(0.015)	(0.0039)	(0.011)
$Post_{\kappa-}$	−0.015	−0.15***	0.011**	0.026*	0.012***	0.077***
	(0.015)	(0.046)	(0.0046)	(0.015)	(0.0032)	(0.010)
N	3,585	3,585	7,904	7,904	11,709	11,709
Adjusted R^2	0.198	0.288	0.179	0.265	0.178	0.249

Notes. The upper panel reports the effects on revisits within the same medical specialty, whereas the lower panel reports the effects on revisits across different medical specialties. Standard errors in parentheses are clustered at the user level. All regressions contain individual and time fixed effects.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Table 18. The Revisit Effect on Browsing

	log*Browse*		
Variables	$\kappa = 1$	$\kappa = 2$	$\kappa = 3$
$Adopt \times Post_{\kappa-}$	−0.25***	−0.19***	−0.16***
	(0.048)	(0.026)	(0.019)
$Post_{\kappa-}$	−0.055	0.17***	0.14***
	(0.058)	(0.026)	(0.018)
N	3,585	7,904	11,709
Adjusted R^2	0.279	0.244	0.231

Notes. Standard errors in parentheses are clustered at the user level. All regressions contain individual and time fixed effects.
***$p < 0.01$.

in less browsing compared with nonadopters. To test this hypothesis, we analyze the same subset of paired users mentioned above who underwent a consultation or appointment within κ months after the Q&A service adoption, where $\kappa = 1, 2, 3$. The outcome variable is the logarithm of the number of Q&A browsed. The estimation results are presented in Table 18. These findings reveal a decrease in browsing activity on the health platform, suggesting that patients may experience improved health outcomes as they feel less compelled to seek additional medical information.

One potential concern regarding our findings is that the reduction in revisits could be indicative of attrition, where users discontinue seeking medical services altogether as they have a low acceptance of or trust in the app. To address this concern, we implement several additionally analyses. First, we examine a subgroup of users who scheduled an appointment or consultation within six weeks of their Q&A session. We then track their demand for services six months after their initial visit and compare it with users who did not engage in the Q&A service. In Table A.8 in the Online Appendix, we present our findings, which indicate a sustained positive and significant impact on online consultations. However, we did not observe a significant effect on offline appointments. This suggests that the decrease in short-term revisits does not imply attrition as users continue to engage in online consultations even after the initial period. Second, we examine a subgroup of old users who registered before the introduction of the Q&A service and thus, are reasonably familiar with the platform (as we have done in Section 5.3.2). We examine the impact of Q&A on revisits for this subsample of users and present the results in Table A.9 in the Online Appendix. We see a reduction in online or offline revisits after two or three months post-Q&A adoption, suggesting a consistent positive impact on health outcomes. Third, we plot the browsing and service usage patterns of Q&A adopters over time. As shown in Figure A.2 in the Online Appendix, the volume of user activity exhibits an overall increasing trend, suggesting that users remain engaged with the platform over time.

6. Robustness Checks

6.1. Alternative Specifications

To enhance the robustness of our analysis, we carry out a range of robustness checks.

6.1.1. Coarsened Exact Matching. We employ the coarsened exact matching method to create comparable groups of adopters and nonadopters. The matching process follows a similar approach to our main analysis using propensity score matching with adjustments on covariates. We consider attributes such as the number of consultations, appointments, and questions browsed in each medical specialty up to two months before Q&A adoption. Additionally, we include information on appointments and consultations with top doctors as well as patient demographic details, such as age, gender, city, and registration time. The automatic binning algorithm is applied for the coarsening strategy. Ultimately, the CEM algorithm results in 5,476 pairs of matched adopters and nonadopters, with 59.7% of adopters successfully matched. As in our main analysis, we utilize the DID specification to assess the effect of Q&A service adoption on consultations and appointments. Panel A of Table 19 showcases that the main effects remain consistent; the Q&A service leads

Table 19. Robustness Checks

	Panel A: CEM		Panel B: LA + PSM		Panel C: Two-stage DID	
Variables	log*Con*	log*App*	log*Con*	log*App*	log*Con*	log*App*
$Adopt \times Post$	0.0054***	0.050***	0.014**	0.092***	0.023***	0.049***
	(0.0019)	(0.0059)	(0.0064)	(0.021)	(0.0028)	(0.0090)
$Post$	0.0041***	0.014***	0.0038	0.024		
	(0.00090)	(0.0035)	(0.0048)	(0.020)		
N	130,903	130,903	26,903	26,903	101,704	101,704
Adjusted R^2	0.133	0.214	0.274	0.287	0.08	0.27

Notes. Standard errors in parentheses are clustered at the user level. All regressions contain individual and time fixed effects.
**$p < 0.05$; ***$p < 0.01$.

to an increase in online consultations and offline appointments.

6.1.2. LA-PSM. If the Q&A adoption process is influenced by unobserved characteristics and these characteristics cause the differences between control and treatment groups to change over time in their effect on user behaviors on the platform, we can address this issue using a look-ahead propensity score matching procedure coupled with a difference-in-difference estimator as outlined by Bapna et al. (2018). Following similar procedures to those in Bapna et al. (2018) and Khurana et al. (2019), we split the time under study into two equal nine-month intervals labeled as period 1 and period 2. Our quasiexperimental design includes a treatment group composed of individuals who started using the Q&A feature during the first period. Each participant in this group is paired with a corresponding member from the control group, which includes users who did not engage with Q&A in period 1 but did in period 2, aligning with our primary analysis criteria. Of the 3,996 participants who began using the Q&A feature in the initial period, we are able to successfully pair 1,842 (46.1%) with control users. We estimate our DID model by using this matched data set, which confirms the results obtained from our initial analysis (panel B of Table 19).

