MIS Quarterly

SPECIAL ISSUE

UNDERSTANDING THE DIGITAL RESILIENCE OF PHYSICIANS DURING THE COVID-19 PANDEMIC: AN EMPIRICAL STUDY[1]

Yinghao Liu
SILC Business School, Shanghai University,
Shanghai, CHINA {liuyh0729@gmail.com}

Xin Xu
Faculty of Business, The Hong Kong Polytechnic University
Kowloon, Hong Kong SAR, CHINA {xin.xu@polyu.edu.hk}

Yong Jin
Faculty of Business, The Hong Kong Polytechnic University
Kowloon, Hong Kong SAR, CHINA {jimmy.jin@polyu.edu.hk}

Honglin Deng
Advanced Institute of Business, Tongji University
Shanghai, CHINA {denghonglin@tongji.edu.cn}

The COVID-19 pandemic has underscored the urgent need for healthcare entities to develop resilient strategies to cope with disruptions caused by the pandemic. This study focuses on the digital resilience of certified physicians who adopted an online healthcare community (OHC) to acquire patients and conduct telemedicine services during the pandemic. We synthesize the resilience literature and identify two effects of digital resilience—the resistance effect and the recovery effect. We use a proprietary dataset that matches online and offline data sources to study the digital resilience of physicians. A difference-in-differences (DID) analysis shows that physicians who adopted an OHC had strong resistance and recovery effects during the pandemic. Remarkably, after the COVID-19 outbreak, these physicians had 35.0% less reduction in medical consultations in the immediate period and 31.0% more bounce-back in the subsequent period as compared to physicians who did not adopt the OHC. We further analyze the sources of physicians' digital resilience by distinguishing between new and existing patients from both online and offline channels. Our subgroup analysis shows that, in general, digital resilience is more pronounced when physicians have a higher online reputation rating or have more positive interactions with patients on the OHC platform, providing further support for the mechanisms underlying digital resilience. Our research has significant theoretical and managerial implications beyond the context of the pandemic.

Keywords: Digital resilience, resistance effect, recovery effect, online healthcare community, COVID-19 pandemic, natural experiment

Introduction

Recent information systems (IS) studies have found that many entities apply digital technologies to bolster their resilience to disruptive events, which the literature refers to as *information technology resilience* or *digital resilience* (e.g., Boh et al., 2023; Park et al., 2015; Shin et al., 2012). For example, under conditions of outpatient overcrowding—a typical disruption in the healthcare sector—physicians are often encouraged to join online healthcare platforms to provide diagnoses and prescriptions for patients online. Such platforms also provide patients with greater access to competent online healthcare services.[2] In today's turbulent environment, healthcare entities

[1] Waifong Boh, Panos Constantinides, Balaji Padmanabhan, and Siva Viswanathan were the accepting senior editors for this paper. Guodong Gordon Gao served as the associate editor.

[2] Please see https://pwcc.upenn.edu/en/hospital-overcrowding-a-global-problem/.

are particularly susceptible to various disruptions, such as supply chain disruptions, data breaches, and severe overcrowding in outpatient departments (e.g., Bhakoo & Choi, 2013; Davis et al., 2020; Kwon & Johnson, 2014). Developing resilient strategies to manage and cope with disruptions effectively is of paramount importance for healthcare entities (Achour & Price, 2010).[3] Existing IS studies on digital resilience have mainly been conducted in contexts where digital technologies are applied to build resilience against predictable disruptions—i.e., disruptions that happen regularly (e.g., Kwon & Johnson, 2013). For example, during influenza season, physicians might increase their use of telemedicine platforms to cope with outpatient overcrowding (Metzger & Flanagin, 2011). Information systems can improve resilience by reducing the reoccurrence probability of identical disruptions (Ambulkar et al., 2015). However, in the context of disruptions caused by unpredictable and unprecedented exogenous shocks—e.g., the sudden outbreak of the COVID-19 pandemic—whether the utility of information systems can build digital resilience remains a research gap.

To fill the above gap, our study focuses on individual physicians' digital resilience in an online healthcare setting during the first wave of the COVID-19 outbreak. COVID-19 represents a worldwide exogenous shock that has caused unprecedented challenges to public health systems and global economies (Trang et al., 2020). Given the fast spread and severity of the COVID-19 pandemic, there is an urgent need to investigate the role of information systems in the fight against the pandemic. Specifically, we focus on a particular healthcare information system—an online healthcare community (OHC) that serves as a telemedicine system and also a marketplace to match patients with physicians. The focal OHC is an online healthcare platform on which certified physicians can provide information about their profiles and medical services. Patients can search for physicians based on the information and receive professional telemedicine services such as diagnoses and prescriptions. We examine the effectiveness of this OHC in increasing physicians' resilient responsiveness against a significant exogenous shock—i.e., the first wave of the COVID-19 pandemic.

This study makes three contributions to the IS research on digital resilience. First, we operationalize and empirically investigate the nuances of what constitutes digital resilience. Resilience is an interdisciplinary concept with various forms in different time periods of disruption. For example, while entities may need to reduce the probability of a disruption occurring in the pre-disruption period (Kim et al., 2015; Sanchis et al., 2020), after a disruption, entities need to minimize the severity of short-term negative consequences and maximize the recovery speed (Zobel, 2011). Therefore, digital resilience may take different forms during different phases of the COVID-19 pandemic. However, since previous studies of digital resilience in the IS field have mainly captured entities' general perceptions of resilience in the context of predictable disruptions—e.g., supply chain disruptions (Chen et al., 2019; Pirkkalainen et al., 2019)—their operationalization and conclusions may be insufficient to explain the dynamics of digital resilience following a sudden shock such as the COVID-19 pandemic.

This study draws upon the resilience literature (e.g., Kouvelis & Li, 2008; Tomlin, 2006) and identifies two types of digital resilience in two time periods following the first wave of the COVID-19 outbreak in 2020. We empirically examine physicians' use of an OHC to achieve a *resistance effect* (i.e., to mitigate reductions of physicians' caseloads) in the *immediate period* of the COVID-19 outbreak and a *recovery effect* (i.e., to facilitate increases of physicians' caseloads) in the *subsequent period* of the outbreak. We theorize that using the OHC enabled physicians to acquire new patients and provide telemedicine services, resulting in their resilient responsiveness against the effects of the pandemic. We thus postulate and test whether the OHC enabled different forms of digital resilience across different time periods following the disruption.

Second, we reveal the underlying mechanisms of digital resilience in the COVID-19 context. While there is emerging research on resistance and recovery trends in the healthcare sector, the analyses have thus far been mainly conceptual and descriptive based on the overall supply and demand of telemedicine services (e.g., Wosik et al., 2020). One econometric challenge involves matching physicians' offline and online behaviors to identify whether and why physicians' adoption of an OHC led to digital resilience (e.g., Wang et al., 2020). As such, the underlying mechanisms of digital resilience in the COVID-19 context remain a black box. In this study, we go beyond simply examining the effectiveness of the OHC in building digital resilience and further investigate the sources of such resilience. In particular, we present a unique dataset that matches data collected from the OHC channel and the offline outpatient channel. We then posit and empirically examine how the OHC enabled physicians to improve their levels of *new patient acquisition*. We show that new patients in the online channel mitigated the loss of offline outpatients in the immediate period following the COVID-19 outbreak (i.e., the resistance effect). In the subsequent period, new offline outpatients transferred from the online channel allowed physicians' caseloads to rebound quickly to normal levels (i.e., the recovery effect).

[3] Please see https://www.mckinsey.com/business-functions/operations/our-insights/building-resilient-operations.

Third, we enrich the understanding of how physicians' effective use of information systems and online reputation contribute to digital resilience. Current IS studies mainly focus on adopting information systems to build digital resilience (e.g., Park et al., 2015). However, how the effective use of information systems actually contributes to digital resilience remains unclear. For example, over 888,800 registered physicians currently use haodf.com—one of the largest OHCs in China.[4] It is unlikely that all of these physicians possess the same degree of digital resilience because some physicians will use the OHC more effectively than others. We employ the sentiment of physicians' online consultations as the indicator of their effective use of the OHC to examine how the sentiment of online consultations influences their digital resilience. Our research thus responds to the call for shifting the focus of IS research from use to effective use, especially in healthcare contexts (e.g., Burton-Jones & Volkoff, 2017; Tong et al., 2017). Moreover, we investigate the impact of physicians' online reputation on their digital resilience. In our research, online reputation is operationalized as the overall rating of a physician's online service quality (Li et al., 2019)—a signal that may attract new patients and thus strengthen digital resilience. Considering physician OHC adoption as a "treatment," our investigation of the variation in the resistance and recovery effects across different physicians using the OHC essentially tests the heterogeneous treatment effects of the OHC on digital resilience. Our findings have significant implications for academic research and IS strategies involving healthcare.

To empirically test our theorization, we exploited a natural experiment in a healthcare setting by matching two longitudinal datasets collected from online and offline channels before and after the first COVID-19 outbreak in China. We applied a difference-in-differences (DID) model and conducted a series of rigorously designed analyses. The empirical results support the proposed resistance and recovery effects and the heterogeneous treatment effects of the OHC on digital resilience based on the sentiment of online consultations and physicians' online reputation. In addition, this study has implications for the business continuity and disaster recovery literatures, thus extending beyond the boundaries of healthcare research. Finally, we provide healthcare entities with digital resilience strategies to combat unpredictable disruptions.

The remainder of this paper proceeds as follows. The following section reviews the literature related to this research. Next, we develop the research hypotheses and then introduce the natural experiment and present our empirical methodology and results. We conclude by discussing our findings and offering implications for research and practice.

Literature and Conceptual Foundation ■

The Online Healthcare Community

In our research context, online healthcare communities (OHCs) are platforms on which patients can search for and directly interact with certified physicians to solve healthcare-related problems (e.g., Goh et al., 2016; Liu et al., 2020a). Existing research has examined the impacts of two major functions of OHCs on physicians' and patients' decisions and behaviors. The first function of OHCs is as a marketplace to match physicians and patients: physicians provide information via an OHC and potential patients select physicians for online consultations and/or outpatient visits based on this information (Xiao et al., 2014; Yan & Tan, 2017). OHCs provide various informational cues allowing potential patients to judge physicians' service quality, such as physician reputation ratings in the OHC (Wu & Deng, 2019) and detailed contents of physicians' online consultations (Barrett et al., 2016).

The second function of OHCs is to enable physicians to provide professional telemedicine services (e.g., Wang et al., 2020). Physicians can use OHCs anytime and anywhere to conduct online consultations to, for example, diagnose patients, and prescribe medicine (Cao et al., 2017). Existing research has examined patient satisfaction with online consultations (e.g., Liu et al., 2020b; Tan & Yan, 2020) and the positive impacts of physicians' participation in OHCs on patient well-being and patient-physician relationships (Liu et al., 2020a).

Previous studies have also suggested that OHCs can facilitate more equal relationships between patients and healthcare professionals since OHCs effectively reduce the information gap between patients and physicians (e.g., Bartlett & Coulson, 2011), making patients more willing to engage in offline medical care. Other studies have revealed that OHCs may impair the relationship between patients and physicians because OHCs may motivate patients to challenge physicians' medical authority (Jarvenpaa & Majchrzak, 2010), leading to suboptimal patient-physician interactions and thus decreasing patients' intentions to engage in offline medical care (Rupert et al., 2014). However, these studies were all conducted prior to the COVID-19 pandemic. In the current study, we focus on a different context—physicians' digital resilience following the initial outbreak of the pandemic.

[4] See https://www.haodf.com.

