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Effects of Online–Offline Service Integration on e-Healthcare Providers: A Quasi-Natural Experiment

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E-healthcare platforms start to integrate medical services across online and offline channels, where providers can perform online consultations, schedule patients' offline visits, synchronize relevant medical records, and finally, answer online inquiries regarding follow-up and recovery anytime and anywhere within one operations management function (i.e., online–offline service integration). In this study, we seek to quantify the effects of online–offline service integration on the e-healthcare providers' demand and reputational outcomes, noting that it is not altogether clear how the service integration function will affect the providers who adopt such a function in e-healthcare platforms. Leveraging a quasi-natural experiment on an e-healthcare platform, we conducted difference-in-differences analyses in tandem with a variety of matching strategies, including propensity score matching and look-ahead propensity score matching. Furthermore, we explored the moderating roles of provider-specific characteristics. Our results reveal a set of robust and interesting findings: (i) e-healthcare providers, on average, experience increases in online demand and decreases in offline demand post online–offline service integration; (ii) the service integration function also improves the professional reputation of participating providers; (iii) the impact of channel integration on the outcomes is weaker for providers with lower (vs. higher) professional titles; and (iv) the providers who specialize in treating chronic (vs. acute) diseases experience greater increases in online demand and reputational outcomes, yet insignificant changes in offline demand. This work contributes to related prior literatures on healthcare operations management, e-healthcare, and online–offline channel integration, offering design implications for the service operations of e-healthcare platforms.

Key words: online–offline service integration; healthcare operations management; e-healthcare; difference-in-differences; look-ahead propensity score matching
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1. Introduction

Online healthcare (a.k.a., e-healthcare) platforms—such as *LiveHealth*, *Doctor on Demand*, and *MDLive*—have emerged as a valuable and accessible healthcare resource (Oh 2012). Compared with offline healthcare organizations (Osadchiy and Kc 2017, Qian et al. 2017), e-healthcare platforms help patients and providers effectively overcome time and space constraints (Cline and Haynes 2001), which potentially improve patient experience and bridge the disparity in medical resources across geographical areas (Goh et al. 2016). For example, online healthcare platforms[1] often support (a) healthcare providers perform online consultation and provide offline appointment services (Bavafa et al. 2018, Wu and Lu 2017); (b) patients sharing their experience of disease treatment and pharmaceutical protocols in the online community (Maloney-Krichmar and Preece 2005, Yan et al. 2016); and (c) platforms predicting and monitoring contagious disease, like seasonal influenza, based on patient's search and share behavior as well as media reports, which help reduce the severity of disease outbreaks (Dong et al. 2020, Kagashe et al. 2017). Therefore, online healthcare platforms have grown significantly in popularity and prominence, particularly when patients hesitate to go to hospitals and clinics during the Covid-19 pandemic.[2]

In online healthcare platforms, most of the technology features serve independent, stand-alone purposes. For example, e-healthcare providers can either offer online consultations through different telecommunication channels[3] or arrange offline visits with their patients via separate features on the platform. In our study, we explore a type of novel healthcare operations management (OM) function for providers that streamline various healthcare services across online and offline channels and to synchronize patients' medical documents, thereby resulting in the provision of continual and synchronized healthcare services for patient–provider pairs. Hereby, we refer to this type of function as "online–offline service integration." With online–offline service integration, the providers on an e-healthcare platform can offer consultations online, with convenient access to the patients' medical documents, perform medical treatments in a hospital or clinic, and then, follow-up with the patients online with regard to recovery and future plans within one function of the platform. Alternatively, the variety of healthcare services in online and offline channels was performed as isolated and disconnected functions on an e-healthcare platform.

Note that for e-healthcare providers, adopting the service integration function not only creates opportunities like interoperable healthcare services but also introduces potential challenges, such as possible management complexity and channel cannibalization (Kollmann et al. 2012, Stone et al. 2002). Although service integration across channels is relatively new in e-healthcare possibly due to hurdles of patient privacy and government policy compliance, it is important that we understand the implications of such practice. While related prior work on e-healthcare platforms explored the distinct roles or the interdependency of online and offline channels (e.g., Bavafa et al. 2018, Bergmo et al. 2005, Wang et al. 2020, Wu and Lu 2017), there is limited research on the consequences of service integration across online and offline channels, which provides insights for optimizing operations management in e-healthcare. Therefore, our work aims to address this gap in the e-healthcare and operations research literature. Formally, we explore the following research questions:

In online healthcare platforms, how does online–offline service integration affect the demand and reputation for e-healthcare providers across both channels? How do the effects of such an integration vary by provider characteristics?

To empirically answer the research questions, we leverage a quasi-natural experiment on a prominent online healthcare platform in China. Specifically, we collected panel data of 32,635 e-healthcare providers over 8 months. We then employed a difference-in-differences (DID) model to analyze the impact of online–offline service integration on the provider-level outcomes of interest—namely, the number of online consultation and offline visits as well as the e-healthcare providers' professional reputation in terms of rating and gift value. Meanwhile, considering the potential self-selection issue in this empirical setting, we incorporated three complementary identification strategies: the DID estimations with the entire sample (Angrist and Pischke 2008, Lechner 2011), the DID estimations with the sample after propensity score matching (DID + PSM) (Khurana et al. 2019, Sun and Zhu 2011), and the DID estimations with the sample after a look-ahead propensity score matching procedure (DID + LA-PSM) (Bapna et al. 2016, Kumar et al. 2018b). Furthermore, we explored the different moderating factors for the main effects of online–offline service integration on the e-healthcare service providers (i.e., the providers' professional title and medical specialty).

Our analyses yielded a set of robust and consistent results. Specifically, the baseline DID estimates indicated that the e-healthcare providers who enabled online–offline service integration, on average, experienced an increase of approximately 26.1% in the demand for online consultation, a decrease of approximately 4.4% in the demand for offline visits, and an increase of approximately 12.6% in the total demand across both online and offline channels. Moreover, after the adoption of online–offline service integration by providers, we observe a growth of approximately 13.7% in the value of voluntary gifts given to the providers by patients and an increase of approximately 6.0% in the online ratings of providers, thereby suggesting the enhancement of providers' professional reputation in the online healthcare platform. In addition, the estimations from the relative time model—DID + PSM, as well as DID + LA-PSM—displayed consistent results as the baseline DID estimates, thereby attesting to the robustness of our findings. Furthermore, we explored the heterogeneity in our main results and found that the observed main effects are moderated by e-healthcare providers' professional title and medical specialty. Specifically, the providers with relatively lower (vs. higher) professional title experienced smaller increases in online demand, attenuated decreases in offline demand, and less reputation advancement. Meanwhile, the providers who specialized in chronic disease (vs. acute disease) experienced stronger increases in online demand, insignificant changes in offline demand, as well as greater reputation enhancement.

Our study contributes to the related prior research on healthcare operations management, e-healthcare, and online–offline channel integration. To begin with, this study adds to the prior research on healthcare operations management, particularly in the interface of operations management (OM) and information systems (IS) (Guha and Kumar 2018, Kumar et al. 2018a), by investigating online–offline service integration as an important antecedent to the provider-level outcomes in e-healthcare. While a majority of the prior work focused on the implementation of information technology in offline healthcare contexts as well as the impact of healthcare technology on operational outcomes (Angst et al. 2011, Gardner et al. 2015, Li and Benton 2006), recent studies have begun exploring the design and impact of technology in online healthcare (Khurana et al. 2019, Yan et al. 2019). Extending Khurana et al. (2019), which examined the influence of supply-side technology usage (question-and-answer forums) on demand-side recommendations, we attempt to understand the effects of supply-side technology adoption on the subsequent supplier/provider demand and reputation in e-healthcare.

Meanwhile, our study also contributes to the relevant work in the e-healthcare context. The online–offline service integration in this study involves using one comprehensive operations management function to streamline various healthcare services across online and offline channels and to compile the relevant medical records for storage and transfer, which informs the design of service operations in e-healthcare platforms. Although related previous work that explored the dynamics of online and offline channels in e-healthcare primarily considered a single service (e.g., online booking of offline visits in Wu and Lu (2017) and offline arrangement of online visits in Bavafa et al. (2018) that enabled a one-way transition from one channel to the other (Bergmo et al. 2005) or assumed that channel integration was fully utilized (Wang et al. 2020), this study advances our understanding of e-healthcare operations by examining how the adoption (vs. absence) of online–offline service integration influence the providers on an e-healthcare platform.