6.1.3. Two-Stage DID. Recent econometrics literature indicates that when the adoption of a treatment is staggered and the average treatment effects differ across groups and over time, DID regression does not yield an easily interpretable measure of the typical effect of the treatment. To resolve this potential issue, Gardner (2022) proposes an alternative two-stage estimation framework, which is robust to treatment-effect heterogeneity under staggered adoption. We adopt this method and re-estimate the main effects (panel C of Table 19). Again, we find that the Q&A service drives both online consultations and offline appointments.

6.1.4. Analysis with Repeated Q&A. In our main specification, we investigate the impact of a user first-time adopting the Q&A service. Because such a service, as discussed in Sections 5.2.3 and 5.5, could help match patients to specialists and therefore, reduce revisits, we observe users repeatedly using the Q&A service as they seek more information for the proper medical care. In our sample, recurrent purchase of the Q&A service can be associated with 11.9% of the adopters. The first- and second-time Q&A purchases together cover 90.7% of all Q&As. In Table 20, we separately estimate the effect of the first and second Q&As, where the dummy $Post_{1-2}$ is coded as one for months between the first and second Q&As (if any) and $Post_{2-}$ is coded as one for months after the second Q&A. We observe positive and significant effects for both times of Q&A purchases. This suggests that repeat users of Q&A are also more likely to sign up for online consultations or offline appointments.

Table 20. The Effect of Using Q&A for the Second Time

Variables	log*Consultation*	log*Appointment*
$Adopt \times Post_{1-2}$	0.020***	0.042***
	(0.0015)	(0.0058)
$Adopt \times Post_{2-}$	0.024***	0.058***
	(0.0081)	(0.014)
Post	0.0099***	0.10***
	(0.00093)	(0.0046)
N	101,704	101,704
Adjusted R^2	0.114	0.173

Notes. Standard errors in parentheses are clustered at the user level. All regressions contain individual and time fixed effects.
$^{***}p < 0.01$.

6.1.5. Higher-Level Clustering. Because different users may interact with the same providers or providers within the same geographic location, we employ a higher level of clustering at the city level and report the results in Table 21, confirming previous findings.

6.1.6. Controlling for Time-Varying Factors. Our fixed effects absorb the effect of static variables. We test robustness of our results by accounting for additional time-varying observables. Specifically, we repeat the analysis including the variable log*Brw*, which corresponds to the logarithm of the number of Q&A browsed. Table 22 shows consistent effects for both online and offline visits.

6.1.7. Effect of Previously Booked Appointment. It is possible that Q&A is just an intermediate step for users who had already planned on an offline appointment.[14] In that case, the effect of Q&A on appointments would be biased. In order to eliminate this bias, we repeat our analysis by focusing on a subset of users who had not utilized the appointment service prior to adopting the Q&A. This analysis,

Table 21. Main Effect Analysis Clustering at the City Level

Variables	log*Consultation*	log*Appointment*
$Adopt \times Post$	0.020***	0.043***
	(0.0012)	(0.0075)
Post	0.0098***	0.10***
	(0.00047)	(0.0038)
N	101,704	101,704
Adjusted R^2	0.114	0.173

Notes. Standard errors in parentheses are clustered at the city level. All regressions contain individual and time fixed effects.
$^{***}p < 0.01$.

Table 22. Main Effect Analysis Controlling for Time-Varying Activities

Variables	log*Consultation*	log*Appointment*
Adopt × *Post*	0.027***	0.045***
	(0.0017)	(0.0059)
Post	0.015***	0.10***
	(0.0011)	(0.0047)
log*Browse*	0.028***	0.010***
	(0.0020)	(0.0029)
N	101,704	101,704
Adjusted R^2	0.130	0.174

Notes. Standard errors in parentheses are clustered at the user level. All regressions contain individual and time fixed effects.
***$p < 0.01$.

presented in Table 23, mirrors the results of our main specification.

6.1.8. Staggered DID. We conduct an additional staggered DID analysis using the estimator proposed by Callaway and Sant'Anna (2021) (CS-DID), which accommodates variation in treatment timing and allows for dynamic treatment effects. Figure A.3 in the Online Appendix presents event study plots based on this specification. We also include estimations allowing for a one-period anticipation window. In both cases, we observe posttreatment effects consistent with our main analysis and no significant pretrends, supporting the validity of the parallel trends assumption and confirming the robustness of our main findings.

6.2. Placebo Test

We conducted a placebo test to mitigate the risk of false significance. We excluded observations for adopters occurring after the adoption time and introduced a placebo treatment in the remaining sample. Specifically, we randomly selected 10,000 users from the sample (matching the magnitude of the number of adopters) and assigned them as treated. For each treated user, we generated a random adoption period. Subsequently, we estimated the pseudocausal effect of adoption on the number of consultations and appointments. This process was repeated 5,000 times, with a different randomization of treatment each time.

Table 23. Main Effect Analysis for the User Without Prior Appointments

Variables	log*Consultation*	log*Appointment*
Adopt × *Post*	0.020***	0.048***
	(0.0015)	(0.0055)
Post	0.010***	0.13***
	(0.00095)	(0.0045)
N	92,159	92,159
Adjusted R^2	0.121	0.164

Notes. Standard errors in parentheses are clustered at the city level. All regressions contain individual and time fixed effects.
***$p < 0.01$.

The estimation results for consultations and appointments are presented in the two panels of Figure 3. Notably, we observed that the distributions of the estimations are centered around zero. Furthermore, through a t-test, we failed to reject the null hypothesis that the estimations are equal to zero ($p > 0.1$). These outcomes confirm the robustness of our results, indicating that the observed effects are not because of chance or random variation.