Digital Resilience

Digital resilience is generally defined as designing, deploying, and using information systems to prevent, resist, and recover from disruptions (Davis et al., 2020). Building resilience to cope with the risks and consequences of disruptions is an essential theme in various fields of literature, including organizational behavior, operations management, and information systems. Previous studies have investigated different factors that may affect an entity's digital resilience, such as firm size (Ambulkar et al., 2015) and the online reputation of the entity (Sahebjamnia et al., 2015). For example, in assessing the service quality of physicians, while offline information (e.g., title) provides limited cues, online reputation information (ratings and reviews) provides richer information about physicians and their service quality (Zhang et al., 2017), allowing physicians with higher reputation ratings to enjoy competitive advantages over those who have not adopted an OHC or those with lower reputation ratings. High online reputation ratings may serve as a positive signal to attract more patients after an exogenous shock (e.g., the pandemic outbreak), thus contributing to physicians' digital resilience.

Existing literature classifies organizational/supply chain resilience into three forms—prevention, resistance, and recovery—in both pre- and post-disruption periods (e.g., Bakshi & Kleindorfer, 2009; Davis et al., 2020). Prevention focuses on the pre-disruption period and refers to an entity's ability to reduce the probability of a disruption's (re)occurrence (Wein et al., 2006). This form of resilience emphasizes that entities proactively develop strategies to minimize the possibility of a disruption occurring (Paton & Johnston, 2001). Current digital resilience research in the IS field devotes significant attention to this form of resilience. For example, given the high risk of medical data theft, many healthcare entities take precautions against data breaches by proactively making investments in security technologies such as antivirus software and encryption (Kwon & Johnson, 2014).

By contrast, resistance and recovery occur in the post-disruption period. Resistance involves entities' ability to minimize the initial loss caused by a disruption (Ivanov & Dolgui, 2019). When a disruption occurs, entities immediately experience reduced performance after the disruption; a low level of performance loss is considered an indicator of high resistance (Munoz & Dunbar, 2015; Park et al., 2023). Recovery is the attempt to minimize the amount of time that entities take to return to normal performance levels (Bennis, 2013). This form of resilience highlights entities' ability to rebound quickly from the adversity following a disruption (Cohen & Kouvelis, 2020; Tremblay et al., 2023). For example, Japanese companies with multiple suppliers (a typical resilient strategy of supply chain management) recovered their production more quickly than their competitors following the massive 2011 earthquake (Ambulkar et al., 2015; Olcott & Oliver, 2014).

In summary, each form of digital resilience has a distinct temporal focus. Prevention emphasizes the strategies that entities use to deal with predictive disruptions in the pre-disruption period. Resistance highlights the minimization of the initial loss immediately following the occurrence of a disruption (i.e., in the immediate period). Recovery focuses on entities' performance following a disruption after some time has passed (i.e., in the subsequent period).

This study adopts the above categorization of resilience. Given the unpredictable and unprecedented nature of the first wave of the COVID-19 pandemic, prevention is not applicable in our research context. Therefore, we focus on the post-disruption period and address the resistance and recovery effects of individual physicians in this study. Specifically, we distinguish two time periods in the aftermath of the initial COVID-19 outbreak: *the immediate period* and *the subsequent period*. The key characteristic of the immediate period following a disruption is that people and organizations suffer significant losses in production and lack sufficient knowledge about the disruption (Pan et al., 2020). In the subsequent period following a disruption, affected entities take action to compensate for losses caused by the disruption and restore their production to normal levels (Gupta et al., 2016). Accordingly, in the current research context, resistance is reflected by the extent to which physicians used the focal OHC to mitigate the production loss caused by the pandemic (e.g., the reduction in outpatient visits). Recovery is indicated by the extent to which physicians used the OHC to enable the rapid resumption of their healthcare services.

Hypothesis Development

We investigate the effects of physicians' use of digital technologies to improve their resilient responsiveness across different time periods following a disruption. In particular, we contextualize digital resilience as enabled by an OHC in *the first wave of the COVID-19 outbreak*. As we focus on the impacts of the OHC on digital resilience, we distinguish between two types of physicians, namely, *OHC* and *non-OHC physicians*. OHC physicians refer to those who participate in the OHC to provide telemedicine services (i.e., online consultations) and also provide offline services in hospitals. Non-OHC physicians refer to those who do not participate in an OHC and provide offline services *only*. Digital resilience consists of a resistance effect in the immediate period and a recovery effect in the subsequent period following the COVID-19 outbreak. Specifically, the *resistance effect* refers to physicians having less reduction of their production in the *immediate period*, and the *recovery effect* refers to physicians having a more significant resumption of their production in the *subsequent period*. We develop hypotheses for these two effects and the heterogeneity of the two effects related to the sentiment of physicians' online consultations and online reputations.

Resistance Effect in the Immediate Period Following the COVID-19 Outbreak

A physician's production is often measured by the number of patient consultations per day/week (e.g., Cayirli & Veral, 2003; Salzarulo et al., 2011). These consultations can be outpatient visits in a clinical setting or telemedicine services conducted via an OHC. Given that the outbreak of the COVID-19 pandemic represented a major exogenous shock to physicians' production, we theorize physicians' digital resilience to the effects of the pandemic by comparing the number of consultations conducted by OHC physicians vs. non-OHC physicians before and after the outbreak. While the COVID-19 outbreak obviously would be expected to have a negative exogenous influence on the number of offline consultations for both types of physicians, we argue that in the immediate period after the outbreak, OHC physicians had immediate access to the OHC to compensate for the losses in their offline production whereas non-OHC physicians did not. As such, the *resistance effect* manifests in this ability to compensate for losses in offline production caused by the pandemic.

In the immediate period after the COVID-19 outbreak, physicians faced difficulties conducting offline consultations due to social distancing requirements, lockdown policies, and patients' avoidance of offline visits to minimize the risk of infection despite their need for medical care (Waizenegger et al., 2020). In addition, the healthcare system was unprepared for such a shock, leading to a disruption in the supply of offline healthcare services (Sakurai & Chughtai, 2020). OHCs are built on a digital infrastructure that is robust to disruptions such as the COVID-19 pandemic (Hollander & Carr, 2020). Thus, immediately after the COVID-19 outbreak, OHCs were accessible to both physicians and patients anytime and anywhere. Unlike non-OHC physicians, OHC physicians were able to utilize the OHC to continue their healthcare delivery in the immediate period following the outbreak in two ways. First, existing patients in the OHC were able to continue seeking telemedicine services during this time. Second, OHC physicians were able to acquire two types of new online patients during this time: (1) *new online patients transferred from the offline channel*—patients who had visited an OHC physician in the offline channel and continued to access telemedicine services from the same physician; (2) *totally new online patients* seeking an OHC physician for telemedicine services who used online profiles and telemedicine records to choose a physician (Cao et al., 2017; Liu & Chan, 2011).

We postulate that acquiring new online patients was the primary source of OHC physicians' *resistance* in the immediate period following the COVID-19 outbreak because they were able to replace their losses in offline outpatient visits with online consultations. By contrast, we anticipate that non-OHC physicians were less resistant to the pandemic effects because they were unable to immediately make the switch to the online channel. Therefore, we hypothesize:

H1 (resistance effect): *In the immediate period following the COVID-19 outbreak, OHC physicians experienced less reduction in consultations provided than non-OHC physicians.*

Recovery Effect in the Subsequent Period Following the COVID-19 Outbreak

In the subsequent period after a disruption, affected entities need to take action to restore their production to normal levels (Gupta et al., 2016; Malgonde et al., 2023). In the context of the COVID-19 pandemic, the offline outpatient channel became less constrained and was gradually restored in the subsequent period (Fahey & Hino, 2020). During the subsequent period, OHC physicians were able to not only expand online consultations, as in the immediate period, but could also speed up their recovery by increasing their number of offline consultations by transferring patients from the online channel to the offline channel. Thus, in the subsequent period, we would expect a greater magnitude of recovery for OHC physicians vs. non-OHC physicians because of the positive effects of the OHC on restoring offline production.

During the subsequent period, existing offline patients (i.e., patients who only consult with their physicians offline) started returning to hospitals for outpatient visits. This stream of patients obviously would have contributed to recovery for both OHC and non-OHC physicians. OHC physicians' traditionally offline patients who needed telemedicine services during the immediate period would likely continue seeing the same OHC physicians via the offline channel in the subsequent period. Moreover, the OHC can be useful for generating *new offline patients* in two ways. First, *new offline patients transferred from the online channel* are those who had visited OHC physicians via the online channel *only* before or during the immediate period and needed further in-person treatments or examinations in the subsequent period (Li et al., 2016). These patients thus contributed to OHC physicians' offline consultations in the subsequent period. Second, the OHC may have also generated *totally new offline patients* for OHC physicians—i.e., those who had not visited OHC physicians online or offline before or during the immediate period. The OHC allows patients to research and compare information about physicians, making it more likely that they would choose an

OHC physician vs. a non-OHC physician for an offline visit as well (Gong et al., 2021; Yuan & Deng, 2021). Given these likely positive impacts of the OHC on offline patient acquisition, we anticipate that OHC physicians attained normal-level production more quickly than non-OHC physicians in the subsequent period. Therefore, we hypothesize:

H2 (recovery effect): *In the subsequent period following the COVID-19 outbreak, OHC physicians experienced greater increases in consultations than non-OHC physicians.*

The Heterogeneous Treatment Effects of the OHC on Digital Resilience

In this section, we further develop the hypotheses regarding the heterogeneous treatment effects of the focal OHC on physicians' digital resilience. Since the effective use of information systems can lead to better performance (Burton-Jones & Grange, 2013), it is necessary to investigate how physicians' individual use of the OHC affects their digital resilience. In this study, we employ the *sentiment* of physicians' online consultations as an indicator of their effective use of the OHC.

The sentiment of a physician's online consultations refers to the extent to which communications between the physician and patients are *positive* and thus reflects whether the physician effectively uses the OHC to maintain good relationships with patients (e.g., Homburg et al., 2015; Lu et al., 2017). OHC physicians with highly positive online consultations will likely have stronger digital resilience. In the immediate period after the COVID-19 outbreak, the *resistance effect* was based on new online patients—both totally new online patients and those switching from the offline to the online channel. New patients searching for physicians in the OHC have access to the details of online consultations with other patients. Research has shown that customers prefer vendors that have good relationships with their customers (e.g., Gefen & Ridings, 2002). In our research context, this would mean that patients would prefer and be more likely to choose physicians that demonstrate good relationships with patients through signals of positive sentiment reflected in online consultations.

In the subsequent period after the COVID-19 pandemic, the *recovery effect* was mainly based on totally new offline patients and new offline patients transferred from the online channel. Like totally new online patients in the immediate period, totally new offline patients in the subsequent period would similarly use signals of sentiment in OHC records to determine whether a physician is a good fit. For new patients switching from the online to the offline channel, if a physician has maintained good relationships with them as reflected in the positivity of the online consultation records, these patients would be more likely to visit the physician for offline medical care as well. Therefore, we hypothesize:

H3a: *The resistance effect in the context of the COVID-19 pandemic is stronger for OHC physicians with higher levels of positivity in online consultations.*

H3b: *The recovery effect in the context of the COVID-19 pandemic is stronger for OHC physicians with higher levels of positivity in online consultations.*

We also investigated the impact of physicians' online reputation on their digital resilience. We argue that a high online reputation rating may attract new patients and thus strengthen digital resilience. In general, a physician's overall reputation rating is a reliable signal of service quality (e.g., Gao et al., 2015). However, obtaining a high reputation rating is difficult for OHC physicians because it requires a long-term investment of time and effort in providing various high-quality online services (e.g., Lin et al., 2018). The reputation of OHC physicians was likely crucial for their ability to acquire totally new patients in both the immediate period and the subsequent period because new patients often seek cues/signals such as online reputation ratings as a key criterion for selecting physicians (Guo et al., 2017). In the immediate period, totally new online patients presumably chose high-reputation OHC physicians for online consultations. In the subsequent period, totally new patients searching for physicians in the OHC would have relied on the same signal, whether for offline or online consultations. Therefore, we argue that OHC physicians with a high online reputation rating likely attained stronger resistance and recovery effects. In sum, we hypothesize:

H4a: *The resistance effect in the context of the COVID-19 pandemic is stronger for OHC physicians with higher reputation ratings in the OHC.*

H4b: *The recovery effect in the context of the COVID-19 pandemic is stronger for OHC physicians with higher reputation ratings in the OHC.*

Empirical Methodology and Results

Empirical Context and Data

The COVID-19 outbreak in China offered a natural experiment to test our hypotheses. We exploited the COVID-19 outbreak as the exogenous shock that created plausible variations in online and offline healthcare consultation behaviors among physicians and patients. We matched two comprehensive datasets (one online and the other offline) covering a time window of 26 weeks before and after the first COVID-19 outbreak in China. We then analyzed the resistance and recovery effects of OHC physicians compared with non-OHC physicians in the immediate and the subsequent period following the outbreak.