Moreover, the current study advances prior research on online–offline channel integration in e-commerce (Avery et al. 2012, Bell et al. 2018, Cao and Li, 2015, Gallino and Moreno 2014) to the context of e-healthcare. Such an extension across research contexts is important because the operations of online–offline integration are rather different in e-healthcare compared with e-commerce. Unlike the channel integration in e-commerce that largely facilitates separate transactions across online and offline channels (Gupta et al. 2009, Tian et al. 2018), channel integration in e-healthcare encompasses the continual provision of a variety of healthcare services (Das et al. 2015, Goh et al. 2016), such as supporting online consultation, booking online for offline visits, storing and transferring medical records, performing online follow-up of health management, etc. Note that the online–offline service integration in e-healthcare encompasses the unique characteristics of service continuity and synchronization, which was not adequately addressed in e-commerce and, thus, requires empirical investigation. Finally, our study also explores the heterogeneity in the impact of online–offline service integration on the providers by provider characteristics such as professional title and medical specialty; the corresponding results provide useful practical implications for the operational design of channel integration in e-healthcare platforms.

2. Related Literature

2.1. Healthcare Operations Management

Healthcare operations management involves employing digitization and technology to optimize health-related planning and operations (Brandeau et al., 2004, Diamant et al. 2018, Safadi and Faraj 2011). While a proportion of research on healthcare operations management uses mathematical modeling approaches such as linear programing and Markov chain processes as well as simulations (Chen and Robinson 2014, Liu 2016, Marshall et al., 2005), our study is more closely related to the empirical work on this broad stream. Empirical research on healthcare operations management can be categorized into two main camps: understanding the drivers of successful implementation of technology (Angst et al. 2011, Li and Benton 2006, Venkatesh et al. 2011) and evaluating the effects of technology deployment on healthcare outcomes (Gardner et al. 2015, Janakiraman et al. 2017). For example, Angst et al. (2011) suggest that the optimal sequences of implementing technology into the general information system in hospitals can help to reduce healthcare process costs. Meanwhile, Janakiraman et al. (2017) find that using health information exchange technology in the emergency departments results in improved healthcare quality, in terms of duration of stay and readmission probability. This study examines the effects of online–offline service integration adoption on providers' healthcare outcomes and, thus, aims to add to the latter group of empirical work on healthcare operations management that considers the consequences of technology implementation.

Furthermore, recent studies on healthcare operations management extends from offline hospitals to online context—namely, online healthcare (Khurana et al. 2019, Yan et al. 2019). For example, Yan et al. (2019) demonstrate that the shared information in online healthcare communities leads to social influences on patients' perceived treatment quality. In addition, Khurana et al. (2019) indicate that doctors' participation of the question-and-answer (Q&A) forums on online healthcare portals can help to reduce information asymmetry and improve the patients' recommendation of those doctors. As indicated by Kumar et al. (2018a, p. 1900), healthcare management online is "an interesting and useful research domain for future researchers, especially for those working at the interface of OM and IS." Our study extends this emerging research field by making the first attempt to explore the implications of online–offline service integration to healthcare providers.

2.2. E-healthcare

Research on e-healthcare explores how the development of online healthcare platforms influences healthcare quality (Agarwal et al. 2010; Yan and Tan 2014). E-healthcare providers, the cornerstone of online health communities, remain at the center of research attention (Khurana et al. 2019). For example, participating in online health communities has been shown to lead to increased provider demand (Goh et al. 2016, Weiner et al. 2013), improve provider performance (Ball and Lillis 2001, Liu et al. 2014), and strengthen communication between healthcare providers and patients (Khurana et al. 2019). Although prior research in e-healthcare has considered several antecedents of provider performance, the notion of integrating healthcare services across online and offline channels remains an underexplored aspect.

Specifically, related prior work that explores the interplay of online and offline channels in e-healthcare has primarily focused on the directional transition from offline to online channels or vice versa. For example, Wu and Lu (2017) investigated the effects of consultation activities of healthcare providers in online communities on their performance in an online booking service platform that supports patients' online booking of offline hospital visits. Meanwhile, Bavafa et al. (2018) employed analytical modeling to understand how providers can manage the demand for healthcare services by adjusting offline revisits and diverting offline visits to online ones. In addition, Bergmo et al. (2005) examined the use of a secure e-messaging system to reduce the number of office visits by patients. Furthermore, Khurana et al. (2019) found that the introduction of healthcare providers' responses in the Q&A forum of an online healthcare portal has a significant causal impact on demand-side user perception of the medical services offered. While prior research focused on a specific service—such as online booking (Wu and Lu 2017), online consultation (Bavafa et al. 2018), e-messaging (Bergmo et al. 2005), and online Q&A forums (Khurana et al. 2019)—our study attempts to probe into the role of the online–offline service integration, which relates to integrating a series of fragmented services in different channels, from online consultation, online booking of offline visit, and synchronization of medical records, to online follow-up to track health status and recovery, and how the integration differentially impacts different providers (professional title and medical specialty), which informs the design of service operations in e-healthcare provision.

One related work that our study extends from is that of Wang et al. (2020), which explored the online–offline interaction of providers' activities. In particular, the authors indicated that providers' online healthcare services influence their offline demand, which in turn negatively affects their online service. The current study is different from Wang et al. (2020) in several ways. First, Wang et al. (2020) consider an e-healthcare platform as an entire system that supports and tracks all providers' online and offline services and then explore the providers' dynamics of cross-channel activities. In contrast, our work considers the scenario that not all providers have fully enabled the online–offline integration and investigates the differences in the provider-level outcomes before vs. after the introduction of online–offline service integration. Second, while Wang et al. (2020) regard the online–offline connection of an e-healthcare platform solely as an instrument for directing patient demand across channels, our study considers online–offline service integration via one operations management function for providers to offer streamlined healthcare services. In other words, the online–offline service integration in our study not only enables the providers' online and offline activities but also support the coordination of providers' continual healthcare services and synchronization of medical records across online and offline channels. In sum, advancing related prior work, our study employs a design perspective in the operations of e-healthcare to examine the impact of online–offline service integration for e-healthcare providers on their performance metrics.[4]

2.3. Online–offline Channel Integration

Online–offline channel integration refers to the phenomenon by which a platform integrates a distinct extant offline operations into an online channel or vice versa (Beck and Rygl 2015, Kumar et al. 2019). Prior research on online–offline channel integration has mostly been constrained to the context of e-commerce, examining outcome variables such as sales (Gallino and Moreno 2014, Geyskens et al. 2002, Homburg et al. 2014), supply chain management (Ishfaq et al. 2016, Kulp et al. 2004), and service quality (Ba and Johansson 2008, Berry et al. 2010, Cenfetelli et al. 2008). For example, Cao and Li (2015) revealed that cross-channel integration has a positive effect on sales growth and offline presence negatively moderates such an effect. In addition, Bell et al. (2018) find that multichannel integration increases demand overall and in the online channel but decreases demand in the offline channel. Avery et al. (2012) demonstrate that channel integration cannibalizes sales in the offline channel but not the online channel and show that channel integration benefits both online and offline channels over time. Furthermore, Gallino and Moreno (2014) show that retail integration of online and offline channels is associated with a reduction in online sales and an increase in-store sales and traffic.

Nonetheless, the previous findings on online–offline channel integration in e-commerce might not be directly applicable to e-healthcare. While e-commerce mostly involves distinct transactions of goods via online or offline channels (Gupta et al. 2009, Nault and Rahman 2019, Tian et al. 2018), e-healthcare often requires repeated interactions and continual correspondence between providers and patients across channels (Ayabakan et al. 2017, Detz et al. 2013, Hewitt-Taylor and Bond 2012). For example, by accessing both channels, a consumer in e-commerce could place an order online and pick up the product offline and the transaction is considered completed (Mehra et al. 2018). However, a patient in e-healthcare often needs to consult a provider online, make offline visits, and then communicate with the provider online for follow-up health management (Das et al. 2015, Goh et al. 2016). Hence, online–offline integration might serve substantially different functions in e-healthcare vs. e-commerce. Instead of simply supporting intermittent transactions across online and offline channels in e-commerce, online–offline service integration plays an important role in the continual provision of healthcare services and synchronization of medical records for patients in e-healthcare. The continuity and synchronization aspects of channel integration in e-healthcare are expected to result in unique effects that warrant empirical investigation, and the current study extends the stream of research on online–offline integration by examining the impact of online–offline service integration on the demand and reputation of providers in e-healthcare.

3. Hypotheses

Before diving into the empirics, we elaborate on a set of hypotheses that aims at providing the conceptual motivation and theoretical consideration of the relationships that we examine in this study. Specifically, we hypothesize the effects of online–offline service integration on two types of provider-level outcomes in e-healthcare, including the providers' demand (i.e., online demand, offline demand, and the total demand combining online and offline channels) and reputation (i.e., values of symbolic gifts and online rating). In addition, we also articulate the potential moderating role of two provider characteristics (i.e., providers' professional title and medical specialty) on the main relationships.

3.1. Main Relationships

We first consider the impact of online–offline service integration on providers' online demand. The ability to virtually connect providers with patients and support online consultations has been a unique advantage of e-healthcare compared with traditional healthcare services where patients are required to meet with providers face-to-face (Bavafa et al. 2018, Griffiths et al. 2006, Liu 2016). Thus, prior literature in e-healthcare has identified multiple antecedents of the demand for providers' online consultations. For example, the offline healthcare activities of providers correlate with the number of their online consultations (Wang et al. 2020). In addition, the quality of social interactions between providers and patients online can influence the providers' online demand (Chang et al. 2019, Hewitt-Taylor and Bond 2012). Furthermore, changes in health insurance systems affect the demand for providers online (Yu et al. 2016).