6.3. Field Experiment

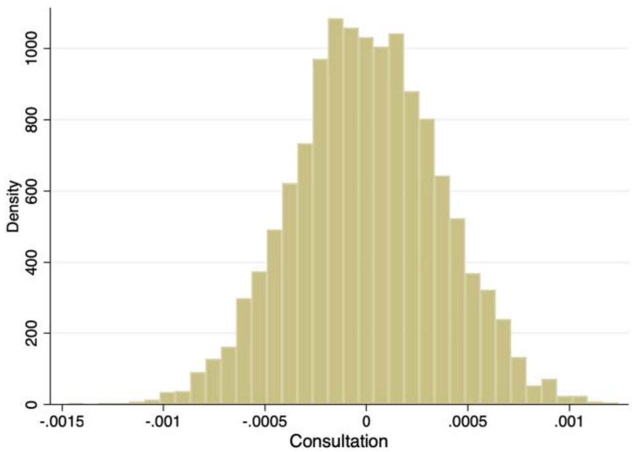
To further validate our findings, we collaborated with the on-demand platform to execute a field experiment. The ideal scenario would be to assign users randomly to the treatment group (where all users ask a question) and the control group (where users do not raise a question). However, this kind of setup faces a noncompliance issue as we cannot fully control users' decisions and compel them to ask or not ask a question unless they had a genuine medical need.

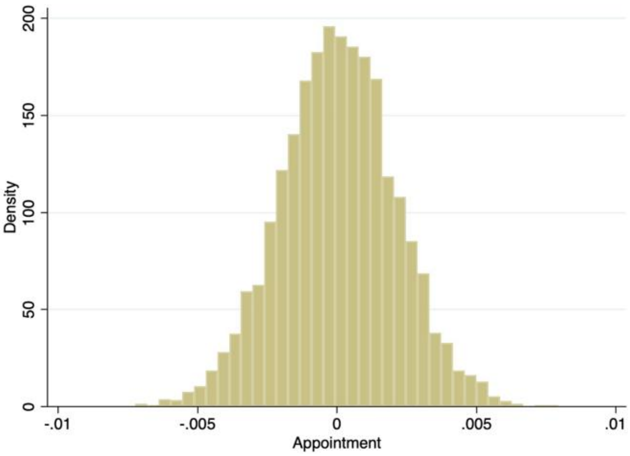
To address this challenge, we devised a field experiment to establish instrumental variables for identification. Specifically, we randomly provided users with different discount coupons and employed the resulting exogenous variation as an instrument for the decision to adopt the Q&A service in our matched sample as before. The use of the matched sample of adopters and nonadopters ensures that we are focusing on patients who are likely to have a medical need. The random provision of discounts served as an exogenous incentive for users to adopt the Q&A service. However, it is unlikely that these coupons directly influenced the choice of scheduling an online consultation or offline appointment. This is because the discounts were relatively small and unlikely to offset the cost associated with these services for users.

6.3.1. Experiment Design. Prior to conducting the experiment, we developed two types of coupons: coupon *a* and coupon *b*. Coupon *a* offers a 25% discount, and coupon *b* offers a 15% discount. Both coupons could only be utilized for the Q&A service. We dispatched these coupons to users through app push notifications accompanied by a message informing them of the coupon for the Q&A service. However, we deliberately withheld the information regarding the discount level at this stage to prevent users from selecting a coupon based solely on the discount offered.

If a user clicked on the notification, they were directed to a f where they could claim the coupon and view the discount after claiming it. If a user did not click on the notification or disabled notifications, they would find an unread message in the app's message

Figure 3. (Color online) Distribution of Coefficients for the Placebo Test





box. This message guided the user to the page for claiming the coupon. Both coupons could be claimed within 30 days of receipt and remained valid for 7 days after being claimed. This information was provided on the claim page. Once claimed, the coupons were stored in the "coupon pocket," where users could check the validity period. Furthermore, three days before a coupon's expiration date, users received a reminder notification.

The experiment was conducted over a four-week period, commencing on September 12, 2019. At the beginning of each week, all users on the platform were randomly assigned to one of three groups, Group *A*, Group *B*, or Group *C*, with 297,000 users in each group. Simultaneously, coupon *a* was sent to all users in Group *A*, whereas coupon *b* was sent to all users in Group *B*. Group *C* served as the control group. The assignment of users to the groups was independent across the weeks. Table 24 provides a summary of the experiment statistics.[15] The balance check is provided in Table A.10 in the Online Appendix.

6.3.2. Empirical Strategy and Results. Although the coupon was randomly assigned across all users on the platform, its effect on Q&A adoption was relatively weak in the broader population (refer to Table 24). This likely reflects the infrequent nature of medical needs and the fact that many users had no immediate reason to engage with the Q&A service during the experiment period. A weak instrument analysis is discussed in Online Appendix A.3, but the results remain consistent and robust. To address this, we focus our IV analysis on a matched sample of users. Within this selected sample, the coupon assignment remains random, preserving the exogeneity of the instrument.

To assess the impact of utilizing the Q&A service, we begin by matching Q&A users with nonusers and accounting for selection issues using the exogenous shocks generated by the experiment. Specifically, for any user who utilized the Q&A service during the four-week experiment period, we pair them with another user who did not use the Q&A service during that same period. The matching procedure employed is the same as the one utilized in the main analysis (refer to Section 4.2). Of the total 549 users who sought the Q&A service during the four-week period, 498 of them (91%) were successfully matched. We have selected these 996 users to form our subsample for further analysis.