The Immediate Period and the Subsequent Period

To generate credible causal evidence for our hypotheses, we exploited two events to divide the time period after the first outbreak of the COVID-19 pandemic into the *immediate* and *subsequent* periods to analyze the resistance and recovery effects, respectively. The *first event* was the *initial COVID-19 outbreak*. On January 20, 2020, the Chinese government announced that the novel coronavirus could spread among human beings and suggested social distancing to prevent the spread of COVID-19. On January 23, 2020, the Chinese government officially locked down Wuhan and several other cities in Hubei province. We consider these two official announcements of COVID-19 to be signals of the initial COVID-19 outbreak. Following these two announcements, many cities in China began to enforce self-isolation, social distancing, and (partial) lockdown measures to prevent the spread of COVID-19. Thus, we define the COVID-19 outbreak as beginning on January 20, 2020, with the *immediate* period beginning on this day and lasting until the second event, which occurred on February 23, 2020.

The *second event* was the announcement that people could *resume their normal lives and work activities.* On February 23, 2020, the Chinese government announced that work could resume, which signaled that the spread of COVID-19 was under control. People's lives and work activities began to return to normal, as did the healthcare system. Thus, for our research purposes, the second event occurred on February 23, 2020. We designate the time window between the first and the second event as the *immediate* period and the time window after the second event as the *subsequent* period.

The Offline and Online Datasets

We collected offline and online data of physicians working at a leading hospital located in a city in northern China (Hospital A hereafter).[5] The offline dataset includes the outpatient consultation records from Hospital A. These records were generated from traditional medical consultations involving patients visiting Hospital A to consult with physicians and receive prescriptions or medical treatments. The data includes the offline outpatient consultations of all physicians from Hospital A (OHC and non-OHC physicians) as well as the physicians' profiles. This dataset thus consists of a time series of offline consultations conducted by both OHC and non-OHC physicians. Specifically, each offline consultation record consists of the physician's information, the date of the consultation, and the primary diagnosis, identified by the International Classification of Diseases, Tenth Revision, Clinical Modification (ICD codes hereafter).[6] The ICD coding system provides a global standard for diagnostic classification; for example, code number "K40" represents the diagnosis of "inguinal hernia" (Catena et al., 2020). ICD codes are widely adopted in healthcare management studies to control for patient heterogeneity and physician specialization (e.g., Bartel et al., 2020) because ICD codes reflect patients' medical conditions (e.g., the diseases and symptoms) and are associated with patients' primary motivation for visiting a specific physician (Clark & Huckman, 2012; Kuntz et al., 2019). Therefore, in this study, we also adopted ICD codes to control for patient heterogeneity and physician specialization. We conducted our data collection process under the supervision of professional physicians, who provided guidance regarding the ICD system.

The online dataset was collected from the OHC platform haodf.com. This platform was established in 2006 and is one of the largest OHCs in China. The haodf.com platform has been widely adopted as the empirical context for previous studies in the IS field (e.g., Guo et al., 2017; Liu et al., 2020a). As of April 2022, more than 888,800 certified physicians from 10,001 hospitals across China had registered with the platform.[7] The platform maintains a homepage for each certified physician, showing biographies, specializations, reputation ratings, and the contents of their online consultations (Figure 1). Patients can utilize such information to select physicians for paid consultations. The platform thus enables certified physicians to present profile information on their homepage and provide professional telemedicine services. Figure 1 depicts screenshots of a physician's homepage and online consultation records on the OHC platform.

[5] In our research context, the pandemic situation in the focal city was not as serious as that in Wuhan. While the local city government did not implement formal lockdowns and the focal hospital did not implement any nonacceptance policy regarding noncritical outpatients/inpatients, the local government did follow the central government's announcements and instructions to (1) discourage citizens from outdoor activities in the immediate period, and (2) encourage citizens to resume normal life and work in the subsequent period.

[6] The Centers for Disease Control and Prevention (2021) provides a detailed description of the ICD system (see https://www.cdc.gov/nchs/icd/ icd10cm_pcs_background.htm).

[7] See https://www.haodf.com.

Figure 1. Screenshots of a Physician's OHC Homepage and Online Consultation

Physicians mainly use the OHC to provide online consultations (i.e., telemedicine services).[8] These online consultations are paid services that involve formal and publicly accessible one-to-one communications between patients and physicians (Wang et al., 2020). We collected data about physicians' profiles (e.g., reputation ratings) and their online consultations. We identified the ICD code for each online consultation according to the diagnostic information included in the consultation record (see Figure 1). The online dataset thus consists of a time series of online consultations of OHC physicians from Hospital A. Following data desensitization, we matched the online dataset with the offline dataset of each OHC physician to investigate the physicians' online and offline behaviors at the individual level.

Empirical Strategy

We implemented a difference-in-differences (DID) model to examine the resistance and recovery effects. For the resistance effect, we ran a DID model using the data from the immediate period after the COVID-19 outbreak and a parallel period before the outbreak. For the recovery effect, we ran a DID model using data in the subsequent period after the COVID-19 outbreak and a parallel period before the outbreak. Moreover, we examined the heterogeneous treatment effects using two factors: *the sentiment of physicians' online consultations* and *physicians' overall reputation in the OHC*. Figure 2 presents the timeline of our analysis.

The time unit is one week and our data covers a total of 26 weeks (13 weeks before and 13 weeks after the outbreak day). The weeks are marked from -13 to 13, excluding 0. We specify the week before and after the outbreak day (January 20, 2020) as the reference period for our analyses. The signal day of recovery (i.e., the second event) is between Week 5 and Week 6. Hence the immediate period is from Week 2 to Week 6, and the subsequent period is from Week 7 to Week 13. Specifically, we tested the resistance effect with Week -6 to Week -2 as the pre-treatment period and Week 2 to Week 6 as the post-treatment period (i.e., the immediate period). We tested the recovery effect with Week -13 to Week -7 as the pre-treatment period and Week 7 to Week 13 as the post-treatment period (i.e., the subsequent period).

Variables

The unit of the analysis is each physician (OHC vs. non-OHC physicians). The production of physicians is operationalized as offline consultations of OHC and non-OHC physicians and online consultations of OHC physicians.[9] $Total\_consultation_{it}$ is the number of consultations provided by physician i in week t. For OHC physicians, this number is the sum of their online and offline consultations. For non-OHC physicians, this number equals the number of offline consultations because non-OHC physicians provide offline consultations only. $Offline\_consultation_{it}$ denotes the total number of outpatient visits of physician i in week t. $Online\_consultation_{it}$ is the total number of online consultations of physician i in week t. The binary variable $OHC\_physician_i$ indicates whether physician i is registered in the OHC or not (1 means physician i is an OHC user and 0 otherwise). The outbreak of COVID-19 is operationalized as a binary variable $outbreak_t$ with 1 indicating after the outbreak and 0 indicating before the outbreak.

We used several physician-level variables and COVID-19 statistics variables as controls, including ICD codes used, title, educational level, work experience, age, and gender. In line with previous studies (e.g., Anderson et al., 2014; Wani et al., 2020), we generated ICD code vectors for physicians by considering all the individual cases during the time window of our study. If a physician had one consultation case with a particular 3-digit ICD code, we set this ICD code dummy to 1 and 0 otherwise. In our dataset, there were 792 elements in each ICD code vector. We collected data to calculate physicians' average weekly offline consultations in the six months prior to Week -13. We included this variable to control for physician i's medical service demand, denoted as $overall\_medical\_demand_i$. The COVID-19 statistics contain new cases, cured cases, and death cases per week in the province where Hospital A is located (there is no official report of cases in the focal city).[10] Table 1 presents the list of variables and measures.

[8] We interviewed the senior management and the OHC physicians of Hospital A. They pointed out that (1) Hospital A had not implemented its own telemedicine system, and (2) the OHC physicians did not provide telemedicine services on OHC platforms other than haodf.com.

[9] We conducted interviews with both the senior management of Hospital A and the physicians in our sample. They all indicated that multiple affiliations are not allowed in Hospital A. Thus, the number of consultations of a physician in Hospital A sufficiently captures that physician's offline production. All OHC physicians in our sample only used the focal OHC for telemedicine services. The number of consultations via the OHC thus sufficiently captures their online production.

[10] We also accessed national-level data about the statistics of COVID-19 and found that the national trend is significantly correlated with the provincial trend. Thus, we concluded that the provincial statistics of COVID-19 sufficiently captured the progression of the pandemic.

Table 1. Variables and Measures

Variable	Measure	Data source
Online_consultation$_{it}$	The total number of physician *i*'s online consultations in week *t*	Physician *i*'s OHC page
Offline_consultation$_{it}$	The total number of physician *i*'s outpatient consultations in week *t*	Hospital A
Total_consultation$_{it}$	Sum of *Offline_consultation*$_{it}$ and/or *Online_consultation*$_{it}$ representing physician *i*'s total consultations in week *t*	Physician *i*'s OHC page and Hospital A
OHC_physician$_{i}$	A binary variable that indicates whether physician *i* had registered in the OHC, which takes 1 for OHC physicians, and 0 for non-OHC physicians	Physician *i*'s OHC page
icd_codes$_{i}$	A vector that if the physician *i* has a consultation with a particular ICD code, this ICD code dummy takes 1, and 0 otherwise	Physician *i*'s OHC page and Hospital A
title$_{i}$	The medical title of physician *i*, which takes the value 1 for "attending physician," 2 for "associate chief physician," and 3 for "chief physician"*	Hospital A
education$_{i}$	The educational qualification of physician *i*, which takes 1 for physicians with the "Clinical Medicine Postgraduate" qualification and 0 for lesser qualifications	Hospital A
experience$_{i}$	Years of work experience of physician *i* by Week 13	Hospital A
age$_{i}$	Age of physician *i* by the end of Week 13	Hospital A
gender$_{i}$	Gender of physician *i*, 1 for female and 0 for male	Hospital A
overall_medical_demand$_{i}$	Average weekly offline consultations provided by physician *i* in the six months before Week -13	Hospital A
new_case$_{t}$	Number of new confirmed cases of COVID-19 in the local province in week *t*	Government
cured_case$_{t}$	Number of cured cases of COVID-19 in the local province in week *t*	Government
death_case$_{t}$	Number of death cases of COVID-19 in the local province in week *t*	Government

Note: *The categorization of *title*$_{i}$ is widely adopted in IS research on OHCs in China (e.g., Li et al. 2021). The empirical results are consistent and robust using two dummies representing the three titles.