In our study context, online–offline service integration supports instantaneous communication between providers and patients, which provides patients convenient access to the providers. For example, using the service integration function, the providers can react to comments and questions from patients in real-time and effectively interact with the patients. As patients often seek information before paying for any formal online consultations (Hu et al. 2012, Xiang and Stanley 2017), such an opportunity of communication via the online–offline service integration function can be particularly useful for providers to address information asymmetry, understand their patients' healthcare needs, and develop provider–patient relationships. Related qualitative work by Tieu et al. (2015) suggests that the improvements in the convenience and security of patient–provider communication can effectively increase the usage of the online patient portal. In the same vein, we expect that, with the service integration function, the providers' communication with the patients might elevate the patients' intention to request online consultations, thereby leading to increases in providers' online demand. Thus, we propose the following hypothesis:

HYPOTHESIS 1. *Online–offline service integration will increase the online demand for providers.*

Next, we explore the possible impact of online–offline service integration on providers' offline demand. Prior research suggests that bridging the online and offline channels in e-healthcare can effectively help providers manage their offline demand and it is up to the providers to determine whether they would increase or decrease offline demand. For example, providers' online activities in tandem with an online booking feature on an e-healthcare platform can increase the providers' offline demand (Chang et al. 2019, Santana et al. 2010, Wu and Lu 2017). Alternatively, providers in e-healthcare can use online consultations to substitute face-to-face visits, thereby resulting in reduced offline demand (Bavafa et al. 2018, Bergmo et al. 2005). Meanwhile, providers' offline demand is also subject to other factors such as the providers' online reputation (Liu et al. 2016), the patients' satisfaction level with their online interactions with the providers (Chung 2013), the patients' specific beliefs of their illnesses such as the timeline and severity of illnesses (Hu et al. 2012), and the usability and security of the e-healthcare platform (Kim and Oh 2011).

In our study context, online and offline service integration supports the synchronization of medical records, and providers can offer a series of healthcare services in continuity. After enabling online–offline service integration, the relevant healthcare services are streamlined into one function, and thus it offers the technological ease of use for providers (Segars and Grover 1993, Venkatesh 2000). Specifically, it would be convenient for providers to manage offline visits with patients right after an online consultation. As such, providers can make a timely judgment on whether or not a patient needs offline visits post online consultation and can directly schedule the offline visits within the integrated function. Otherwise, providers have to wait for the patient to initiate offline visits via a separate booking feature. Note that the standalone online booking feature has an inherent issue of patient–provider fit uncertainty, as patients might simply request an offline visit without online consultation (Hong and Pavlou 2014). Thus, after (vs. before) the adoption of the online–offline service integration, the offline demand for providers will be more guided by the initial provider–patient communication in the channel integration function, and the variation in offline demand is likely to follow the online demand. We expect that providers will experience an increase in online demand after the service integration and, thus, we anticipate that the offline demand for providers will increase in quantity as well. Formally, we propose the following hypothesis:

HYPOTHESIS 2. *Online–offline service integration will increase the offline demand for providers*

Apart from impacting the demand for healthcare services, the providers' adoption of online–offline service integration might also influence their professional reputation. Related prior work has identified a number of driving factors for providers' reputational outcomes. For example, Liu et al. (2014) find that the effort that healthcare providers put in e-healthcare platforms improves their reputation as measured by the number of virtual thanks, virtual gifts, and patient evaluations. Moreover, Guo et al. (2017) indicate that the reputation capital of e-healthcare providers (e.g., professional, academic, hospital, regional reputations) and decision capital (e.g., number of published articles, number of online consultations) is positively correlated with their professional reputations. In our study, we propose that online–offline service integration optimized the process of e-healthcare services in terms of technological ease-of-use, cross-channel information flow, and service continuity, thereby resulting in increased service value and self-efficacy over the service process (Ba and Johansson 2008), which in turn improves patient satisfaction and provider reputation. Furthermore, we expect that the e-healthcare providers could build stronger long-term relationships with patients through the continual provision of healthcare services and synchronized medical records after (vs. before) the adoption of online–offline service integration, thereby enhancing patient satisfaction and resulting in improved provider reputation.

Alternatively, note that the providers inherently have resource constraints (Wang et al. 2020). According to the resource-based view (Barney 1991, Teece et al. 1997), if the adoption of online–offline service integration leads to an unmanageable spike in the service demand and workload, e-healthcare providers might have less attention and time with each patient, which could jeopardize service quality, decrease patient satisfaction, and potentially negatively affect provider reputations. However, a counterargument to the abovementioned scenario is that the potentially negative impact of demand increases could be redressed by enhanced operations efficiency, medical records synchronization, and service continuity after online–offline service integration. Consequently, we expect that the providers' professional reputation will benefit from online–offline service integration. Formally, we propose the following hypothesis related to providers' reputation:

HYPOTHESIS 3. *Online–offline service integration will result in improvements in the providers' professional reputation in terms of gift value and online rating*

3.2. Moderating Relationships

Beyond the average impact of online–offline service integration on providers in general, the magnitude of the main relationships might vary by the different characteristics of e-healthcare providers. Here, we first consider the professional title of e-healthcare providers as a moderator. The professional title of e-healthcare providers signals the providers' experience and credentials that potentially lead to variation in the demand for and reputation of providers after online–offline service integration. Note that there exists an information asymmetry issue in e-healthcare, and it is more severe than in other industries, such as hotels and restaurants (Khurana et al. 2019, Kumar et al. 2018b, Proserpio and Zervas 2017). Consequently, patients in e-healthcare tend to seek treatment from the providers with higher (vs. lower) professional titles, which contributes to the "cold start" problem encountered by the less experienced providers and in turn might negatively affect the economic and reputational returns of healthcare providers (Guo et al. 2017).

Furthermore, healthcare providers with lower professional titles generally attract fewer patients through online healthcare communities (Wu and Lu 2017). Consequently, the providers with lower (vs. high) professional titles may make additional efforts to servicing patients in the hopes of increasing their popularity (Liu et al. 2014). Meanwhile, the benefits of the extra effort by providers with lower (vs. higher) professional titles might not transpire because those providers can be less successful in attracting new patients due to information asymmetry in e-healthcare (Khurana et al. 2019). Therefore, even if the providers with lower (vs. higher) professional titles enable the integration function and can leverage the streamlined healthcare services to help cater to the patients' medical needs, those providers might not attract many new patients after adopting online–offline service integration to begin with. In turn, we expect that the providers with lower (vs. higher) professional titles might experience less variation in demand and reputation after the online–offline service integration; we propose the following hypothesis in this regard:

HYPOTHESIS 4. *Providers' professional title will be a significant moderator, such that the effects of online–offline service integration on providers' demand and reputational outcomes will be weaker for providers with lower (vs. higher) professional titles.*

Next, we consider the medical specialty of e-healthcare providers because various diseases might need to be managed differently through the operations of online–offline service integration. Generally speaking, chronic diseases (e.g., asthma, cancer, diabetes, psoriasis, etc.) require planned regular interactions and continuous follow-up with healthcare providers, which includes systematic assessments, attention to treatment guidelines, and behavioral support that focuses on function and prevention of exacerbations and complications. (Lorig et al. 1999, Wagner 1998). Compared with acute diseases, chronic diseases often can neither be vaccinated against nor completely cured by treatments and the symptoms can persist over time (Bernell and Howard 2016). Accordingly, medical professionals maintain that healthcare for chronic diseases must be "focused on and integrated across the entire spectrum of the disease and its complications, the prevention of comorbid conditions, and relevant aspects of the delivery system" (Norris et al. 2003, p. 477).