Within this subsample of matched users, the assignment of users to the coupon groups (Group *A* or Group *B*) or the control group (Group C) represents a

Table 24. Statistics for the Field Experiment

	A			*B*			*C*
Variables	*# of Q&A*	*# of coupons claimed*	*# of coupons used*	*# of Q&A*	*# of coupons claimed*	*# of coupons used*	*# of Q&A*
Week 1	83	198	28	66	203	18	45
Week 2	72	196	26	74	179	13	38
Week 3	93	201	32	50	188	12	43
Week 4	74	170	21	61	183	10	45

Notes. *# of Q&A* measures the total number of Q&As purchased by a group in an experiment week with and without coupons. *# of coupons claimed* measures the number of coupons claimed by a group in a week. *# of coupons used* measures the number of Q&As with coupon used by a group in a week.

valid instrumental variable for Q&A adoption. As users were randomly assigned to these groups, the receipt of a coupon or lack thereof is independent of any unobservable confounding factors that could influence users' decision to use the Q&A service or pursue online/offline healthcare services. Additionally, users in Group A, who received a larger discount, are more likely to utilize the Q&A service compared with users in Group B. Projection of the adoption decision on this exogenous variable should allow us to remove the effect of unobservables that may be correlated with the decision to buy a premier consultation or make an offline appointment.

To establish a causal identification of the effect of the Q&A service, we employ a two-stage least squares approach as follows:

$$Y_{i,t} = \beta Q\&A_{i,t} + \alpha_i + \delta_t + \epsilon_{i,t};$$

first stage:

$$Q\&A_{i,t} = \gamma Group_{i,t} + \eta_i + \zeta_t + \nu_{i,t},$$

where $Group_{i,t}$ refers to the group (A, B, or C) to which user i was assigned in week t. For the outcome variables, we count the number of online consultations purchased and the number of offline appointments made.

Table 25 presents the estimation results for both the first-stage and second-stage regressions. In comparison with the control group, which did not receive any coupon, both the 25%-off coupon (Group A) and the 15%-off coupon (Group B) exhibited a significant increase in the number of individuals using the Q&A service. Moreover, the effect size was larger for coupons with greater discounts. Through the second-stage analysis, we discovered that the Q&A service had a significant impact ($p < 0.05$), resulting in a 0.43 increase in the number of consultations and a 0.85 increase in the number of appointments. We complement the above specification with additional analyses, which are presented in Online Appendix A.3. These findings align with the results obtained in the main analysis, thereby reinforcing the support for our main findings discussed in the preceding sections.

Table 25. The Results of the Experiment—Matched Sample

	First stage	Second stage	
Variables	*Q&A*	*Consultation*	*Appointment*
GroupA	0.063*** (0.020)		
GroupB	0.056*** (0.020)		
Q&A		0.43** (0.32)	0.85** (0.40)
N	2,832	2,832	2,832
Adjusted R^2	0.23	0.28	0.15

Notes. Standard errors in parentheses are clustered at the user level. All regressions contain individual and time fixed effects.
** $p < 0.05$; *** $p < 0.01$.

It is important to note that the instrumental variable estimates on the matched sample from the experiment should be interpreted as local average treatment effects. These estimates reflect the impact of Q&A usage among a subset of users who are both in the matched sample and responsive to the coupon encouragement. As such, the estimated effects reflect the impact of Q&A usage on this local group—restricted both by matching on observed characteristics and by compliance with the instrument. Thus, caution is warranted in generalizing these results to the broader user population. The differences in effect magnitudes compared with the observational analysis may reflect this more selective population in addition to changes in service offerings and user behavior over time (as discussed in Online Appendix A.3).

7. Discussion and Conclusion

On-demand healthcare platforms have the potential to meet the healthcare needs of patients while reducing healthcare costs and providing accessibility. However, scant research has evaluated the efficacy of various services provided by such platforms. In this research, we investigate the effect of an online Q&A service on the online consultations and offline appointments provided by the healthcare platform. We use a rich panel data set from an on-demand platform in China for this purpose. We find that the Q&A service leads to an increase in the demand for both online consultations and offline appointments. In addition, the nuanced effects pertain to doctor titles and medical categories. Finally, the platform earns a higher revenue from the resulting increase in demand. However, patients also benefit from this service as consultations and appointments through Q&A lead to fewer future visits and fewer browsing sessions.

Our study also uncovers different mechanisms that play a role in generating the outcome. We show that Q&A service leads to increased online consultations for the doctor participating in Q&A. This is similar to the sampling effect (Liu et al. 2014, Runge et al. 2016, Arora et al. 2017, Deng et al. 2018), which allows us to reduce some uncertainty about the provider. However, unlike these studies, we also test the sampling effect across different channels and find that the channel also plays a role in determining the outcome. Specifically, we find that Q&A only helps the demand for online consultations with the same doctor but not offline appointments. This suggests that the form of interaction is also important in adjusting the user perception of a provider or service. We also demonstrate spillover effects to other doctors in the same specialty. Previous works have demonstrated such spillovers for e-commerce products and digital goods through advertising. Tan et al. (2019) show how chat can help the sales process for the same product. We illustrate that awareness created through Q&A-like interactions can also lead to spillover effects. Finally, we illustrate the matching capability of such a service by showing how Q&A leads to higher demand for other medical specialties, especially complex ones. Previous studies have established the role of information provision in the search process and matching in the e-commerce context (Van Den Bulte et al. 2018, Tan et al. 2019, Gu and Wang 2022). Our results show that such information provision can also work in the healthcare setup and even help patients to seek consultations in complex specialties.