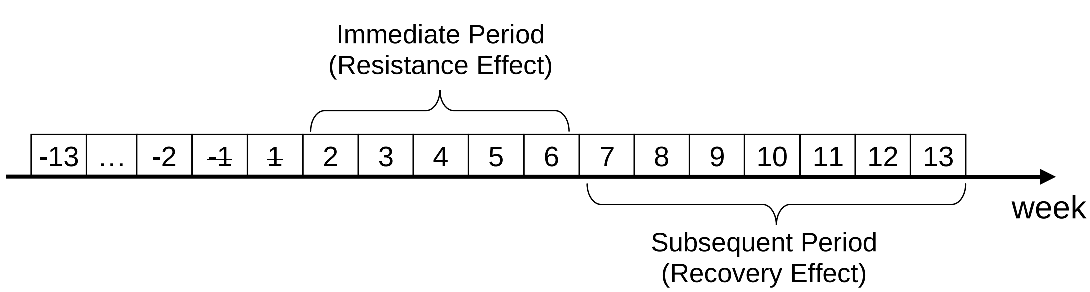

Figure 2. Timeline of the Analysis

Data Analysis

We utilized propensity score matching (PSM) to match OHC physicians as the treatment group with non-OHC physicians as the control group before the DID analysis. We then ran DID models for the immediate period and the subsequent period, respectively, to analyze the resistance and recovery effects of OHC physicians (i.e., H1 and H2). We also analyzed the sources of OHC physicians' digital resilience (i.e., the mechanisms of new patient acquisition). To investigate the heterogeneous treatment effects, we separated the OHC-physicians into two subgroups of high vs. low sentiment positivity of online consultations. We then included each subgroup of the OHC physicians and their matched non-OHC physicians in a sample to run the DID models to analyze how OHC physicians' digital resilience was affected by their online consultation sentiment (i.e., H3a and H3b). We adopted the same approach to analyze the impacts of the online reputation of OHC physicians on digital resilience (i.e., H4a and H4b).

Propensity Score Matching

We utilized PSM to match OHC physicians with non-OHC physicians who were similar on a set of observable characteristics. We ran a logit model to evaluate the probability that a physician would adopt the OHC, controlling for the following physician-level variables: the physician's (1) title, (2) age, (3) gender, (4) years of work experience, (5) overall medical service demand before the pandemic, (6) educational qualifications, and (7) ICD codes used.[11] The detailed results of the logit regression are summarized in Table A1 in Appendix A. We then matched the OHC physicians with non-OHC physicians using the one-to-one nearest-neighbor matching method (Pamuru et al., 2021). After matching, there were 77 OHC physicians and 77 non-OHC physicians in our sample. The descriptive statistics of all the variables after the PSM are reported in Table A2 in Appendix A. To verify the validity of the matching, we applied paired *t*-tests to compare the seven matching variables between the treatment and the control groups before and after matching. The results indicate no significant differences in these variables between the treatment and control groups. Table 2 reports the summary statistics of the comparisons.

To further alleviate the concern of heterogeneity among different groups of physicians and consultations, we first checked the cross-sectional variation of ICD codes (3-digit) between OHC physicians and non-OHC physicians during the entire time period (i.e., from Week -13 to Week 13). We then compared the ICD codes used by OHC physicians before vs. after the outbreak (i.e., Week -13 to Week -2 vs. Week 2 to Week 13, for ICD codes used by OHC physicians). We also compared the ICD codes used by OHC physicians for online vs. offline consultations for the entire time period. In particular, we utilized Hotelling's T^2 tests to examine the potential differences among ICD code vectors (Hotelling, 1951; Redinger, 2011). Hotelling's T^2 has been widely adopted to assess the potential differences between two vectors (e.g., Colin et al., 2015).

Table 3 reports the results of the Hotelling's T^2 tests, which show that the differences are all insignificant for ICD codes used by OHC physicians vs. non-OHC physicians, ICD codes used by OHC physicians before vs. after the pandemic outbreak, and ICD codes used by OHC physicians for online vs. offline consultations. The findings are robust to 1- and 2-digit ICD codes as well. The results suggest that (1) both OHC and non-OHC physicians were facing similar medical service demands from patients; (2) for OHC physicians, the pandemic did not change their patients' demands; and (3) the patients' demands on OHC physicians did not vary across different channels.

Estimating the Resistance and the Recovery Effect: Difference-in-Differences Analysis

We plot the total consultations of OHC and non-OHC physicians and the offline consultations of OHC physicians in Figure 3. We observe that the production of OHC and non-OHC physicians was stable with small variations in the normal period before the outbreak. However, the COVID-19 outbreak substantially reduced total consultations and offline consultations for both OHC and non-OHC physicians in the immediate period (Weeks 2-6). Moreover, there were no significant differences in the magnitude of reduction in offline consultations of OHC vs. non-OHC physicians in the immediate period (dotted vs. dashed line). However, there was a significant difference in the magnitude of reduction in total consultations for OHC vs. non-OHC physicians in this period (solid vs. dashed line). In the subsequent period (Weeks 7-13), OHC physicians' total consultations and offline consultations increased, approaching the levels seen in the normal period before the outbreak (solid and dotted lines). However, non-OHC physicians were left behind (dashed line).

[11] In the PSM, we applied the ICD code vectors using the first digit of the ICD codes (26 elements in total). We did not use the 3-digit codes because this would have produced 792-element vectors and led to the nonconvergence of the logistic model. We controlled the 792-element ICD code vectors in the DID models.

Table 2. Comparisons of Matching Variables Before and After PSM

Variable		Mean: Treatment (OHC physicians)	Mean: Control (Non-OHC physicians)	*t*-value
$title_i$	Before	1.89	1.69	1.53
	After	1.89	1.74	0.77
age_i	Before	43.27	42.45	0.87
	After	43.27	42.97	0.24
$gender_i$	Before	0.47	0.53	-1.05
	After	0.47	0.42	0.65
$experience_i$	Before	17.88	16.74	0.96
	After	17.88	17.03	0.54
$overall\_medical\_demand_i$	Before	38.20	29.97	1.75
	After	38.20	37.53	0.09
$education_i$	Before	1.00	1.00	/
	After	1.00	1.00	/
icd_codes_i *(1-digit)*	Before	Yes	Yes	All insignificant
	After	Yes	Yes	All insignificant

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3. Results of the ICD Codes Comparisons

Comparisons	Hotelling's T^2	*p*-value
ICD codes used by OHC vs. non-OHC physicians	1.04	0.441
ICD codes used by OHC physicians before vs. after the pandemic outbreak	0.66	0.964
ICD codes used by OHC physicians online vs. offline	1.35	0.153

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

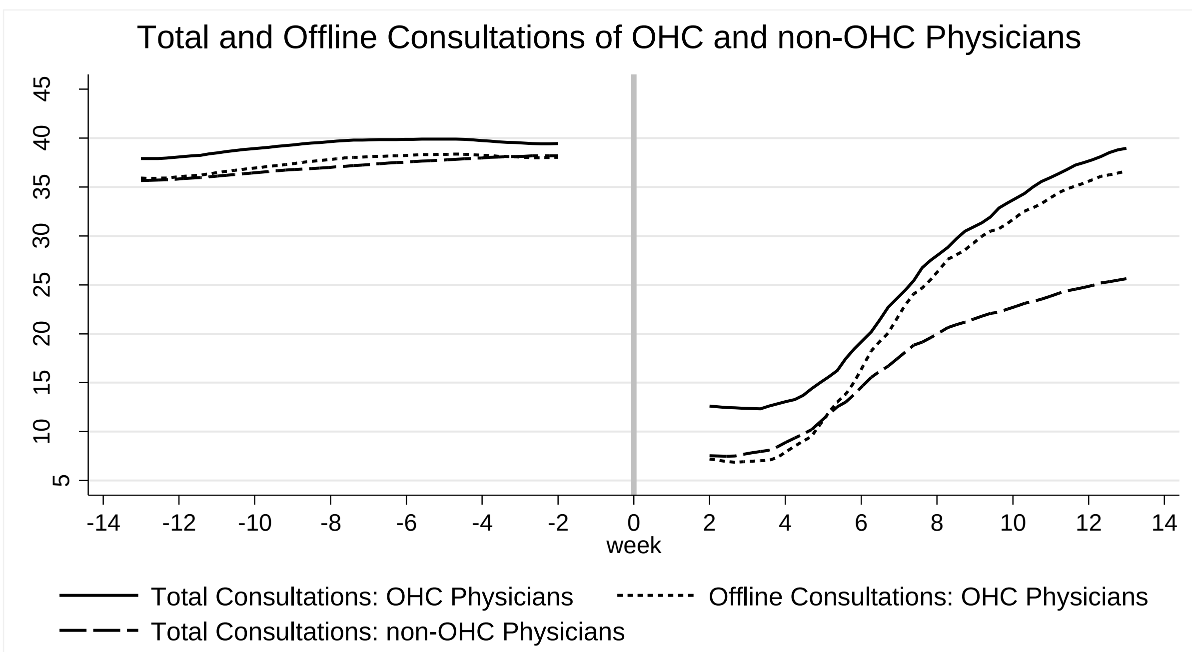

Figure 3. Physicians' Consultations

We also observed a decrease in the online consultations of OHC physicians in the subsequent period, as depicted in Figure 3 by the shrinking distance between the solid line representing OHC physicians' total consultations and the dotted line representing their offline consultations. Note that in Week 13 the numbers of online and offline consultations for OHC physicians were approaching those seen in the period before the pandemic (Weeks -13 to -2), suggesting that OHC physicians' consultations were nearly back to normal. In the immediate period of the pandemic, OHC physicians utilized the online channel to see patients because of social distancing requirements and fears of infection, which led to a relatively large proportion of online vs. offline visits compared to the pre-pandemic period. In the subsequent period, after pandemic precautions were relaxed, OHC physicians resumed their normal consultation pattern by transferring patients from the online to the offline channel and receiving more direct outpatient visits, which led to a relative decrease in online vs. offline consultations.

To provide statistical support for the model-free evidence above, we employed the following DID specifications to examine and quantify the treatment effects:

$$
\begin{aligned}
total\_consultation_{it} &= \beta_1 * OHC\_physician_i * outbreak_t + \beta_2 * OHC\_physician_i + \beta_3 * outbreak_t + \boldsymbol{\tau X} + \alpha_i + \delta_t + \varepsilon_{it}
\end{aligned} \tag{1}
$$

$$
\begin{aligned}
offline\_consultation_{it} &= \beta_1 * OHC\_physician_i * outbreak_t + \beta_2 * OHC\_physician_i + \beta_3 * outbreak_t + \boldsymbol{\tau X} + \alpha_i + \delta_t + \varepsilon_{it}
\end{aligned} \tag{2}
$$

Existing literature suggests that physicians' production/performance follows the power law distribution (e.g., Aguinis & O'Boyle Jr., 2014). Our data follows the same pattern. Therefore, we applied a natural logarithm transformation to the number of physicians' consultations.[12]

Specifically, in Equation (1), $total\_consultation_{it}$ is the log of the number of physician i's total consultations in week t, i.e., $ln(Total\_consultation_{it}+1)$, and in Equation (2), $offline\_consultation_{it}$ is the log of the number of physician i's offline consultations in week t, i.e., $ln(Offline\_consultation_{it}+1)$. **X** contains all the control variables—physician-level variables (i.e., title, age, gender, work experience, the overall medical service demand, educational qualification, and the 3-digit ICD code vector) and COVID-19 statistics (i.e., the new cases, cured cases, and death cases per week in the local province). Finally, α_i captures physician-fixed effects and δ_t captures time-fixed effects.

We ran the DID models to verify the resistance effect with data from the immediate period following the outbreak and the parallel period before the outbreak (from Week -6 to Week -2 and from Week 2 to Week 6). Moreover, we verified the recovery effect with data from the subsequent period and the parallel period before the outbreak (from Week -13 to Week -7 and from Week 7 to Week 13). The coefficient of $OHC\_physician_i*outbreak_t$ (i.e., $\widehat{\beta_1}$) is of interest because it is the estimate of the percentage of change in the dependent variables (DVs) for OHC physicians (vs. non-OHC physicians) after the COVID-19 outbreak. Therefore, $\widehat{\beta_1}$ captures the effect of COVID-19 on the production of OHC physicians, relative to the production of non-OHC physicians (i.e., the resistance and recovery effects). Table 4 reports the results of the DID regressions.