In our study context, the online–offline service integration enables e-healthcare providers to synchronize the patients' medical records across online and offline channels and continually track patients' health conditions, communicate with patients, and maintain stable provider–patient relationships. This would likely be of great value for patients with chronic diseases since those patients would receive planned, interactive, and continual healthcare from the providers who have enabled online–offline service integration. Note that the development of professional relationships is a dynamic process, which can be strengthened with frequent and efficient communication (Burke and Kraut 2014). When the relationship between e-healthcare providers and patients becomes stronger, providers may experience higher economic and professional reputation returns (Guo et al. 2017). Therefore, we anticipate that the providers who specialize in chronic (vs. acute) diseases may experience higher online and offline demand and obtain greater reputational gains; thus, we propose the following hypothesis:

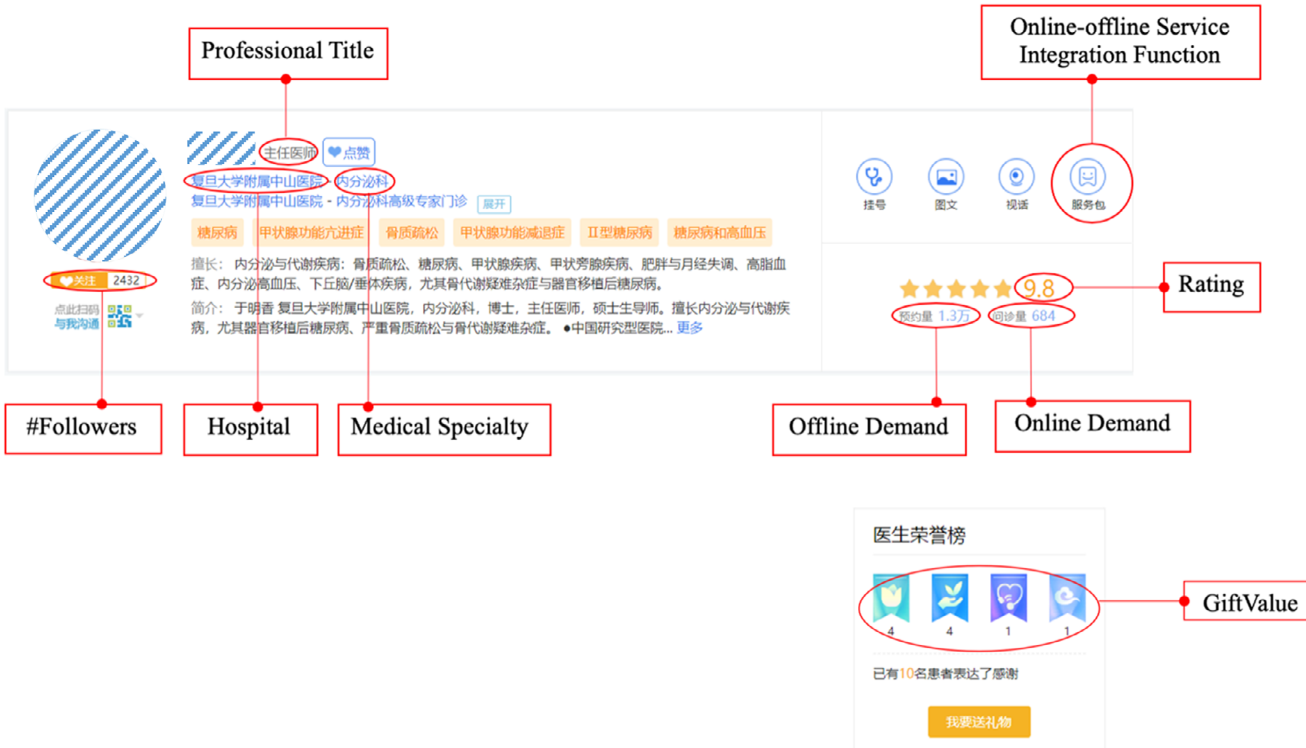
HYPOTHESIS 5. *Providers' medical specialty will be a significant moderator, such that the effects of online–offline service integration on providers' demand and reputational outcomes will be stronger for providers who specialize in chronic (vs. acute) diseases.*

4. Methodology

4.1. Background

Our study context resides in one of the pioneering e-healthcare platforms in China.[5] We provide a screenshot of a healthcare provider's homepage on the platform in Figure 1.[6] On the e-healthcare platform, the providers could separately offer online consultation and offline appointment services for registered users. After receiving healthcare service, the users (i.e., patients) have the option to post their reviews regarding the providers as well as gift the providers. On April 19, 2018, the platform rolled out a new service function that integrates the online and offline channels by streamlining the services of online consultation, online booking of offline visit, and online follow-up to track health status and recovery. In other words, instead of separately using different features in the platform to schedule online consultations, make appointments for offline visits, or independently following up with the providers after medical treatments, the providers could synchronize the relevant medical records and continually offer all the services in one integrated function. For example, after

Figure 1 Screenshot of a Provider's Homepage on the E-healthcare Platform [Color figure can be viewed at wileyonlinelibrary.com]



enabling the online–offline service integration function, the providers can offer online consultations and then schedule offline sessions with the patients. Thereafter, the providers can use the service integration function to offer follow-up recommendations and track the patients' recovery and health status online. Meanwhile, such continuity of medical services and synchronization of medical documents enable the providers and the patients to keep track of the patients' medical history and treatments, as those records are readily available and transferrable across providers through the integrated function.

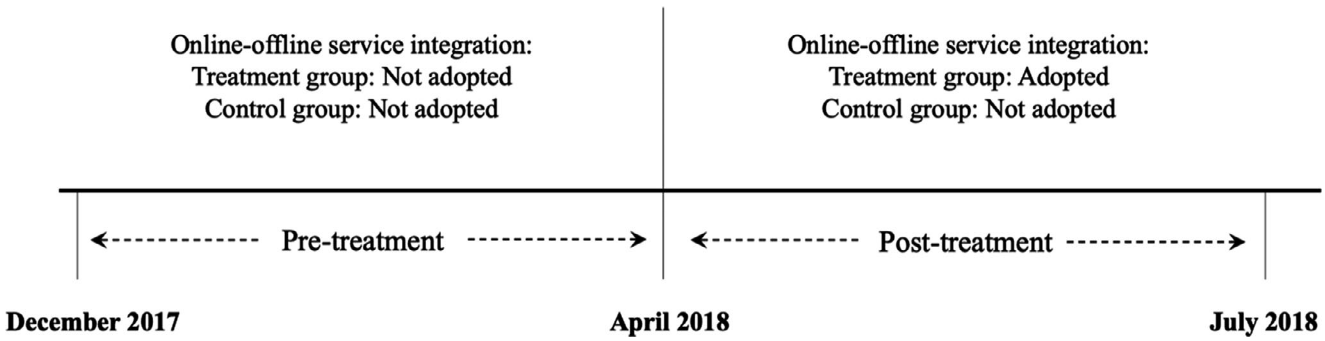
The online–offline service integration function is free for providers to enable/adopt on the platform, but it is not mandatory.[7] Thus, not all healthcare providers on the platform adopted the service integration function simultaneously. Such an empirical setup embodies a quasi-natural experiment, which enables us to analyze the effects of the online–offline service integration function on the provider-level outcomes. Understanding the role of the online–offline service integration function provides important implications for the design of business operations in the provision of e-healthcare services. To the providers, the adoption of the service function could facilitate the integration of the patients' healthcare activities across both online and offline channels, enable accurate access to the patients' health record, and possibly improve efficiency and healthcare quality (e.g., Ayabakan et al. 2017, Kohli and Tan 2016, Yaraghi et al. 2014). Therefore, as elaborated in the hypotheses section earlier, we expect that the adoption of the online–offline service integration function by the providers might significantly influence the demand for the providers (i.e., measured by the number of online consultations and offline visits) as well as their professional reputations (i.e., measured by online rating and gift value from patients).

Figure 2 illustrates the timeline of the quasi-natural experiment. Specifically, we observe the quasi-natural experiment in an 8-month window between December 2017 and July 2018. During this period, we consider the introduction of the online–offline service integration function in April 2018 as a natural shock that generated variations among the providers (i.e., treatment). We define the period from December 2017 to the launch time (April 19) of the integration function as the pre-treatment stage and from the launch time to July 2018 as the post-treatment stage. In addition, we categorize the providers who have adopted the free integration function as the treatment group ($\# Observations_{treatment} = 3{,}502$), and the providers who did not enable the function as the control group ($\# Observations_{control} = 29{,}133$).

4.2. Data and Measures

We collected data on the providers' online and offline healthcare service records on a monthly basis for 8

Figure 2 Timeline of the Quasi-Natural Experiment



months, with 4 months before and after the channel integration on the platform, respectively. Thus, the unit of analysis for this study is at the provider-month level. We summarize the list of key variables and the corresponding definitions in Table 1 and also report the descriptive statistics of the variables in Table 2. Our key outcome variables are online and offline demand for providers as well as the online reputation of providers, which are archived on the e-healthcare platform.[8] Specifically, *OnlineDemandit* refers to the volume of online channel consultation, measured by the number of online consultations a healthcare provider i conducted in month t. *OfflineDemandit* refers to the number of offline visit appointments a healthcare provider i received via the healthcare platform in month t. We then sum the healthcare providers' online demand with offline demand to a measure of *TotalDemandit*, which captures the total demand of a healthcare provider i across online and offline channels in month t. Please note that the offline demand in our study captures the number of offline visit appointments for the providers via the online healthcare platform that we collected data from. The offline demand as well as total demand are the demand that the providers received through the online healthcare platform.