These results illustrate the important role of information disseminated through the Q&A service for a market-based healthcare platform. Although such platforms can lower the costs of medical care, there is also a concern about finding the right care as these typically lack coordination found in the traditional medical setup. Patients can choose their own doctors and have to rely on online information to decide on their medical condition and potential care. Thus, it is important to devise mechanisms such that patients are seeking the right medical care. Our results show that Q&A service can help alleviate concerns about finding the right care in such a market-based setup by providing relevant information to the patients.

Our study contributes to the literature on online healthcare forums by empirically identifying the complementary effects of forum-like Q&A capabilities on the consultation services offered by on-demand healthcare platforms. Our study also sheds light on the importance of information-based services on healthcare platforms and generates insights for the design of such services. Finally, our results also reveal patients' behavior when interfacing with such platforms. Patients use the Q&A service to resolve uncertainty and gravitate to the doctors with senior titles after consuming the service. By contrast, doctors with junior titles can experience a positive spillover only in the online channel.

Our research has practical implications for the design of on-demand healthcare platforms. Specifically, we find that offering a Q&A service can help users become more comfortable with the online channel for medical care and increase demand for more comprehensive consultation services, leading to a boost in revenue for the platform. Our research shows that Q&A can increase revenue for online consultations by 6.6%. Furthermore, we find that Q&A can be particularly useful for disseminating knowledge about complex medical specialties and can help increase demand for follow-up consultations and appointments.

Our study also has important implications for healthcare resource management associated with Q&A. We find that Q&A does not lead to an increase in demand for the offline appointments with the same doctor. Thus, the platform has to create appropriate incentives for such doctors to participate in Q&A if they are primarily seeking offline appointments. Additionally, from the supply side, top physicians are less engaged in responding to questions. However, from the demand side, users tend to select top doctors after using the Q&A service, and Q&A does not increase demand for offline appointments with nontop doctors. This skewed supply combined with uneven demand has several implications. First, top doctors, who are often regarded as the most critical human capital for hospitals and are occupied with a wide range of complex medical requests, should have their service requests managed conservatively in case there is a shortage. Second, nontop doctors, who are more likely to provide the Q&A service, receive fewer visits, creating a disincentive for them. Therefore, platforms should consider compensating nontop doctors for their participation in the Q&A service. Moreover, our study suggests that platforms should balance the allocation of Q&A services among general doctors and specialists. Because generalists can provide guidance on more specialized and complex medical care, platforms should ensure that they are available to handle Q&A requests. This can help ensure that patients are matched with the most appropriate provider for their needs and ultimately, lead to better health outcomes.

Besides the platform, the Q&A service also has managerial implications for hospitals. Some hospitals fully embrace partnering with the platform, whereas other hospitals perceive this online channel as potentially detrimental to their offline traffic and physician productivity. Hospitals' differing views on the platform arise from uncertainties about its impact. Our findings confirm that the Q&A service offered by the platform directly generates higher traffic for hospitals. Additionally, as Fan et al. (2023) demonstrate, online consultations by doctors lead to an increase in offline appointments. Consequently, the Q&A service can also benefit hospitals' offline visits by driving more online interactions. These results suggest that hospitals could introduce a similar Q&A service or participate in the platform's offerings to better manage patients' needs.

Although we used a specific healthcare platform for our analysis, the results that we obtained can be applied to other platforms as well. Our research shows that Q&A features can also improve health outcomes, which may increase patients' use of healthcare platforms. Thus, it is in the platform's interest to adopt such innovations. Generally, healthcare platforms allow patients to select their providers, with some restrictions imposed by insurance providers. However, even within the restricted set, patients still have some degree of choice.

Additionally, many of these platforms cater to uninsured patients, who have even more freedom to choose. Nevertheless, all platforms face the challenge of ensuring that patients receive the appropriate type of care. Q&A features can help platforms match patients with the right doctors more effectively. One concern is that doctors may charge high fees for their time and may not be willing to participate in Q&A sessions, especially as they build their online reputations. However, platforms can mandate a certain level of Q&A participation as part of their contracts. Additionally, given the heterogeneous effects of the Q&A service benefiting top doctors and the demand shift from generalists to specialists that we have observed, the platform can implement revenue-sharing schemes to manage physicians with varying levels of expertise. This would incentivize them to provide services aligned with their capabilities and interests. Lastly, although attracting top physicians to the platform enhances its brand and reputation, it is also important to recruit junior physicians for Q&A and other supportive services to ensure that patients receive appropriate care. Moreover, our findings can also inform recent initiatives that use artificial intelligence (AI)-based symptom checkers to help patients choose appropriate care. Although using algorithms to recommend services or products to consumers is common in various business contexts, healthcare recommendations are less explored compared with recommendations in other application settings, with gaps in personalization and diversification (Zhou et al. 2023). Current professional healthcare delivery continues to highlight physicians' expertise. Our study demonstrates that interacting with a real doctor to confirm symptoms is valuable to patients, who place value on doctor attributes, like titles. Therefore, platforms should evaluate whether AI-based tools can generate similar demand compared with having doctors evaluate symptoms.

Our results indicate that the Q&A service is driving increased demand for both online consultations and offline appointments, suggesting that the platform should encourage greater user participation in Q&A. One approach could be to make Q&A an optional step before booking an online consultation or appointment, nudging users to utilize it for improved appointment outcomes. Additionally, AI-based tools could assist users in composing their questions, thereby boosting the demand for the Q&A service. Recent studies have shown that AI-enabled assistants increase user engagement in Q&A forums (Borwankar et al. 2023, Shan and Qiu 2023). These tools can also help doctors respond more efficiently, enhancing the service's supply.