The empirical results support H1 and H2. We assessed the resistance effect of OHC physicians by using data from Week -6 to Week -2 and from Week 2 to Week 6. First, in the immediate period after the COVID-19 outbreak, OHC physicians retained significantly higher numbers of total consultations than non-OHC physicians (i.e., positive $\widehat{\beta_1}$s in Columns 1-3). In other words, the magnitude of the reduction in OHC physicians' production was lower than that of non-OHC physicians' production. Specifically, $\widehat{\beta_1}$ in Column 3 indicates 35.0% less reduction in total consultations for OHC physicians than for non-OHC physicians (significant at the 5% level).[13] Second, OHC physicians were not different from non-OHC physicians in terms of offline consultations (i.e., insignificant $\widehat{\beta_1}$s in Columns 7-9). In other words, the COVID-19 outbreak reduced the number of offline consultations performed by both OHC and non-OHC physicians to a similar level. However, OHC physicians were able to utilize the OHC to provide online consultations and thus had stronger resistance than non-OHC physicians. Therefore, the resistance effect for OHC physicians is supported by empirical evidence.

[12] We also conducted the tests by *not* taking the natural logarithm transformation of the numbers of physicians' consultations and found consistent results.

[13] Given that the DV is in the form of logarithm, the percentage change in the DV is calculated by $e^{\text{coefficient}} - 1$.

Table 4. Resistance and Recovery Effects of OHC Physicians

DV	*total_consultation$_{it}$*						*offline_consultation$_{it}$*					
Time window	[-6, -2] & [2, 6] (Resistance)			[-13,-7] & [7,13] (Recovery)			[-6, -2] & [2, 6] (Resistance)			[-13,-7] & [7,13] (Recovery)		
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
OHC_physician$_i$* * *outbreak$_t$	**0.30** (0.14)**	**0.30** (0.15)**	**0.30** (0.15)**	**0.27* (0.15)**	**0.27* (0.15)**	**0.27* (0.15)**	**0.10 (0.15)**	**0.10 (0.15)**	**0.10 (0.15)**	**0.29** (0.14)**	**0.29* (0.15)**	**0.29* (0.15)**
OHC_physician$_i$	-0.27 (0.23)	-0.24 (0.19)	4.24*** (0.07)	-0.22 (0.23)	-0.72 (0.48)	1.22*** (0.08)	-0.33 (0.23)	-1.79*** (0.11)	2.22*** (0.08)	-0.35 (0.23)	-2.01*** (0.34)	-1.50*** (0.08)
outbreak$_t$	-1.19*** (0.09)	-0.77*** (0.16)	-1.39*** (0.30)	-0.29*** (0.11)	-3.11*** (0.61)	-3.63*** (1.23)	-1.19*** (0.09)	-0.63*** (0.16)	-1.41*** (0.28)	-0.29*** (0.11)	-2.91*** (0.57)	-2.92** (1.16)
Control variables	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Physician FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Time FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
No. of physicians	154	154	154	154	154	154	154	154	154	154	154	154
Adj. *R*-squared	0.13	0.76	0.76	0.04	0.75	0.75	0.15	0.77	0.77	0.07	0.78	0.78

Note: Standard errors in parentheses are robust and clustered by time and physician. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

We assessed the recovery effect for OHC physicians using data from Week -13 to Week 7 and from Week 7 to Week 13. In the subsequent period after the COVID-19 outbreak, OHC physicians retained significantly higher numbers of total consultations (i.e., positive $\widehat{\beta_1}$s in Columns 4-6) and offline consultations (i.e., positive $\widehat{\beta_1}$s in Columns 10-12) than non-OHC physicians. In other words, the magnitude of increased production for OHC physicians was higher than that for non-OHC physicians. The recovery effect of OHC physicians was significantly positive for both total consultations (Columns 4-6) and offline consultations (Columns 10-12). Specifically, our results reveal that the OHC physicians enjoyed 31.0% more bounce-back of total consultations (significant at 10% level, Column 6) and 33.6% more bounce-back of offline consultations (significant at 10% level, Column 12) than non-OHC physicians. The recovery effect of OHC physicians is thus also supported. To conclude, our findings are consistent with our observations from the model-free evidence and provide empirical support for H1 and H2.

Validation Tests for DID Analysis

In this section, we report the results of several robustness checks to validate our findings in the DID analysis. First, we ensured that the parallel-trend assumption was satisfied for our DVs. That is, before the COVID-19 outbreak, OHC physicians' and non-OHC physicians' consultations followed similar trends. We employed the augmented Dickey-Fuller (ADF) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests of stationarity to test the parallel-trend assumption (e.g., Khern-am-nuai et al., 2018). The results show no pre-treatment differences in the DVs of OHC physicians and non-OHC physicians, thus supporting the parallel-trend assumption (see details in Table B1 in Appendix B).

Second, since the treatment impact may vary given the progression of COVID-19, we applied *New_case$_t$* (i.e., the log of the number of new confirmed cases of COVID-19 in the local province in week t) as a continuous measure to reflect "treatment intensity." In line with existing studies that use a continuous treatment in DID analysis (e.g., Acemoglu et al., 2004), we ran the following DID analysis:

$$DV_{it} = \beta_1 * OHC\_physician_{i_i} * outbreak_t * New_{case_t} + \beta_2 * OHC\_physician_i + \beta_3 * outbreak_t + \boldsymbol{\tau X} + \alpha_i + \delta_t + \varepsilon_{it}, \quad (3)$$

where the DV is *total_consultation$_{it}$* or *offline_consultation$_{it}$*. As we used the new confirmed COVID-19 cases as the treatment variable, the COVID-19 statistics variables (i.e., the new cases, cured cases, and death cases per week in the local province) were excluded from **X** in Equation (3). The results are qualitatively similar to those of Equations (1) and (2) (see Table 5), thereby demonstrating that our findings are robust to this alternative specification.

Table 5. Treatment Intensity and Digital Resilience

DV	*total_consultation$_{it}$*		*offline_consultation$_{it}$*	
Time window	[-6, -2] & [2, 6] (Resistance)	[-13,-7] & [7,13] (Recovery)	[-6, -2] & [2, 6] (Resistance)	[-13,-7] & [7,13] (Recovery)
Column	(1)	(2)	(3)	(4)
OHC_physician$_i$* * *outbreak$_t$* * *New_case$_t$	**0.07*** (0.04)**	**0.15** (0.07)**	**0.02 (0.04)**	**0.15** (0.07)**
OHC_physician$_i$	3.15*** (0.07)	1.43*** (0.03)	1.09*** (0.07)	-1.07*** (0.03)
outbreak$_t$	-0.72*** (0.11)	0.10 (0.11)	-0.71*** (0.11)	0.11 (0.10)
Control variables	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
No. of physicians	154	154	154	154
Adj. *R*-Squared	0.76	0.75	0.77	0.78

Note: Standard errors in parentheses are robust and clustered by time and physician. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Third, we performed two falsification tests to further establish the robustness of our findings. For the first falsification test, we created a placebo event (Week -6). The results show that this placebo event had no significant effects on the DVs (see Table B2 in Appendix B). In the second falsification test, we examined whether the resistance and recovery effects were artifacts of seasonality because the COVID-19 outbreak occurred during the 2020 Chinese New Year period—the most important holiday season in China. Thus, one may argue that the observed effects may have been caused by seasonal trends associated with the Chinese New Year. We examined whether a similar reduction and bounce-back in physicians' production also occurred during the 2019 Chinese New Year to rule out this possibility. We repeated the same DID analysis using the same physician-level data in 2019 for the same time window in 2020. The results show that this placebo event (Chinese New Year in 2019) had no significant effect on the DVs (see Table B3 in Appendix B).

Fourth, although the official recovery announcement was made in Week 7, some people may have resumed their normal work and lives earlier (or later) than that week. Thus, we used Week 6 and Week 8 as thresholds for the subsequent period and reran the DID models. The results are consistent with our main findings (see Table B4 in Appendix B).

Fifth, an alternative operationalization of physicians' overall medical service demand is the average weekly total consultations before the pandemic because OHC physicians have both online and offline demands. Therefore, we included physicians' average weekly total consultations from the six-month period before Week -13 as the physicians' medical service demand before the pandemic and reran the PSM and DID. The findings are consistent with the main results regarding the resistance and recovery effects (see Table B5 in Appendix B).

Finally, six physicians registered in the OHC after the COVID-19 outbreak, and we did not include them in our analyses reported above. We reran two additional PSMs by specifying the six physicians as either OHC physicians or non-OHC physicians. After each PSM, we reran the DID analyses. The results are consistent with the main findings regarding the resistance and recovery effects (see Table B6 in Appendix B). In sum, we conclude that our DID analyses generated robust causal evidence.

Analyses of the Mechanisms of New Patient Acquisition

Utilizing the uniqueness and richness of the matched offline and online datasets, we further explored the new-patient-acquisition mechanism. We first identified different types of online patients. For each online consultation of an OHC physician, we assessed whether this was the first record of the patient's online consultation with the physician (see Figure 1: the box highlighted with the annotation "The patient's 1st record of online consultation with the physician"). If yes, this patient was identified as a new online patient (otherwise an existing online patient). We further classified this new online patient as *transferred from the offline channel* or *totally new*. For new online patients, the online consultation page also recorded whether the patient had previously seen the physician as an offline outpatient (see Figure 1: the box highlighted with the annotation "Indicating whether the patient has seen the physician as an offline outpatient before"). If yes, this new patient was identified as transferred from the offline channel; otherwise, we identified the patient as totally new.

Regarding offline patients, the outpatient consultation records from our offline dataset indicated whether a patient had visited the physician before, allowing us to classify offline patients as new or existing patients. We further classified new offline patients as *transferred from the online channel* or *totally new*. Note that for non-OHC physicians, their new offline patients were all totally new because they lacked an online channel to acquire new patients. With regard to OHC physicians' new offline patients, in line with the literature on medical record linkage (e.g., Sauleau et al., 2005), we applied three criteria to identify new offline patients as having been transferred from the OHC: (1) the patient's last name on the OHC platform and the last name in our outpatient record were the same, (2) the date of the patient's first online visit to an OHC physician was earlier than the date of the patient's first offline visit to the same physician; and (3) the 3-digit ICD code in the online consultation was the same as that in the outpatient record. Otherwise, the new offline patient was classified as a totally new offline patient. The variables and measures related to new patients are presented in Table 6, and the descriptive statistics of these variables are reported in Table A2 in Appendix A.

To better articulate the source of OHC physicians' digital resilience, we employed the following DID specifications to examine the effects of the COVID-19 outbreak on physicians' new patient acquisition:

$$new\_patient_{it} = \beta_1 * OHC\_physician_i * outbreak_t + \beta_2 * OHC\_physician_i + \beta_3 * outbreak_t + \boldsymbol{\tau X} + \alpha_i + \delta_t + \varepsilon_{it}, \tag{4}$$

$$offline\_new\_patient_{it} = \beta_1 * OHC\_physician_i * outbreak_t + \beta_2 * OHC\_physician_i + \beta_3 * outbreak_t + \boldsymbol{\tau X} + \alpha_i + \delta_t + \varepsilon_{it}, \tag{5}$$

where $new\_patient_{it}$ is the log of $New\_patient_{it}$ and $offline\_new\_patient_{it}$ is the log of $Offline\_new\_patient_{it}$. Table 7 presents the DID results that support our theoretical justifications. Specifically, for the resistance effect, OHC physicians acquired significantly more new patients than non-OHC physicians (i.e., positive $\widehat{\beta_1}$ in Column 1) and these new patients were mainly new online patients (i.e., insignificant $\widehat{\beta_1}$ for offline new patients in Column 3). In other words, because of these new online patients, the magnitude of the reduction in OHC physicians' production was lower than that of non-OHC physicians' production in the immediate period. In terms of the recovery effect in the subsequent period, OHC physicians also acquired more new offline patients (i.e., positive $\widehat{\beta_1}$ in Column 2 and positive $\widehat{\beta_1}$ in Column 4).