Table 1 Variables and Definitions

Variable	Definition
$OnlineDemand_{it}$	The total number of online consultations for a provider i in month t.
$OfflineDemand_{it}$	The total number of offline appointments for a provider i in month t.
$TotalDemand_{it}$	The combined numbers of online consultation and offline appointments for a provider i in month t.
$GiftValue_{it}$	The monetary value of online gifts that a provider i receives in month t.
$Rating_{it}$	The average rating of a provider i in month t.
$OnlineVolume_{i,\ t-1}$	The cumulative number of reviews a healthcare provider i received from online consultation up until month t.
$OfflineVolume_{i,\ t-1}$	The cumulative number of reviews a healthcare provider i received from offline appointments up until month t.
$PriorRating_{i,\ t-1}$	The cumulative average rating a healthcare provider i received on the online healthcare platform up until month t.
$\#Followers_{i,\ t-1}$	The cumulative number of followers a healthcare provider i has in the online healthcare platform up until month t.
$Price_i$	The average price of a provider i's online consultation services.
$TreatGroup_i$	When the variable value equals to 1, a provider i is in the treat group; otherwise, it equals to 0, denoting a provider i in the control group.
$PostTreatment_t$	The variable value equals to 1 if month t is on or after April 2018, and otherwise it equals to 0.

Next, we measure the healthcare provider's reputation using two variables: *Ratingit* and *GiftValueit*. Patients can voluntarily rate a healthcare provider i, on a scale of 1 to 10, after an online consultation or offline consultation in month t. Thus, *Ratingit* represents the average score of all ratings a healthcare provider i acquired in month t. In addition, *GiftValueit* measures the value of gifts that a healthcare provider i received in month t. Patients can express their gratitude to healthcare providers by voluntarily gifting them after online consultation or offline visits.[9] In this regard, the gift value indicates a service premium, which is the additional price that patients are willing to pay beyond the consulting fees.

Our main independent variables are *TreatGroupi* and *PostTreatmentt*. If the *TreatGroupi* variable value is 1, the healthcare provider i adopted the online–offline

Table 2 Descriptive Statistics

Variable	Mean	SD	Min	Max
$OnlineDemand_{it}$	0.301	3.305	0	273
$OfflineDemand_{it}$	0.778	4.326	0	141
$TotalDemand_{it}$	1.080	6.062	0	297
$GiftValue_{it}$	0.090	2.992	0	990
$Rating_{it}$	0.043	0.395	0	10
$OnlineVolume_{i,t-1}$	9.508	85.675	0	8810
$OfflineVolume_{i,t-1}$	7.388	50.687	0	1519
$PriorRating_{i,\ t-1}$	1.511	3.475	0	10
$\#Followers_{i,\ t-1}$	40.581	224.464	0	8273
$Price_i$	14.181	32.784	0	1000

service integration function and is in the treatment group; otherwise, the value of the *TreatGroupi* variable is 0. Meanwhile, if the *PostTreatmentt* variable value is 1, the month *t* denotes a month in and after April 2018; alternatively, the value of the *PostTreatmentt* variable is 0. We then consider a number of control variables that potentially influence our outcomes of interest. For example, the total number of prior reviews, prior ratings, and number of followers might induce observational learning and serve as a source of popularity and quality signals for the prospective patients, which influences the subsequent demand for the provider (e.g., Banerjee 1992, Zhang 2010; Khurana et al. 2019). Thus, in our analyses, we account for the total volume of prior patient reviews on a providers' service via the online and offline channels (*OnlineVolumei,t_1* and *OfflineVolumei,t_1*), a provider's prior cumulative average rating ($PriorRating_{i,\ t-1}$), number of followers ($\#Followers_{i,\ t-1}$), and the average price of a provider's online consultation services ($Price_i$).

4.3. Main Effects

4.3.1. Identification Strategies. Our empirical analyses aim at quantifying the effects of online–offline service integration on the online and offline demand for providers as well as on their reputation. The key variation we leverage is the adoption of the service integration function by certain providers, which is free and optional to the providers. While the providers do not pay to enable this function, the patients need to pay a fixed amount to use this function (they may also choose not to use integrate their online and offline service experiences). Given that our analyses and outcomes are at the provider level, the patients' cost to use the integration will not jeopardize the validity of the empirical identification. Therefore, causal identification in this context is largely subject to provider-level selection issues.

Even if the service integration function is free and optional for the providers, two hurdles related to provider selection must be overcome. First, relatively stable features of a healthcare provider (e.g., individual characteristics) may systematically influence the demand for the healthcare provider. To address this issue, we leveraged the longitudinal nature of our data, incorporating provider-level fixed effects, which accounted for the static provider-level features capable of influencing healthcare provider performance. Second, although the individual fixed effects can account for time-invariant factors associated with a specific hospital or cross-sectional shocks across a broader e-healthcare market, concerns will remain regarding unobserved dynamic factors that are specific to a healthcare provider and which correlate with healthcare provider performance. Accordingly, we employed multiple strategies for identifying exogenous (with respect to our outcome variable) variation in provider-level performance, which complement one another: the DID estimations with the entire sample (e.g., Angrist and Pischke 2008, Lechner 2011), the DID estimations with propensity score matched samples (DID + PSM) (e.g., Kuang et al. 2019, Sun and Zhu 2011), and a look-ahead propensity score matching procedure coupled with a DID estimator of the treatment effect (DID + LA-PSM). Our DID + LA-PSM approach closely follows extant work in similar empirical setups (e.g., Bapna et al. 2016, Kumar et al. 2018b).

4.3.2. Difference-in-Differences (DID) Estimations. We first adopt the regression framework to detect the shifts in the provider-level outcome variables after the introduction of the online–offline service integration function on the platform. In doing so, we rely on a DID approach that enables us to leverage our panel data structure while controlling for time-specific and provider-specific effects. We specify our estimating equation of the DID analyses in Equation (1). Note that the conventional DID variable $TreatGroup_i$ is subsumed by u_i and $PostTreatment_t$ is subsumed by $MonthDummy_t$. Therefore, they were both omitted from the estimations.

$$\begin{aligned} Outcome_{it} = \beta_0 + \beta_1(TreatGroup_i * PostTreatment_t) \\ + Controls_{i,t-1} + MonthDummy_t + u_i + \varepsilon_{it} \end{aligned} \tag{1}$$

In Equation (1), *Outcomeit* represents the variables *OnlineDemandit*, *OfflineDemandit*, *TotalDemandit*, *GiftValueit*, and *Ratingit*, respectively. The outcome variables were log-transformed due to dispersed distributions. The coefficient β_1 of the interaction term *TreatGroupi*PostTreatmentt* quantifies how the healthcare providers' outcome measures in the treatment group vary after adopting the online–offline service integration function compared with those of the providers in the control group during our observation window. Furthermore, we control for healthcare providers' average price of online consultation, as well as their prior cumulative review volume (on online and offline consultations), average rating, and number of followers in the online healthcare platform up until month *t*. In addition, we introduce individual-level fixed effects to account for unobserved time-invariant user characteristics.[10] We also include dummy variables for each month from December 2017 to July 2018 to control for time-specific effects.

We present the estimation results of Equation (1) in Table 3. To begin with, the adoption of the online–offline service integration function appears to

Table 3 Difference-in-Differences (DID) Estimations

Variable	(1) Online Demand	(2) Offline Demand	(3) Total Demand	(4) Gift Value	(5) Rating
$TreatGroup_i$*$PostTreatment_t$	0.261***	−0.044***	0.126***	0.137***	0.060***
	(0.011)	(0.006)	(0.009)	(0.009)	(0.004)
$log(OnlineVolume_{i,\ t-1})$	−0.102	0.062	−0.089	0.206***	−0.144***
	(0.069)	(0.038)	(0.068)	(0.052)	(0.030)
$log(OfflineVolume_{i,\ t-1})$	0.111**	−0.351***	−0.318***	0.211***	−0.102***
	(0.042)	(0.055)	(0.060)	(0.046)	(0.028)
$PriorRating_{i,\ t-1}$	0.017***	0.004	0.021***	−0.004+	0.070***
	(0.004)	(0.003)	(0.004)	(0.002)	(0.003)
$log(\#Followers_{i,\ t-1})$	0.002	0.005	0.002	−0.005	−0.000
	(0.006)	(0.005)	(0.006)	(0.004)	(0.002)
Constant	0.024	0.267***	0.326***	−0.152***	0.009
	(0.031)	(0.025)	(0.034)	(0.026)	(0.015)
Observations	261,080	261,080	261,080	261,080	261,080
Within R-squared	0.042	0.006	0.009	0.041	0.087
No. of healthcare providers	32,635	32,635	32,635	32,635	32,635
Month dummies	YES	YES	YES	YES	YES
Healthcare provider FE	YES	YES	YES	YES	YES

Notes: Clustered-robust standard errors in parentheses.