Although our study provides important insights into the impact of Q&A services on demand outcomes for users of on-demand healthcare platforms, there are several limitations that should be addressed in future research. First, our study measures health outcomes in terms of the reduction in revisits and information-seeking behavior through browsing. Future studies should consider evaluating actual health outcomes, such as patient-reported outcomes or medical records. Second, we do not explicitly consider the heterogeneity in how users engage with the Q&A service. Although this does not affect our main results because of user-specific fixed effects, future studies should evaluate the role of different types of interactions in demand outcomes. Analyzing the actual content of the Q&A interactions can also reveal the efficacy of different types of information received by patients to select future care, which can provide guidance to doctors about their engagement with patients during Q&A sessions. Additionally, many more users engage with the platform by browsing public Q&A content. Investigating how such browsing behavior influences subsequent healthcare decisions presents a promising direction for future research. We also observe that certain user characteristics are associated with a higher likelihood of engaging with the Q&A service. Exploring the underlying psychological or behavioral drivers behind such differences—such as risk aversion, health concerns, or trust in online channels—could be a fruitful avenue for future research. Third, our research focuses on the impact of platform Q&A services on demand outcomes for users. It would be worthwhile for future research to evaluate the impact of the platform strategy on the productivity of healthcare providers. Additionally, because the effect of Q&A services differs across providers, future research could explore its impact on the appointment scheduling problem across different providers.

Endnotes

[1] Throughout the paper, we use the terms "doctor," "practitioner," and "provider" interchangeably.

[2] The prominent on-demand healthcare platforms in China all launched a Q&A channel that charges a meager price and routes patients' questions to doctors.

[3] Hospitals vary in their policies and attitudes toward collaborating with third-party telehealth platforms and permitting their physicians to participate in such platforms. Some hospitals fully embrace these partnerships, allowing and even encouraging their physicians to practice online. Conversely, other hospitals perceive these online channels as potentially detrimental to their offline traffic and physician productivity, thus prohibiting their physicians from joining the platform. Notably, when physicians are allowed to offer services on the platform, they are not required to share their online revenue with the hospitals.

[4] In China, doctor professional titles follow a structure that is comparable with academic titles. The advancement of doctors in their professional titles is determined based on factors such as their educational background, qualifications, work experience, academic achievements, and other relevant criteria.

[5] The platform offers multiple options for the duration of service, ranging from one day to one year. However, throughout the study period, the vast majority of consultation services purchased by users were for a one-day duration. Therefore, our study focuses solely on the one-day service option.

[6] Before January 2018, the app's home page featured only the buttons for appointment and consultation services at the top. With the introduction of the new Q&A service, a button for this service was added to the home page as shown in Figure 1. When users click on the Q&A icon, they are directed to a page displaying a list of all answered Q&As, categorized by medical departments and listed in chronological order. The questions are shown only partially, with the first two lines visible, and the full answers are hidden behind a "Click to See the Full Q&A" button. Users can click this button to view the complete dialogue of any past Q&A for free. This feature enables us to track each user's browsing history. Additionally, at the bottom of the browsing page, there is a button that allows users to purchase the Q&A service.

[7] Within the data set, we have access to the time stamp indicating when each user registers for an appointment. However, the data set does not provide information regarding the actual time that the user visits the doctor. Nevertheless, based on the hospital policy, we know that the user's visit will take place within two weeks after scheduling the appointment. To approximate the actual visit times, we add a two-week interval to the scheduling time for all appointments. It is important to note that this approximation does not pose any issues when measuring the time stamp of consultations as we directly observe the actual service start times for those interactions.

[8] The number of Q&As browsed ranges from 0 to 32, with a median of 3.

[9] When calculating the outcome variables, we specifically exclude consultations and appointments with the same doctor who provided the Q&A service. Instead, we focus on those interactions with different doctors within the same medical specialty.

[10] In our data set, we noticed that only a small number of doctors mentioned the availability of consultation services when closing their responses. A common phrase used by these doctors is "Feel free to ask me any other questions using the consultation service."

[11] To determine the variable *AdvOffline*, we conducted a search for keywords indicating the possibility of an offline visit. We then carefully reviewed all of the responses and manually checked for any explicit recommendations that suggested seeing a doctor offline.

[12] We exclude pediatrics and gynecology from our analysis as these specialties primarily focus on specific patient populations, such as children and pregnant women.

[13] For example, for $\kappa = 2$, we identify pairs of adopters and nonadopters who underwent a consultation or appointment within the first and second months after adopting the Q&A service. To measure revisits, we track visits occurring in the third and fourth months following the adoption period (which we call "revisits"). We then estimate the effect of Q&A adoption on the frequency of these revisits.

[14] Although this can apply for online consultations, we do not consider users with previously scheduled online consultations in our main analysis.

[15] For Group A or Group B, the coupon claim rate appears to be low, which could be attributed to two main reasons. First, the coupons were distributed via push notifications, and many users have opted out of app notifications because of the overwhelming number of notifications that they receive from various apps. Second, medical visits or needs are relatively infrequent, so users are less likely to actively respond to promotions compared with retail offers. Despite the overall low coupon usage rate, the rate is reasonably high among users who purchased Q&As during the experiment.

References

Arora S, Ter Hofstede F, Mahajan V (2017) The implications of offering free versions for the performance of paid mobile apps. *J. Marketing* 81(6):62–78.

Ashwood JS, Mehrotra A, Cowling D, Uscher-Pines L (2017) Direct-to-consumer telehealth may increase access to care but does not decrease spending. *Health Affairs (Millwood)* 36(3):485–491.

Atasoy H, Chen P-y, Ganju K (2018) The spillover effects of health it investments on regional healthcare costs. *Management Sci.* 64(6): 2515–2534.