Given that the primary mechanism underlying the digital resilience of OHC physicians was their acquisition of new patients, we further analyzed the different types of these new patients. We plotted the proportions of all four types of new patients for the OHC physicians in Figure 4—i.e., new online patients from the offline channel, totally new online patients, new offline patients from the online channel, and totally new offline patients. Table 8 reports the proportions of these four types across different time periods—i.e., before the pandemic outbreak vs. the immediate period after the outbreak vs. the subsequent period after the outbreak. Before the outbreak, most OHC physicians' new patients were totally new offline patients (close to 70%). In the immediate period after the outbreak, the two primary sources of resistance for OHC physicians were both from the OHC and consisted of (1) totally new online patients (the proportion of *online_totally_new* significantly increased from 11.03% to 23.96%, $p < 0.05$ in the paired comparison using Bonferroni test) and (2) new offline patients from the online channel (the proportion of *offline_new_from_online* significantly increased from 11.80% to 21.90%, $p < 0.05$). In the subsequent period after the outbreak, the OHC remained the primary channel for OHC physicians to acquire new offline patients and realize a quick recovery—the proportion of *offline_new_from_online* significantly increased from 21.90% to 30.99% ($p < 0.05$). In sum, these findings provide solid evidence of the OHC as the primary source of both the resistance and recovery effects of OHC physicians.

Effects of the Sentiment of Physicians' Online Consultations on Digital Resilience

In line with previous studies (Luo et al., 2019; Qiao et al., 2020), we applied subgroup analysis to investigate the heterogeneous treatment effects on OHC physicians' digital resilience. Specifically, we first divided the OHC physicians into different subgroups (e.g., high- vs. low-positivity groups with regard to online sentiment). Second, we paired each OHC physician with the non-OHC physician matched in the PSM to benchmark the focal OHC physician's levels of resistance and recovery (Qiao et al., 2020). Note that we applied the one-to-one nearest-neighbor matching method in the PSM, and each OHC physician was matched with a non-OHC physician. Finally, we included each subgroup of OHC physicians and the matched non-OHC physicians in the sample and repeated the DID analyses. We compared the results from the subgroup analyses.

Table 6. Variables and Measures related to New Patients

Variable	Measure	Data source
online_new_from_offline$_{it}$	The number of new online patients of OHC physician *i* in week *t* who are transferred from the offline channel	Physician *i*'s OHC page
online_totally_new$_{it}$	The number of totally new online patients of OHC physician *i* in week *t*	Physician *i*'s OHC page
Online_new_patient$_{it}$	Sum of *online_new_from_offline$_{it}$* and *online_totally_new$_{it}$*, representing the number of OHC physician *i*'s new online patients in week *t*	Physician *i*'s OHC page
offline_new_from_online$_{it}$	The number of new offline patients of OHC physician *i* in week *t* who are transferred from the online channel	Physician *i*'s OHC page and Hospital A
offline_totally_new$_{it}$	The number of totally new offline patients of physician *i* in week *t*	Physician *i*'s OHC page and Hospital A
Offline_new_patient$_{it}$	Sum of *offline_new_from_online$_{it}$* and *offline_totally_new$_{it}$* representing the number of physician *i*'s new offline patients in week *t*	Hospital A
New_patient$_{it}$	Sum of *Offline_new_patient$_{it}$* and/or *Online_new_patient$_{it}$*, representing the total number of physician *i*'s new patients in week *t*	Physician *i*'s OHC page and Hospital A

Table 7. Digital Resilience on Physicians' New Patients

DV	***new_patient$_{it}$***		***offline_new_patient$_{it}$***	
Time window	**[-6, -2] & [2, 6] (Resistance)**	**[-13,-7] & [7,13] (Recovery)**	**[-6, -2] & [2, 6] (Resistance)**	**[-13,-7] & [7,13] (Recovery)**
Column	**(1)**	**(2)**	**(3)**	**(4)**
OHC_physician$_i$ * outbreak$_t$	**0.32*** (0.11)**	**0.41*** (0.09)**	**0.08 (0.11)**	**0.43*** (0.08)**
OHC_physician$_i$	-0.44*** (0.05)	-0.31*** (0.04)	-2.23*** (0.06)	-2.82*** (0.04)
outbreak$_t$	-1.07*** (0.19)	-2.40** (0.95)	-1.12*** (0.16)	-1.58* (0.82)
Control variables	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
No. of physicians	154	154	154	154
Adj. R-squared	0.75	0.78	0.78	0.84

Note: Standard errors in parentheses are robust and clustered by time and physician. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

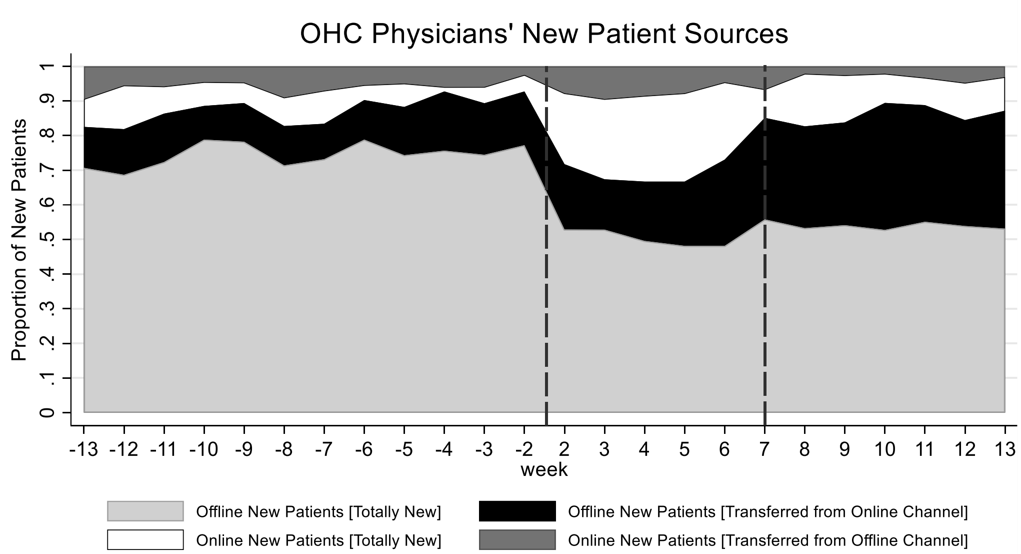

Figure 4. OHC Physicians' New Patients

Table 8. The Proportion of Sources of OHC Physicians' New Patients												
Patients	**Offline new patients (transferred from online)**			**Offline new patients (totally new)**			**Online new patients (transferred from offline)**			**Online new patients (totally new)**		
Period	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
Proportion	11.80%	21.90%	30.99%	69.75%	46.61%	50.60%	7.42%	7.53%	3.48%	11.03%	23.96%	14.92%

Period: 1: Before the pandemic outbreak [Week -13, Week -2]
2: The immediate period after the outbreak [Week 2, Week 6]
3: The subsequent period after the outbreak [Week 7, Week 13]

We collected detailed physician-patient interactions of all online consultations for each OHC physician (see Figure 1). For each utterance within the physician-patient interactions, we extracted the sentiment value embedded in the utterance by applying the deep learning framework of PaddlePaddle (PaddlePaddle, 2021). This BAIDU framework has high prediction accuracy and has been widely adopted in the sentiment analysis of Chinese texts (e.g., Tang et al., 2020). The sentiment value of an utterance ranges from 0 to 1, indicating the probability that an utterance is of positive sentiment—the higher the value, the greater probability of positivity. In line with existing IS literature (e.g., Yan et al., 2019), we then calculated a variable, $sentiment_i$, by summarizing the probability of positive sentiment embedded in the online consultations for physician i across the entire time period. Thus, an OHC physician's $sentiment_i$ describes the likelihood that the OHC physician generally maintains good relationships with patients. Table A2 in Appendix A shows the descriptive statistics of $sentiment_i$. We split the OHC physicians into two subgroups using the median of $sentiment_i$, i.e., high- and low-positivity subgroups. After that, we included each subgroup of OHC physicians and the matched non-OHC physicians in the sample and reran the DID analyses.

Table 9 reports the heterogeneous treatment effects of the OHC on digital resilience regarding the sentiment of physicians' online consultations. In the immediate period, the $\widehat{\beta_1}$ of total consultations is significant only for OHC physicians with high positivity (Columns 1 and 2). In contrast, we found that the $\widehat{\beta_1}$s of offline consultations were insignificant for both high- and low-positivity groups (Columns 5 and 6). In other words, for OHC physicians to obtain a resistance effect, they needed to be more positive than average in their online consultations with patients. These findings prove that the resistance effect of OHC physicians was stronger for those with higher sentiment positivity in online consultations, thereby supporting H3a. Similarly, in the subsequent period, we observe that the $\widehat{\beta_1}$s of both total and offline consultations are significant only for OHC physicians with high positivity (Columns 3, 4, 7, and 8). The results reveal that OHC physicians' recovery effect was stronger for those with higher sentiment positivity in online consultations, and only the physicians with high levels of positivity enjoyed this effect. Thus, H3b is supported.

We also examined the effects of sentiment on physicians' new patient acquisition. We reran the analyses in Equations (4) and (5) for the high- and low-positivity subgroups. The results are presented in Table 10. The results confirm that OHC physicians with high sentiment positivity in online consultations enjoyed stronger resistance and recovery effects because these physicians acquired more new patients after the outbreak of the COVID-19 pandemic than those with lower levels of sentiment positivity.

Effects of Physicians' Online Reputation on Digital Resilience

To verify the heterogeneous treatment effects of the OHC on digital resilience regarding the online reputation of OHC physicians, we first generated a variable $reputation_i$, measured by physician i's overall reputation rating on their OHC homepage (see Figure 1). We adopted an approach similar to the previous section to divide OHC physicians into subgroups of high vs. low online reputation ratings using the median of $reputation_i$. We then included each subgroup of OHC physicians and the matched non-OHC physicians in the sample and repeated the DID analyses. We compared the results.

Table 11 reports the heterogeneous treatment effects regarding OHC physicians' online reputation regarding both the resistance effect (Columns 1-2 and Columns 5-6) and the recovery effect (Columns 3-4 and Columns 7-8). In the immediate period, the resistance effects in terms of both total and offline consultations were only significant for physicians with high reputation ratings. Similar results were found with the recovery effects in the subsequent period. The findings support H4a and H4b.