*$p < 0.05$,
+$p < 0.1$,
**$p < 0.01$,
***$p < 0.001$

significantly yet differently affect the providers. In particular, from Column 1 of Table 3, it is evident that the average number of online consultations per month increased by 26.1% after the e-healthcare providers enabled the online–offline service integration function, thereby supporting H1. On the other hand, in Column 2 of Table 3, the average number of offline visits by the providers per month decreased by 4.4% after the adoption of the service integration function; thus, H2 was not supported. Moreover, in Column 3 of Table 3, our results reveal that the providers' average total demand per month increased by 12.6% after enabling the service integration function. Furthermore, in support of H3, we observe an improvement in the providers' professional reputation on the platform after the adoption of the online–offline service integration function. Specifically, in Column 4 of Table 3, the average value of virtual gifts per month for the providers increased by 13.7%, thereby enabling the service integration function. At last, from Column 5 of Table 3, the average rating of the e-healthcare providers per month increased by 6.0% after the adoption of the service integration function. Meanwhile, in order to test the parallel trend assumption of our DID specification, we explore how our provider-level outcomes vary across the treatment and control groups in each month before vs. after the introduction of the online and offline service integration function using a relative time model (Huang et al. 2017, Xu et al. 2016). We report the results of our relative time estimation in Appendix B.

4.3.3. DID + Look-ahead Propensity Score Matching (LA-PSM). For the interests of space, we report the results of the DID + propensity score matching (PSM) analyses in Appendix C, which shows consistent results as our DID analysis. While the traditional PSM method is commonly used in the operations management and information systems literature, one limitation is that it can only match the e-healthcare providers based on their observed characteristics (Kumar et al. 2018b). There may be a range of unobserved variables that are different for healthcare providers who self-select themselves into the treatment or the control group. Accordingly, we adopt the method of look-ahead propensity score matching (LA-PSM) in order to further account for unobserved characteristics by taking advantage of the data on future adopters (Bapna et al. 2016, Khurana et al. 2019). In the LA-PSM approach, we employ the propensity scores to match the e-healthcare providers who adopted the online–offline service integration function to the providers who did not adopt the service integration function during our observation window (from December 2017 to July 2018) but then become adopters in the near future (between August 2018 and September 2018). The main idea is that the matching was based not only on the observable characteristics but also involved looking ahead to confirm that the matched e-healthcare providers in the control group also actually enabled the service integration function—only slightly later, in the 1-month period that followed. Because both the treatment and the matched control groups ultimately enabled the online–offline service integration function in our observation window, albeit at a slightly different time, we account not only for the observed characteristics in traditional PSM but also for the unobserved time-invariant characteristics linked to healthcare provider's intrinsic propensities to adopt in LA-PSM. We report the comparisons of summary statistics before vs. after LA-PSM using one-to-one nearest neighbor matching without replacement with a caliber of 0.001 in Appendix D.[11] We then re-estimate the DID framework using the matched sample after LA-PSM.

Table 4 presents the results using one-to-one matching without replacement with caliber 0.001 matched samples. The estimations in Table 4 corroborate our main findings, thereby suggesting that for the providers in the treatment group (compared to those in the control group), the demand increased by 21.2% in online consultations and decreased by 3.0% in offline visits; the total demand for the providers increased by 10.2% across the online and offline channels. Meanwhile, enabling the online–offline service integration function also leads to greater advancement in providers' professional reputation in the treatment (vs. control) group, as indicated by the increase in gift values by 13.1% and lifts in rating by 7.7%. In sum, although we cannot fully establish causality, which will require a randomized experimental design, the consistent results across the different identification strategies provide strong evidence of how the online–offline service integration impacts the demand and reputation of e-healthcare providers. For further validation, we also present DID + LA-PSM estimations under different matching strategies and caliber values in Appendix D.

4.4. Moderation Effects

Having estimated the main effects of online–offline service integration on the demand for and the professional reputation of e-healthcare providers, we next consider a few moderating factors proposed in the hypotheses 4 and 5, which enables us to understand which mechanisms are most (or least) prominent. In terms of professional title, the providers' professional titles fall into four categories from relatively lower to higher in status: "resident physician" (primary), "physician-in-charge" (intermediate), "associate chief physician" (deputy senior), and "chief physician" (senior). Accordingly, we dichotomized the different levels of professional titles and categorize the providers with primary and intermediate titles into a group labeled "lower professional titles," as well as the providers with deputy senior and senior titles into a group called "higher professional titles." We then use the variable $LowerTitle_i$ to measure the groups. If the e-healthcare providers were categorized as higher professional titles, their $LowerTitle_i$ value is 0, while the e-healthcare providers categorized as lower professional titles correspond to the $LowerTitle_i$ value of 1. Meanwhile, we divide the medical specialty of providers into two groups—*chronic* and *acute* diseases, and

Table 4 Difference-in-Differences Estimations with LA-PSM

Variable	(1) Online Demand	(2) Offline Demand	(3) Total Demand	(4) Gift Value	(5) Rating
$TreatGroup_i$*$PostTreatment_t$	0.212***	−0.030+	0.102***	0.131***	0.077***
	(0.019)	(0.015)	(0.019)	(0.018)	(0.009)
$log(OnlineVolume_{i,\ t-1})$	−0.116	0.021	−0.088	0.129*	−0.219**
	(0.089)	(0.030)	(0.065)	(0.065)	(0.068)
$log(OfflineVolume_{i,\ t-1})$	0.054	−0.514**	−0.517**	0.425**	−0.082
	(0.179)	(0.166)	(0.174)	(0.153)	(0.097)
$PriorRating_{i,\ t-1}$	0.024+	0.001	0.028*	−0.008	0.087***
	(0.013)	(0.007)	(0.013)	(0.008)	(0.009)
$log(\#Followers_{i,\ t-1})$	0.007	0.016	0.001	0.002	0.005
	(0.018)	(0.015)	(0.019)	(0.014)	(0.008)
Constant	0.202	0.796***	0.973***	−0.509***	0.063
	(0.199)	(0.138)	(0.169)	(0.151)	(0.119)
Observations	12,144	12,144	12,144	12,144	12,144
Within R-squared	0.037	0.010	0.012	0.039	0.113
No. of healthcare providers	1,518	1,518	1,518	1,518	1,518
Month dummies	YES	YES	YES	YES	YES
Provider FE	YES	YES	YES	YES	YES

Notes: Clustered-robust standard errors in parentheses.

***$p < 0.001$,
**$p < 0.01$,
*$p < 0.05$,
+$p < 0.1$

we then use $Chronic_i$ as the indicator for the groups. As per the definition of the U.S. National Center for Health Statistics, we define a chronic disease as a disease that persists for 3 months or more.[12] If the provider's medical specialty focuses on arthritis, cardiovascular disease (i.e., heart attacks and stroke), cancer (e.g., breast and colon cancer), diabetes, epilepsy and seizures, obesity, and oral health problems, the e-healthcare provider is categorized into the chronic disease group and the $Chronic_i$ value is 1. In contrast, if a provider's medical specialty focuses on other diseases, the e-healthcare provider is categorized into the acute disease group and the $Chronic_i$ value is 0. With regression Equation (2), we seek to estimate the moderation effects.

$$\begin{aligned} Outcome_{it} = {} & \beta_0 + \beta_1(TreatGroup_i * PostTreatment_t) \\ & + \beta_2(Moderator_i * PostTreatment_t) \\ & + \beta_3(TreatGroup_i * Moderator_i * PostTreatment_t) \\ & + Control_{i,t-1} + Monthdummy_t + u_i + \varepsilon_{it} \end{aligned} \tag{2}$$

4.4.1. E-healthcare Provider's Professional Title. We present the results of our moderation analyses by provider's professional title in Table 5. In Column 1 of Table 5, we find that the coefficient of the three-way interaction term is significant and negative, thereby suggesting that the providers with lower (vs. higher) professional titles experienced less improvement in online demand after online–offline service integration. In addition, the coefficient of the three-way interaction term in Column 2 is significant and positive, thereby indicating that the providers with lower (vs. higher) professional titles experienced weaker decreases in offline demand after the service integration. This result appears to support the notion that online–offline service integration enabled providers with lower (vs. higher) professional titles to maintain (or possibly increase) their offline demand by pandering to patients' medical needs and offer additional services, like face-to-face interactions (Liu et al. 2014). Lastly, in Columns 4 and 5 of Table 5, we find that the coefficients of the three-way interaction terms on providers' gift value and rating are significant and negative, thereby suggesting that the providers with lower (vs. higher) professional titles harnessed less reputational gain after the online–offline service integration.