Ayabakan S, Bardhan IR, Zheng Z(E) (2024) Impact of telehealth and process virtualization on healthcare utilization. *Inform. Systems Res.* 35(1):45–65.

Babar Y, Burtch G (2024) Recharging retail: Estimating consumer demand spillovers from electric vehicle charging stations. *Manufacturing Service Oper. Management* 26(3):797–813.

Bapna R, Ramaprasad J, Umyarov A (2018) Monetizing freemium communities: Does paying for premium increase social engagement? *MIS Quart.* 42(3):719–736.

Bavafa H, Hitt LM, Terwiesch C (2018) The impact of e-visits on visit frequencies and patient health: Evidence from primary care. *Management Sci.* 64(12):5461–5480.

Bell DR, Gallino S, Moreno A (2018) Offline showrooms in omnichannel retail: Demand and operational benefits. *Management Sci.* 64(4):1629–1651.

Bhargava HK, Nath Mishra A (2014) Electronic medical records and physician productivity: Evidence from panel data analysis. *Management Sci.* 60(10):2543–2562.

Bodenheimer TS, Smith MD (2013) Primary care: Proposed solutions to the physician shortage without training more physicians. *Health Affairs (Millwood)* 32(11):1881–1886.

Borwankar S, Nuai W. K-A, Kannan KN (2023) Unraveling the impact: An empirical investigation of chatgpt's exclusion from stack overflow. Preprint, submitted June 18, https://ssrn.com/abstract=4481959.

Callaway B, Sant'Anna PH (2021) Difference-in-differences with multiple time periods. *J. Econometrics* 225(2):200–230.

Charikar MS (2002) Similarity estimation techniques from rounding algorithms. *Proc. Thirty-Fourth Annual ACM Sympos. Theory Comput.*, 380–388.

Chen C, Walker D (2023) A bitter pill to swallow? The consequences of patient evaluation in online health question-and-answer platforms. *Inform. Systems Res.* 34(3):867–889.

Chen J, He S, Yang X (2024) Platform loophole exploitation, recovery measures, and user engagement: A quasi-natural experiment in online gaming. *Inform. Systems Res.* 35(4):1609–1633.

Deng Y, Lambrecht A, Liu Y (2018) Spillover effects and freemium strategy in mobile app market. Preprint, submitted March 26, http://dx.doi.org/10.2139/ssrn.3149550.

Dulleck U, Kerschbamer R (2006) On doctors, mechanics, and computer specialists: The economics of credence goods. *J. Econom. Literature* 44(1):5–42.

Fan W, Zhou Q, Qiu L, Kumar S (2023) Should doctors open online consultation services? An empirical investigation of their impact on offline appointments. *Inform. Systems Res.* 34(2):629–651.

Gardner J (2022) Two-stage differences in differences. Preprint, submitted July 13, https://doi.org/10.48550/arXiv.2207.05943.

Gottschalk F, Mimra W, Waibel C (2020) Health services as credence goods: A field experiment. *Econom. J.* 130(629):1346–1383.

Gu C, Wang Y (2022) Consumer online search with partially revealed information. *Management Sci.* 68(6):4215–4235.

Guo P, Tang CS, Wang Y, Zhao M (2019) The impact of reimbursement policy on social welfare, revisit rate, and waiting time in a public healthcare system: Fee-for-service versus bundled payment. *Manufacturing Service Oper. Management* 21(1): 154–170.

Hong Y, Pavlou PA (2014) Product fit uncertainty in online markets: Nature, effects, and antecedents. *Inform. Systems Res.* 25(2):328–344.

Hwang EH, Guo X, Tan Y, Dang Y (2022) Delivering healthcare through teleconsultations: Implications for offline healthcare disparity. *Inform. Systems Res.* 33(2):515–539.

Khurana S, Qiu L, Kumar S (2019) When a doctor knows, it shows: An empirical analysis of doctors' responses in a Q&A forum of an online healthcare portal. *Inform. Systems Res.* 30(3):872–891.

Kumar A, Telang R (2012) Does the web reduce customer service cost? Empirical evidence from a call center. *Inform. Systems Res.* 23(3 Part 1):721–737.

Lee MH, Han SP, Park S, Oh W (2023) Positive demand spillover of popular app adoption: Implications for platform owners' management of complements. *Inform. Systems Res.* 34(3):961–995.

Leveille SG, Mejilla R, Ngo L, Fossa A, Elmore JG, Darer J, Ralston JD, Delbanco T, Walker J (2016) Do patients who access clinical information on patient internet portals have more primary care visits? *Medical Care* 54(1):17–23.

Li Y, Lu LX, Lu SF, Chen J (2022) The value of health information technology interoperability: Evidence from interhospital transfer of heart attack patients. *Manufacturing Service Oper. Management* 24(2):827–845.

Liang C, Shi Z, Raghu TS (2019) The spillover of spotlight: Platform recommendation in the mobile app market. *Inform. Systems Res.* 30(4):1296–1318.

Liu J, Bharadwaj A (2020) Drug abuse and the internet: Evidence from craigslist. *Management Sci.* 66(5):2040–2049.

Liu CZ, Au YA, Choi HS (2014) Effects of freemium strategy in the mobile app market: An empirical study of google play. *J. Management Inform. Systems* 31(3):326–354.

Liu QB, Liu X, Guo X (2020) The effects of participating in a physician-driven online health community in managing chronic disease: Evidence from two natural experiments. *MIS Quart.* 44(1b):391–419.

Lu SF, Rui H, Seidmann A (2018) Does technology substitute for nurses? Staffing decisions in nursing homes. *Management Sci.* 64(4):1842–1859.