Table 9. Impacts of Online Sentiment on Digital Resilience

DV	*total_consultation$_{it}$*				*offline_consultation$_{it}$*			
Time window	[-6, -2] & [2, 6] (Resistance)		[-13,-7] & [7,13] (Recovery)		[-6, -2] & [2, 6] (Resistance)		[-13,-7] & [7,13] (Recovery)	
Positivity	High	Low	High	Low	High	Low	High	Low
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
***OHC_physician$_i$* * outbreak$_t$**	**0.42*** (0.22)**	**0.18 (0.20)**	**0.42** (0.19)**	**0.12 (0.23)**	**0.23 (0.21)**	**-0.02 (0.23)**	**0.48*** (0.18)**	**0.11 (0.24)**
OHC_physician$_i$	-42.95*** (0.11)	0.04 (0.10)	-31.02*** (0.09)	-0.04 (0.12)	-55.37*** (0.11)	-0.07 (0.11)	-43.62*** (0.09)	-0.06 (0.12)
outbreak$_t$	-1.60*** (0.42)	-1.18*** (0.43)	-3.00* (1.72)	-4.25** (1.77)	-1.55*** (0.41)	-1.27*** (0.39)	-2.76 (1.74)	-3.08* (1.55)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of physicians	76	78	76	78	76	78	76	78
Adj. *R*-squared	0.76	0.76	0.77	0.74	0.79	0.76	0.82	0.75

Note: Standard errors in parentheses are robust and clustered by time and physician. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 10. Online Sentiment and New Patient Acquisition by OHC Physicians

DV	*new_patient$_{it}$*				*offline_new_patient$_{it}$*			
Time window	[-6, -2] & [2, 6] (Resistance)		[-13,-7] & [7,13] (Recovery)		[-6, -2] & [2, 6] (Resistance)		[-13,-7] & [7,13] (Recovery)	
Positivity	High	Low	High	Low	High	Low	High	Low
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
***OHC_physician$_i$* * outbreak$_t$**	**0.34** (0.17)**	**0.18 (0.20)**	**0.41*** (0.13)**	**0.12 (0.23)**	**0.11 (0.16)**	**0.06 (0.16)**	**0.48*** (0.11)**	**0.11 (0.24)**
OHC_physician$_i$	-8.26*** (0.08)	0.04 (0.10)	-14.42*** (0.07)	-0.04 (0.12)	-31.32*** (0.08)	0.38*** (0.08)	-27.23*** (0.06)	-0.06 (0.12)
outbreak$_t$	-0.98*** (0.22)	-1.18*** (0.43)	-1.96* (1.16)	-4.25** (1.77)	-0.98*** (0.21)	-1.25*** (0.24)	-1.80 (1.10)	-3.08* (1.55)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of physicians	76	78	76	78	76	78	76	78
Adj. *R*-squared	0.75	0.76	0.78	0.74	0.78	0.77	0.86	0.75

Note: Standard errors in parentheses are robust and clustered by time and physician. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 11. Impacts of Online Reputation on Digital Resilience

DV	*total_consultation$_{it}$*				*offline_consultation$_{it}$*			
Time window	[-6, -2] & [2, 6] (Resistance)		[-13,-7] & [7,13] (Recovery)		[-6, -2] & [2, 6] (Resistance)		[-13,-7] & [7,13] (Recovery)	
Reputation	high	Low	high	low	high	low	high	low
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
***OHC_physician$_i$* * outbreak$_t$**	**0.37** (0.19)**	**0.20 (0.25)**	**0.58*** (0.19)**	**-0.11 (0.24)**	**0.37* (0.19)**	**-0.23 (0.25)**	**0.61*** (0.18)**	**-0.12 (0.24)**
OHC_physician$_i$	6.84*** (0.09)	1.24*** (0.12)	-6.12*** (0.10)	2.53*** (0.12)	6.97*** (0.10)	0.44*** (0.12)	-6.78*** (0.09)	1.58*** (0.12)
outbreak$_t$	-1.68*** (0.38)	-1.02** (0.47)	-3.26* (1.66)	-4.10** (1.83)	-1.72*** (0.38)	-1.02** (0.41)	-2.56 (1.56)	-3.39* (1.74)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of physicians	86	68	86	68	86	68	86	68
Adj. *R*-squared	0.78	0.72	0.73	0.77	0.78	0.77	0.75	0.81

Note: Standard errors in parentheses are robust and clustered by time and physician. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

We further examined the effects of online reputation on OHC physicians' new patient acquisition by rerunning the analyses in Equations (4) and (5) for the subgroups of high vs. low online reputation ratings. The results (Table 12) verify that OHC physicians with high online reputation ratings acquired more new patients, leading to stronger resistance and recovery effects.[14]

Given the importance of online reputation (e.g., Boh, 2007; Ye et al., 2014) and its potential relationship with physician performance, we conducted the regression following Equation (6) to check the potential differences in the effects of online reputation on OHC physicians' performance across different time periods—i.e., before the pandemic outbreak vs. after the outbreak, and the immediate period after the outbreak vs. the subsequent period.

$$DV_{it} = \beta_1 * reputation_i * after_t + \beta_2 * reputation_i + \beta_3 * after_t + \boldsymbol{\tau X} + \alpha_i + \delta_t + \varepsilon_{it,} \quad (6)$$

where DV_{it} is OHC physician i's performance in week t, including $total\_consultation_{it}$, $offline\_consultation_{it}$, $new\_patient_{it}$, and $offline\_new\_patient_{it}$; and $after_t$ indicates whether week t is in a certain period. **X** contains all the control variables. Finally, α_i captures the physician fixed effects and δ_t captures the time fixed effects. In Equation (6), $\widehat{\beta_1}$ is of interest because it indicates the impact of online reputation on physician i's performance during a certain period, with the main effect of reputation controlled ($\widehat{\beta_2}$). We conducted two tests. In the first test, we used the time window of Week -13 to Week 13; thus, $after_t$ indicates whether week t is in the period after the outbreak or not. In the second test, we used the time window of Week 2 to Week 13, and $after_t$ indicates whether week t is in the recovery period or not. The results are reported in Table 13.

The results in Table 13 show that the effects of online reputation on digital resilience differed across time periods. In particular, the significant positive $\widehat{\beta_1}s$ in Columns 2 and 4 suggest that online reputation became more important for patients' selecting OHC physicians for offline visits after the immediate period of the outbreak. In other words, patients seemed to become more cautious during the pandemic—i.e., relying more on online information—in choosing physicians for offline consultations. Furthermore, the significant positive $\widehat{\beta_1}s$ in Columns 5, 6, 7, and 8 suggest that online reputation enhanced OHC physicians' performance in the subsequent period more than in the immediate period across all the metrics. The results imply that online reputation played a more important role in OHC physicians' recovery than in their resistance because, compared to the immediate period, patients relied more on online reputation to choose OHC physicians for both online and offline consultations in the subsequent period.

Potential Effects of Physicians' OHC Tenure/ Experience on Digital Resilience

There are likely significant variations in OHC physicians' tenure/experience with the OHC that may have generated heterogeneous treatment effects. Therefore, we used the OHC physicians' date of registration in the OHC, $ohc\_registration_i$, to calculate their tenure with the OHC. We calculated their experience with the OHC using their aggregated number of online consultations, i.e., $aggregated\_patients_i$. We adopted the same approach as the subgroup analysis—i.e., early vs. late registration using the median of $ohc\_registration_i$, and more vs. less experience using the median of $aggregated\_patients_i$. Tables 14 and 15 report the results.

The results show that neither OHC physicians' tenure nor their experience in the OHC generated significant heterogeneous treatment effects on digital resilience. These findings may imply that OHC physicians' effective use of the focal OHC platform is reflected/captured more by their online consultation sentiment and their online reputation ratings than by their tenure or consultation numbers, suggesting that digital resilience may be driven by service quality rather than quantity.

General Discussion

This study focuses on digital resilience in the context of healthcare during the COVID-19 pandemic. Our contextualization provides an in-depth understanding of how physicians use OHCs to enhance their resilient responsiveness against exogenous shocks. In particular, we examined two forms of physicians' digital resilience—resistance and recovery effects—following the the initial outbreak of the COVID-19 pandemic. First, we found a *resistance effect* in the *immediate period* following the outbreak. While the sudden outbreak of COVID-19 rendered offline healthcare ineffective, we found that OHC physicians who conducted online consultations enjoyed significantly lower levels of production loss than non-OHC physicians. We identified the two major constituents of the resistance effect as *totally new online patients* and *those who switched from offline to online channels*.

[14] One concern with the similar patterns of the heterogeneous treatment effects of online sentiment and online reputation is that the two variables are highly correlated. We found a correlation of 0.24 ($p < 0.1$), which is not high.

Table 12. Online Reputation and New Patient Acquisition by OHC Physicians

DV	*new_patient$_{it}$*				*offline_new_patient$_{it}$*			
Time window	[-6, -2] & [2, 6] (Resistance)		[-13,-7] & [7,13] (Recovery)		[-6, -2] & [2, 6] (Resistance)		[-13,-7] & [7,13] (Recovery)	
Reputation	high	low	high	low	high	low	high	low
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OHC_physician$_i$* * *outbreak$_t$	**0.21*** (0.13)**	**0.20 (0.25)**	**0.48*** (0.13)**	**-0.11 (0.24)**	**0.19 (0.13)**	**-0.04 (0.18)**	**0.52*** (0.12)**	**-0.12 (0.24)**
OHC_physician$_i$	-0.63*** (0.06)	-1.45*** (0.12)	-0.50*** (0.07)	-1.55*** (0.12)	-0.66*** (0.07)	-1.46*** (0.09)	-0.52*** (0.06)	-1.55*** (0.12)
outbreak$_t$	-0.48*** (0.08)	-0.64*** (0.21)	-0.24*** (0.08)	0.18 (0.24)	-0.49*** (0.08)	-0.48*** (0.07)	-0.20*** (0.07)	0.15 (0.23)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of physicians	86	68	86	68	86	68	86	68
Adj. *R*-squared	0.78	0.72	0.73	0.77	0.78	0.77	0.79	0.81

Note: Standard errors in parentheses are robust and clustered by time and physician. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 13. Effects of Online Reputation on OHC Physicians' Performance

Time window	[-13, 13] (Before vs. After the Outbreak)				[2, 13] (Resistance Period vs. Recovery Period)			
DV	1	2	3	4	1	2	3	4
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
reputation$_i$* * *after$_t$	**0.18 (0.16)**	**0.37** (0.17)**	**0.04 (0.14)**	**0.26* (0.15)**	**0.55** (0.27)**	**0.54* (0.29)**	**0.46* (0.24)**	**0.43* (0.25)**
reputation$_i$	12.66*** (0.50)	16.81*** (0.53)	8.72*** (0.43)	11.31*** (0.45)	11.71*** (0.14)	16.11*** (0.14)	8.86*** (0.12)	10.99*** (0.13)
after$_t$	-4.26** (1.96)	-2.93 (1.79)	-3.39* (1.87)	-1.86 (1.60)	-2.50 (1.94)	-1.07 (1.88)	-1.95 (1.80)	-0.38 (1.64)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of physicians	77	77	77	77	77	77	77	77
Adj. *R*-squared	0.77	0.81	0.73	0.78	0.81	0.84	0.77	0.83

Note: Standard errors in parentheses are robust and clustered by time and physician. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. DV: 1: total_consultation$_{it}$; 2: offline_consultation$_{it}$; 3: new_patient$_{it}$; 4: offline_new_patient$_{it}$

Table 14. Impacts of OHC Tenure on Digital Resilience

DV	*total_consultation$_{it}$*				*offline_consultation$_{it}$*			
Time window	[-6, -2] & [2, 6] (Resistance)		[-13, -7] & [7, 13] (Recovery)		[-6, -2] & [2, 6] (Resistance)		[-13, -7] & [7, 13] (Recovery)	
Registration	Early	Late	Early	Late	Early	Late	Early	Late
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OHC_physician$_i$* * *outbreak$_t$	**0.26 (0.22)**	**0.33 (0.21)**	**0.36 (0.23)**	**0.18 (0.19)**	**-0.04 (0.24)**	**0.26 (0.19)**	**0.34 (0.24)**	**0.24 (0.19)**
OHC_physician$_i$	-0.36*** (0.11)	1.23*** (0.10)	1.11*** (0.12)	0.15 (0.10)	-0.15 (0.12)	1.29*** (0.10)	0.98*** (0.12)	0.13 (0.09)
outbreak$_t$	-1.84*** (0.47)	-0.92** (0.36)	-1.98 (1.33)	-5.33** (2.08)	-1.72*** (0.47)	-1.08*** (0.29)	-1.53 (1.31)	-4.36** (1.92)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of physicians	78	76	78	76	78	76	78	76
Adj. *R*-squared	0.76	0.76	0.75	0.75	0.75	0.81	0.77	0.79

Note: Standard errors in parentheses are robust and clustered by time and physician. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 15. Impacts of OHC Experience on Digital Resilience

DV	*total_consultation$_{it}$*				*offline_consultation$_{it}$*			
Time window	**[-6, -2] & [2, 6] (Resistance)**		**[-13,-7] & [7,13] (Recovery)**		**[-6, -2] & [2, 6] (Resistance)**		**[-13,-7] & [7,13] (Recovery)**	
Consultation	**More**	**Less**	**More**	**Less**	**More**	**Less**	**More**	**Less**
Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
OHC_physician$_i$* * *outbreak$_t$	**0.26 (0.22)**	**0.33 (0.21)**	**0.36 (0.23)**	**0.18 (0.19)**	**-0.04 (0.24)**	**0.26 (0.19)**	**0.34 (0.24)**	**0.24 (0.19)**
OHC_physician$_i$	-0.36*** (0.11)	1.23*** (0.10)	1.11*** (0.12)	0.15 (0.10)	-0.15 (0.12)	1.29*** (0.10)	0.98*** (0.12)	0.13 (0.09)
outbreak$_t$	-1.84*** (0.47)	-0.92** (0.36)	-1.98 (1.33)	-5.33** (2.08)	-1.72*** (0.47)	-1.08*** (0.29)	-1.53 (1.31)	-4.36** (1.92)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of physicians	78	76	78	76	78	76	78	76
Adj. *R*-squared	0.76	0.76	0.75	0.75	0.75	0.81	0.77	0.79

Note: Standard errors in parentheses are robust and clustered by time and physician. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Second, we found a *recovery effec*t in the *subsequent period* in that OHC physicians' caseload volumes returned to normal levels more quickly than those of non-OHC physicians. While new patients still constituted the majority of the online component of the recovery, we provide evidence that the main source of the recovery was based on offline consultations—*totally new offline patients* and *patients transferred from the online to the offline channel*. Our subgroup analysis of OHC physicians demonstrates the roles of online reputation and online conversations with patients in enhancing digital resilience, providing further support for physicians' use of the OHC artifact as a key mechanism underlying their resistance and recovery.