We also performed split sample analyses to further investigate the net treatment effects of the integration function on the outcomes by the professional title of

Table 5 Moderation Effects by Healthcare Provider's Professional Title

Variable	(1) Online Demand	(2) Offline Demand	(3) Total Demand	(4) Gift Value	(5) Rating
$LowerTitle_i$*$PostTreatment_t$	−0.007	0.013	0.006	0.004	−0.000
	(0.011)	(0.016)	(0.018)	(0.006)	(0.004)
$TreatGroup_i$*$PostTreatment_t$	0.238***	−0.049*	0.096***	0.156***	0.084***
	(0.023)	(0.020)	(0.023)	(0.023)	(0.010)
$LowerTitle_i$*$TreatGroup_i$*$PostTreatment_t$	−0.114**	0.088**	0.026	−0.107**	−0.033+
	(0.038)	(0.029)	(0.040)	(0.033)	(0.019)
log($OnlineVolume_{i,\ t-1}$)	−0.121	0.026	−0.086	0.125+	−0.221**
	(0.089)	(0.030)	(0.065)	(0.065)	(0.068)
log($OfflineVolume_{i,\ t-1}$)	0.039	−0.501**	−0.513**	0.414**	−0.086
	(0.178)	(0.164)	(0.174)	(0.150)	(0.097)
$PriorRating_{i,\ t-1}$	0.024+	0.001	0.028*	−0.008	0.087***
	(0.013)	(0.007)	(0.013)	(0.008)	(0.009)
log(#$Followers_{i,\ t-1}$)	0.007	0.016	0.001	0.002	0.004
	(0.018)	(0.015)	(0.019)	(0.014)	(0.008)
Constant	0.226	0.774***	0.965***	−0.493***	0.069
	(0.199)	(0.137)	(0.169)	(0.149)	(0.120)
Observations	12,144	12,144	12,144	12,144	12,144
Within R-squared	0.039	0.013	0.012	0.042	0.113
No. of healthcare providers	1,518	1,518	1,518	1,518	1,518
Month dummies	YES	YES	YES	YES	YES
Provider FE	YES	YES	YES	YES	YES

Notes: We report the DID estimations with the sample from LA-PSM using 1:1 matching without replacement on a caliber of 0.001. Clustered-robust standard errors in parentheses.

***$p < 0.001$,
**$p < 0.01$,
*$p < 0.05$,
+$p < 0.1$.

providers. The results of the split sample analyses, presented in Appendix E, remain consistent with the estimations of the three-way interactions. Meanwhile, one additional insight is that the negative relationship between online–offline service integration and offline demand primarily manifests through the providers with higher professional titles. In other words, adopting service integration does not lead to significant decreases in offline demand for providers with lower professional titles. To conclude, our empirical evidence on the moderating role of the professional title of providers appears to support H4, which considers the main impact of online–offline service integration as being less prominent for providers with lower (vs. higher) professional titles.

4.4.2. E-healthcare Provider's Medical Specialty. We report the estimation results of moderation effects by provider's medical specialty in Table 6. In Column 1 of Table 6, we find that the coefficient of the three-way interaction term is significant and positive, thereby suggesting that the providers who specialize in chronic (vs. acute) diseases experienced further increases in online demand. Meanwhile, in Column 2 of Table 6, we observe a positive and significant three-way interaction term, thereby indicating that the providers with specialization in chronic (vs. acute) diseases experienced less decreases (or null decreases) in offline visits after adopting online–offline service integration. In Column 3 of Table 6, the results reveal that the overall demand across online and offline channels for the providers who specialize in chronic (vs. acute) disease are significantly higher. Lastly, in Columns 4 and 5 of Table 6, the coefficients of the three-way interaction terms on gift value and rating are significant and positive, thereby suggesting that the providers specializing in the chronic (vs. acute) received greater reputational benefits from online–offline service integration. In order to further understand the net effects of online–offline service integration by providers' medical specialty, we also performed split sample analyses, reported in Appendix E, which indicate largely consistent results with the estimations using the three-way interaction approach. We observe stronger effects of service integration on the increase in online demand and reputational gains for providers specializing in chronic (vs. acute) diseases. Meanwhile, the decreases in offline demand post online–offline service integration in the main analyses primarily occur to the providers who specialize in acute diseases, whereas the relationship between

Table 6 Moderation Effects by Provider's Medical Specialty

Variable	(1) Online Demand	(2) Offline Demand	(3) Total Demand	(4) Gift Value	(5) Rating
$Chronic_i$*$PostTreatment_t$	−0.016	−0.026	−0.041+	0.003	0.004
	(0.010)	(0.021)	(0.022)	(0.005)	(0.004)
$TreatGroup_i$*$PostTreatment_t$	0.168***	−0.049**	0.080***	0.092***	0.061***
	(0.021)	(0.018)	(0.023)	(0.019)	(0.010)
$Chronic_i$*$TreatGroup_i$*$PostTreatment_t$	0.135**	0.058+	0.066+	0.119**	0.047*
	(0.044)	(0.033)	(0.040)	(0.044)	(0.019)
$log(OnlineVolume_{i,\ t-1})$	−0.108	0.024	−0.086	0.136*	−0.216**
	(0.089)	(0.030)	(0.064)	(0.066)	(0.067)
$log(OfflineVolume_{i,\ t-1})$	0.053	−0.512**	−0.514**	0.423**	−0.083
	(0.179)	(0.167)	(0.175)	(0.157)	(0.097)
$PriorRating_{i,\ t-1}$	0.024+	0.001	0.028*	−0.008	0.087***
	(0.014)	(0.007)	(0.013)	(0.007)	(0.009)
$log(\#Followers_{i,\ t-1})$	0.007	0.016	0.001	0.002	0.004
	(0.018)	(0.015)	(0.019)	(0.014)	(0.008)
Constant	0.195	0.800***	0.981***	−0.520***	0.058
	(0.198)	(0.139)	(0.169)	(0.153)	(0.119)
Observations	12,144	12,144	12,144	12,144	12,144
Within R-squared	0.040	0.011	0.012	0.044	0.114
No. of healthcare providers	1,518	1,518	1,518	1,518	1,518
Month dummies	YES	YES	YES	YES	YES
Provider FE	YES	YES	YES	YES	YES

Notes: We report the DID estimations with the sample from LA-PSM using 1:1 matching without replacement on a caliber of 0.001. Clustered-robust standard errors in parentheses.

***$p < 0.001$,
**$p < 0.01$,
*$p < 0.05$,
+$p < 0.1$.

online–offline service integration and offline relationship is negative and insignificant. Thus, the existing results on the moderation effects of the providers' medical specialty do not fully support our H5.

5. Discussion

5.1. Implications for Research

This study makes several contributions to prior literature on healthcare operations management, e-healthcare, and online–offline channel integration. First, our work extends the related previous work on healthcare operations management in the online context (Khurana et al. 2019, Yan et al. 2019). Answering the call for research in online healthcare management (Kumar et al. 2018a), our work adds to the healthcare operations management literature by advancing our understanding of the role of online–offline service integration that uses a single operations function to streamline different healthcare services, supports synchronization of medical records, and enables continual service operations in e-healthcare platforms. Furthermore, contributing to the previous research on the development of e-healthcare platforms and communities (Ball and Lillis 2001, Guo et al. 2017, Liu et al. 2014), we make a pioneering effort to empirically investigate online–offline service integration and understand how such a function impacts e-healthcare providers. Moreover, this study expands the scope of the related prior work on online–offline integration from e-commerce to e-healthcare. Note that existing findings on online–offline integration in e-commerce are not directly generalizable to e-healthcare because of the drastic differences in contexts (Das et al. 2015, Detz et al. 2013, Goh et al. 2016, Hewitt-Taylor and Bond 2012). As such, online–offline service integration in e-healthcare features the provision of continual services as well as the synchronization of medical records, which was not addressed in e-commerce and, thus, deserves further investigation.

Our study finds that online–offline service integration in e-healthcare increased the number of online consultations and the total number of consultations but decreased the number of offline consultations. Although the results related to providers' offline demand were not as expected in our hypothesis, a possible explanation is that with the synchronization of medical records in the service integration function, a few traditional offline visits may have been substituted with online consultations. This finding appears to be consistent with the theoretical prediction of Bavafa et al. (2018) using analytical models—that is, given the opportunity to service and follow-up with the patients online, providers might substitute a few traditionally offline visits with online consultations, thereby leading to decreases in offline visits and increases in online visits. In our study context, after adopting online–offline service integration, e-healthcare providers can leverage integrated consultation and diagnosis processes to increase communication via online consultations and to reduce unnecessary face-to-face visits, which can alleviate intensive utilization of offline healthcare resources. In addition, such transition from offline to online consultation appears to be well-received by patients, as we find an improvement in the professional reputation of e-healthcare providers after enabling online–offline service integration.

Moreover, our exploration of the moderating factors revealed that the impact of online–offline service integration on providers' demand and professional reputation is weaker for providers with lower (vs. higher) professional titles. A possible mechanism is that, after enabling the service integration, the providers with lower (vs. higher) professional titles attracted fewer new patients than other providers due to the "cold start" problem stemming from information asymmetry (e.g., Guo et al. 2017, Khurana et al. 2019) and, thus, experienced lower demand for healthcare services and reputation returns. Meanwhile, we acknowledge that the providers' professional title is endogenous in nature and, thus, our observed moderation effects are subject to alternative explanations. For example, it is possible that the providers with higher (vs. lower) professional titles were more efficient at managing their patients through online–offline service integration, thereby substituting the unnecessary offline visits with online consultations. Alternatively, providers with higher (vs. lower) professional titles might attract different patients after online–offline service integration, with the patients of providers with lower (vs. higher) professional titles preferring offline visits over online consultation. Furthermore, there is a possibility that the patients of providers with higher (vs. lower) professional titles are more likely to buy the service package as it is much more difficult and more expensive for them to visit advanced providers offline, which may explain why the positive treatment effects are larger for providers with higher (vs. lower) professional titles. It is also possible that the patients of providers with higher (vs. lower) professional titles receive better service in online consultations, such that they are more likely to consult providers online in the future.