Malik S, Coulson NS (2010) "They all supported me but I felt like I suddenly didn't belong anymore": An exploration of perceived disadvantages to online support seeking. *J. Psychosomatic Obstetrics Gynaecology* 31(3):140–149.

Menon NM, Kohli R (2013) Blunting Damocles' sword: A longitudinal model of healthcare IT impact on malpractice insurance premium and quality of patient care. *Inform. Systems Res.* 24(4): 918–932.

North F, Crane SJ, Chaudhry R, Ebbert JO, Ytterberg K, Tulledge-Scheitel SM, Stroebel RJ (2014) Impact of patient portal secure messages and electronic visits on adult primary care office visits. *Telemedicine J. E-Health* 20(3):192–198.

Ou M, Ho SS (2022) A meta-analysis of factors related to health information seeking: An integration from six theoretical frameworks. *Comm. Res.* 49(4):567–593.

Pagoto S, Schneider KL, Evans M, Waring ME, Appelhans B, Busch AM, Whited MC, Thind H, Ziedonis DM (2014) Tweeting it off: Characteristics of adults who tweet about a weight loss attempt. *J. Amer. Medical Informatics Assoc.* 21(6):1032–1037.

Petterson SM, Liaw WR, Phillips RL Jr, Rabin DL, Meyers DS, Bazemore AW (2012) Projecting US primary care physician workforce needs: 2010–2025. *Ann. Family Medicine* 10(6):503–509.

Runge J, Wagner S, Claussen J, Klapper D (2016) Freemium pricing: Evidence from a large-scale field experiment. Preprint, submitted December 21, http://dx.doi.org/10.2139/ssrn.2888471.

Rupert DJ, Moultrie RR, Read JG, Amoozegar JB, Bornkessel AS, O'Donoghue AC, Sullivan HW (2014) Perceived healthcare provider reactions to patient and caregiver use of online health communities. *Patient Ed. Counseling* 96(3):320–326.

Sahni NS (2016) Advertising spillovers: Evidence from online field experiments and implications for returns on advertising. *J. Marketing Res.* 53(4):459–478.

Shah SJ, Schwamm LH, Cohen AB, Simoni MR, Estrada J, Matiello M, Venkataramani A, Rao SK (2018) Virtual visits partially replaced in-person visits in an ACO-based medical specialty practice. *Health Affairs (Millwood)* 37(12):2045–2051.

Shan G, Qiu L (2023) Examining the impact of generative AI on users' voluntary knowledge contribution: Evidence from a natural experiment on stack overflow. Preprint, submitted May 31, http://dx.doi.org/10.2139/ssrn.4462976.

Shapiro BT (2018) Positive spillovers and free riding in advertising of prescription pharmaceuticals: The case of antidepressants. *J. Political Econom.* 126(1):381–437.

Shoemaker RW, Shoaf FR (1975) Behavioral changes in the trial of new products. *J. Consumer Res.* 2(2):104–109.

Sun M, Zhu F (2013) Ad revenue and content commercialization: Evidence from blogs. *Management Sci.* 59(10):2314–2331.

Sun S, Lu SF, Rui H (2020) Does telemedicine reduce emergency room congestion? Evidence from New York state. *Inform. Systems Res.* 31(3):972–986.

Swar B, Hameed T, Reychav I (2017) Information overload, psychological ill-being, and behavioral intention to continue online healthcare information search. *Comput. Human Behav.* 70:416–425.

Tan X, Wang Y, Tan Y (2019) Impact of live chat on purchase in electronic markets: The moderating role of information cues. *Inform. Systems Res.* 30(4):1248–1271.

Tonelli M, Wiebe N, Manns BJ, Klarenbach SW, James MT, Ravani P, Pannu N, Himmelfarb J, Hemmelgarn BR (2018) Comparison of the complexity of patients seen by different medical subspecialists in a universal health care system. *JAMA Network Open* 1(7):e184852.

Urbany JE (1986) An experimental examination of the economics of information. *J. Consumer Res.* 13(2):257–271.

Urbany JE, Dickson PR, Wilkie WL (1989) Buyer uncertainty and information search. *J. Consumer Res.* 16(2):208–215.

Uscher-Pines L, Mehrotra A (2014) Analysis of teladoc use seems to indicate expanded access to care for patients without prior connection to a provider. *Health Affairs* 33(2):258–264.

Van Den Bulte C, Bayer E, Skiera B, Schmitt P (2018) How customer referral programs turn social capital into economic capital. *J. Marketing Res.* 55(1):132–146.

van der Linden W, Warg A, Nordin P (2011) National register study of operating time and outcome in hernia repair. *Arch. Surgery* 146(10):1198–1203.

Wentzer HS, Bygholm A (2013) Narratives of empowerment and compliance: Studies of communication in online patient support groups. *Internat. J. Medical Informatics* 82(12):e386–e394.

Yang L, Wang Z, Hahn J (2020) Scarcity strategy in crowdfunding: An empirical exploration of reward limits. *Inform. Systems Res.* 31(4):1107–1131.

Yeow A, Goh KH (2015) Work harder or work smarter? Information technology and resource allocation in healthcare processes. *MIS Quart.* 39(4):763–785.

Zhou T, Wang Y, Yan L, Tan Y (2023) Spoiled for choice? Personalized recommendation for healthcare decisions: A multiarmed bandit approach. *Inform. Systems Res.* 34(4):1493–1512.

Zhou YY, Garrido T, Chin HL, Wiesenthal AM, Liang LL (2007) Patient access to an electronic health record with secure messaging: Impact on primary care utilization. *Amer. J. Management Care* 13(7):418–424.