In addition, we find that the providers who specialize in chronic (vs. acute) diseases experienced less shrinkage in offline demand and greater increases in online demand and reputational outcomes. Such findings speak to the idea that online–offline service integration might effectively support providers specializing in chronic diseases to efficiently communicate with patients; synchronize medical records; continually track patient diagnoses, treatment details, and management of the disease; and potentially improve overall healthcare satisfaction. The continuity and synchronization aspects of online–offline service integration appear to be particularly useful for providers to manage their healthcare services for patients with chronic diseases. Considering that treating chronic diseases is relatively complex and requires additional healthcare services both online and offline (Willis and Royne 2017, Van Woensel et al. 2015), it is reasonable to see that the offline demand for the providers treating chronic diseases did not significantly decrease after the adoption of online–offline service integration, which provides suggestive evidence regarding the unique characteristics of online–offline service integration in e-healthcare that involves service continuity and synchronization of medical records.

5.2. Implications for Practice

Our study also offers several managerial implications for providers of, patients on, and operators of e-healthcare platforms. To begin with, our results indicate that online–offline service integration benefits providers in terms of total demand and professional reputation. As such, e-healthcare platforms that have not implemented online–offline service integration can provide this type of function to the providers and encourage their providers to actively adopt the integration function that results in increased patient demand and elevated professional reputation. Second, our findings on the moderation relationships provide guidance for the different types of e-healthcare providers seeking to know how to adjust their adoption strategy to optimally leverage the service integration function. For example, providers with lower (vs. higher) professional titles experienced null changes in offline demand after adopting online–offline service integration, which suggests that they can focus on improving offline consultations, expanding their patient base offline, and ultimately raising their professional titles.

Furthermore, the e-healthcare platform might want to motivate the providers specializing in chronic diseases to enable the online–offline service integration, given that it was particularly useful for those providers possibly due to continuity of service and synchronization of medical records. Third, prior literature documented that numerous readmissions can be avoided or mitigated through post-discharge monitoring (Helm et al. 2016, Liu et al. 2018) and, thus, the service integration function can be particularly helpful for patients in post-treatment health management. Moreover, previous work indicates that the use of information sharing technology can effectively reduce duplicate testing in healthcare (Ayabakan et al. 2017) and, thus, the synchronization of medical records in online–offline service integration can help avoid redundant medical tests and increase efficiency in e-healthcare. Lastly, leveraging the service integration function, we believe that providers can further offer customized e-healthcare services to accommodate each patient's unique needs across channels and to improve patients' long-term relationship and lifetime value with providers and e-healthcare platforms.

5.3. Limitations and Future Research

This work has several limitations, which also provide ample opportunities for future research. The first limitation is that since that our study context is an e-healthcare platform in China, it is unclear the extent to which our results can be generalized to various other e-healthcare platforms with different countries and cultures, such as *healthtap.com* in America and *practo.com* in India. Since e-healthcare platforms are completely virtual, and thus truly borderless, online–offline service integration has the capacity to help resolve regional shortages of medical resources; however, this will not necessarily be the case for geographically limited platforms. Therefore, future research could explore the effects of local medical resources on medical service providers on a variety of e-healthcare platforms, thereby accounting for variation in healthcare provider supply and demand.

Second, due to data limitations, we were unable to observe the patient-level characteristics. It would be helpful to know the number of customers who have purchased the online–offline service integration function for further verification. In addition, in terms of mechanisms, it is possible that the service integration function attracted more new patients or led to more healthcare activities related to existing patients, thereby considering the increase in the total demand across both the online and offline channels. Moreover, it is possible that the online–offline service integration enabled a few patients to substitute their offline visits with online consultation, thereby considering the decreases in offline demand and increases in online demand for providers. Given that our analyses were solely performed at the provider level, future research could further advance our study by pinning down the precise mechanisms of our provider-level results from the patients' perspective. Furthermore, as a result of data unavailability, we do not observe the providers' registration activities in other online e-healthcare platforms and, thus, we cannot completely eliminate the possibility of the influence of other platforms on the providers' demand. We encourage future research to evaluate the potential multihoming issue of providers in e-healthcare. In the same vein, our observations of offline demand, online demand, and total demand are limited to these types of demand in association with one major healthcare platform. While we do not observe the demand for doctors across different channels (e.g., walk-ins or phone-call appointments), it might be interesting to analyze data from such channels if such data become available.

Moreover, considering that providers can be part of the hospital groups and socially connected with other providers, it will be a fruitful direction for future research to further consider the peer influence or potential competition effects of the e-healthcare providers. In addition, other factors, such as positive sentiment in comments and patient's prior experiences, also affect patients perceived treatment outcome and the impression on healthcare providers (Yan et al. 2019). Future research can extend our work and attempt to address those questions by combining data mining methods. Furthermore, based on relative time estimations, the effects of online–offline service integration on the outcomes remain fairly stable in the observation window of 4 months after the introduction of the service package. However, there might be potential differences between the relatively short-term and long-term effects. Specifically, the negative impact of online–offline service integration on providers' offline demand might diminish in effect sizes over the long-term after reaching the bottom. Furthermore, there might be a ceiling in reputation gains of the service integration function for online providers in the long run. We encourage future research to further explore the long-term effects of online–offline service integration in e-healthcare.

In addition, we primarily explored the heterogeneity in the effects of online–offline service integration on the outcomes by providers' professional titles and medical specialty. Future research can extend our findings by discovering other moderating factors—for example, the disease risk assessment that concerns patient mortality and readmission rates. Due to the fact that disease risk assessment is patient based (i.e., using quantitative health data to predict a patient's risk/probability of developing certain diseases, Dahlöf 2010, Tice et al. 2015), unfortunately, we were unable to obtain such data. Patients with a high risk of developing certain diseases might require additional medical care, and it is possible that providers can further leverage the online–offline service integration to treat patients with high disease risks. Lastly, as with any observational study without random assignment, the causality of the relationships must be interpreted with caution, and future research leveraging randomized field experiments can further enhance the causal interpretation of the findings.

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Notes

[1]Henceforth, "e-healthcare platforms" indicates the specific type of platforms we study in this study, exemplified by the Chinese e-healthcare platform *guahao.com*. Thus, while our findings could have implications for online healthcare platforms in other countries, our analyses and findings reside in the Chinese medical context and the type of function implemented in *guahao.com*.

[2]"Fear of Covid-19 leads other patients to decline critical treatment." 2020. The New York Times. Link: https://www.nytimes.com/2020/05/25/health/coronavirus-cancer-heart-treatment.html (accessed on Jan 19, 2021)

[3]For example, patients can consult the providers by sending text messages or pictures through e-healthcare platforms or by directly calling the providers at a scheduled time.

[4]We also canvased and presented the list of relevant prior literature in e-healthcare and the corresponding contribution of our study in Appendix A.

[5]www.guahao.com

[6]The provider's name and profile image in this screenshot is covered by pattern fill for privacy protection purpose. The gift section was shown in a lower position on the provider's homepage. For presentation purposes, the gift section was moved up in position on the provider's homepage in Figure 1.

[7]The patients are required to pay a fixed amount of fee to use the service integration function. The fee for patients to purchase the service integration function is 300 Chinese yuan, which is equivalent to $42.

[8]The e-healthcare platform indicates the rolling cumulative number of online consultations, offline appointment, ratings, and gift value of the providers. After we obtain the cumulative numbers, we use the observations for each provider at month t minus the data up until month t-1 to calculate the providers' outcome variables in each month. In this manner, the data in our analyses are in a panel structure at the provider-month level.

[9]The providers can receive different types of gifts as specified on the platform. Each gift type has a different unit price, ranging from 2 Chinese yuan (equivalent to 0.28 U.S. dollars) to 100 Chinese yuan (equivalent to 14.02 U.S.

dollars). *GiftValue* = $\sum$(Number of gifts in each gift type $*$ Unit price of each gift type).

[10]Individual-specific effects are determined via the results of the F-test and Breusch–Pagan Lagrange multiplier (LM) test. The Hausman test results indicate that the fixed-effect model is more appropriate than the random effect model.

[11]After matching, we observe in a sample of 1,518 e-healthcare providers, including 759 providers in the treatment group and 759 in the control group that also enabled the service integration function later, for a total of 12,144 observations. As shown in Table D1, the provider-level characteristics in the treatment group are now analogous to those in the control group after LA-PSM with all p-values higher than 0.10 in the t-test results.

[12]Source: https://www.medicinenet.com/script/main/art.asp?articlekey=33490 (accessed on Jan 19, 2021)

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendix S1. Effects of online–offline service integration on e-healthcare providers: a quasi-natural experiment.