Theoretical Contributions

Our study offers several contributions to IS research on digital resilience. First, we provide empirical support for the digital resilience of physicians who adopt an OHC in an understudied context—the sudden exogenous shock of the outbreak of the COVID-19 pandemic. Existing studies have been primarily conducted in contexts where digital technologies built resilience to predictable disruptions, such as supply chain disruptions (Bakshi & Kleindorfer, 2009) and data theft (Kwon & Johnson, 2014). In such cases, digital technologies increase resilience by reducing the probability of the reoccurrence of disruptions. Our research context differs from the existing literature in that the healthcare system was disrupted by an unpredictable and unprecedented shock—the outbreak of the COVID-19 pandemic. Whether or not IT artifacts (the OHC in our case) can build digital resilience after such an exogenous shock has not been addressed in depth in the literature. Moreover, prior research has mainly examined the overall resilient effect of digital technologies using data aggregated across different time periods following a disruption and thus offers a limited understanding of the different digital resilience effects (e.g., Park et al., 2015).

We identify two forms of digital resilience after a disruption—the resistance effect in the immediate period and the recovery effect in the subsequent period. We estimate the magnitude of these two effects using a unique dataset matching online and offline data sources. We achieve quantitative rigor through the nature-experiment design and by controlling for the demand-side effects according to ICD codes. We also take a step forward in analyzing the sources of digital resilience by distinguishing between new and existing patients from both online and offline channels. While there is emerging research on resistance and recovery in the healthcare sector, prior analysis has mainly been conceptual and descriptive, based on the overall demand and supply of telemedicine services (e.g., Wosik et al., 2020). To the best of our knowledge, we are among the first to provide in-depth empirical evidence demonstrating both the existence and the sources of resistance and recovery effects in the healthcare sector.

Second, our subgroup analyses reveal that OHC physicians' use of the OHC platform enhanced resistance and recovery effects. We examined the role of a specific and direct metric of physicians' online behavior—the sentiment of physicians' conversations with their patients during online consultations—and conjecture that higher sentiment positivity of OHC physicians' conversations with their patients indicates a more effective use of the OHC and a better physician-patient relationship. We found significant resistance and recovery effects in the high-positivity group, providing evidence that physicians' effective use of the OHC—as reflected by the sentiment of their online consultations—enhances digital resilience. In addition, we uncovered the effects of online reputation on OHC physicians' resilience across different subgroups and different time periods. Online reputation is critical to digital resilience because the overall ratings of physicians on the OHC platform represent the aggregation of patients' feedback on physicians' online service quality. Physicians' online ratings have been found to be positively associated with patient opinions about physician quality (Gao et al., 2012). We utilized the overall rating as the metric for the online reputation of an OHC physician and found that the highly rated group enjoyed significant resistance and recovery effects but the group with lower reputation ratings did not. Moreover, we found that patients relied more on online reputation to choose physicians for both online and offline consultations in the subsequent period than in the immediate period after the outbreak. Our findings not only reveal that online reputation enhances resistance and recovery, but also shed light on the dynamics of digital resilience.

Third, our research extends beyond the boundaries of healthcare research and has implications for the business continuity and disaster recovery literature. Existing IS research on business continuity and disaster recovery has mainly focused on managing technology risks, IS continuity, and security issues such as hackers, malicious users, and system malfunctions (Kananut et al., 2020). While several studies of IT as supporting business continuity and recovery are emerging in the contexts of business operations (Margherita & Heikkilä, 2021), critical infrastructure (Galbusera et al., 2021), and specific healthcare fields (Liow et al., 2020), most inquiries are *qualitative*. Our research provides *quantitative* evidence that besides supporting production in normal operations, IT artifacts—the OHC in our case—may also serve as a technology enabler of business continuity and disaster recovery. IT users—OHC physicians in our case—can utilize information systems to improve their resilient responsiveness against unexpected shocks such as the COVID-19 pandemic. Our subgroup analysis also suggests the effectiveness of IT use in building organizational resilience (e.g., Kouvelis & Li, 2008) and maintaining business continuity until full disaster recovery (Fakhruddin et al., 2020). Our research thus provides a solid stepping stone for both theorizing and empirical analysis in research on business continuity and disaster recovery.

Practical Implications

This research has several practical implications. First, considering that COVID-19 may persist in the long term and that there may be more outbreaks in the future, our study highlights the key role of digital technologies in enhancing the digital resilience of healthcare entities against new outbreaks. In particular, IT enables both immediate resistance and subsequent recovery, with different approaches enhancing different forms of digital resilience. For example, to strengthen the resistance effect, OHC platforms may need to expand their capacity to manage online consultations immediately following an outbreak to accommodate the sudden increase in the demand for online consultations. To enhance the recovery effect, OHC platforms could assist new patients in efficiently choosing the right physicians for online and offline consultations by providing information about physician profiles, their overall performance, and specific behaviors.

Second, and related to the above point, physicians should be encouraged to adopt and use OHCs. As demonstrated by our subgroup analysis, increased participation by physicians and patients in an OHC can generate the big data needed to facilitate patients' decision-making. OHC platforms can also assist physicians by facilitating their adoption and use of different online functionalities beyond telemedicine—e.g., encouraging physicians to post more articles and share their knowledge with existing and potential patients. Physicians' utilization of OHC features can influence patients' decision-making and improve physician-patient relationships, enhancing physicians' digital resilience.

Third, our research suggests that physicians' online ratings—i.e., their online reputation—function as an important signal that can help new patients choose physicians in the context of disruptions. OHC platforms should consider optimizing the algorithm that calculates this overall rating to better measure OHC physicians' service quality. For example, Gao et al. (2015) found that physicians' online ratings may suffer from a bias "toward the upper end" because unsatisfied patients tend *not* to provide online ratings. Thus, a correction mechanism could be considered, utilizing offline data about physicians' service quality. OHC platforms could collaborate with hospitals to facilitate stronger digital resilience. Finally, unstructured online data could also be incorporated into the overall rating calculation, as implied by our findings regarding the sentiment of online conversations between physicians and patients.

Limitations and Future Research

This study has several limitations. First, we address the generalizability of our research findings. Our research focuses on the first wave of the COVID-19 pandemic. There is a need to validate the application of our findings to subsequent outbreaks. However, we expect that the overall pattern of our results—e.g., the resistance and recovery aspects of digital resilience—would still apply. Moreover, this study does not address another form of resilience—prevention. Future research may explore whether the data gathered by OHCs concerning previous outbreaks can predict the timing and significance of the next outbreak and thus exert a "prevention effect" to help both physicians and patients better prepare for the future. Furthermore, we encourage future studies to validate our findings in other contexts—e.g., external shocks other than the COVID-19 pandemic and sectors beyond healthcare. Finally, while the focal hospital offers the full spectrum of medical services and thus the physicians in our sample represent physicians from different medical specialties, our results are based on data from a single hospital. We acknowledge the limitation regarding the generalizability of our findings and call for future research utilizing more representative samples.

Second, while we demonstrate significant differences in digital resilience between OHC and non-OHC physicians and between subgroups of OHC physicians, we were not able to provide a comprehensive answer to why physicians self-select into different groups. Future research might consider a mixed methods investigation of this issue. One of our conjectures is that both IT skills and sociopsychological factors—e.g., computer self-efficacy and social comparison—may influence physicians' decision-making about the adoption and use of OHCs. Future research could employ both quantitative and qualitative methods to seek answers to these important questions.

Third, while we have incorporated ICD codes in our analysis to mitigate the issue of systematic differences between OHC and non-OHC channels, we cannot completely rule out the possible differences in the characteristics of demand between OHC and non-OHC channels. Also, we focused on the effects of online sentiment and online reputation on OHC physicians' digital resilience in this study. Other factors, such as physicians' sentiment in outpatient consultations and offline reputation, may have influenced our research findings. Thus, we call for future research to collect data about offline patient-physician interactions and physicians' reputations in outpatient settings to examine the impacts of these factors on physicians' performance under exogenous shocks.

Conclusion

This study examines physicians' resistance and recovery effects enabled by an OHC in the context of the exogenous shock of the COVID-19 pandemic. We demonstrate the heterogeneous treatment effects of the OHC on digital resilience regarding physicians' online reputation and the sentiment of online consultations. This study contributes to research and practice by opening the black box of the various forms and sources of digital resilience across different time periods following a disruption. Our work offers a foundation for future research investigating the resilient effects of digital technologies when entities encounter unpredictable exogenous shocks.

Acknowledgments

We thank the guest editors of the MISQ special issue on Digital Resilience and the associate editor for their extremely helpful guidance and insightful feedback throughout the review process as well as the three anonymous reviewers for their excellent feedback, which significantly improved the quality of the paper. Any remaining errors are our own. Honglin Deng (denghonglin@tongji.edu.cn) is the corresponding author of this paper. The work described in the paper was partially supported by grants from the General Research Fund of Research Grants Council (Grant 15503719), the National Natural Science Foundation of China (Grants 72272109 and 71902193), the funding for Projects of Strategic Importance of The Hong Kong Polytechnic University (Project Code: 1-ZE2D), the funding for Research Institutes (Interdisciplinary Project Fund; Project Code: CD51) and the Research Project by the OnlyOwner Technology and The Hong Kong Polytechnic University (Project Code: R-ZDDM). Yong Jin also acknowledges the support from the Center for Economic Sustainability and Entrepreneurial Finance (CESEF), PolyU. Xin Xu acknowledges the support from the Faculty of Business Digital Transformation Centre of The Hong Kong Polytechnic University.

References

Acemoglu, D., Autor, D. H., & Lyle, D. (2004). Women, war, and wages: The effect of female labor supply on the wage structure at midcentury. *Journal of Political Economy*, *112*(3), 497-551. https://doi.org/10.1086/383100

Achour, N., & Price, A. D. (2010). Resilience strategies of healthcare facilities: present and future. *International Journal of Disaster Resilience in the Built Environment*, *1*(3), 264-276. https://doi.org/10.1108/17595901011080869

Aguinis, H., & O'Boyle Jr., E. (2014). Star performers in twenty-first century organizations. *Personnel Psychology*, *67*(2), 313-350. https://doi.org/10.1111/peps.12054

Ambulkar, S., Blackhurst, J., & Grawe, S. (2015). Firm's resilience to supply chain disruptions: Scale development and empirical examination. *Journal of Operations Management*, *33*, 111-122. https://doi.org/10.1016/j.jom.2014.11.002

Anderson, D., Gao, G., & Golden, B. (2014). Life is all about timing: An examination of differences in treatment quality for trauma patients based on hospital arrival time. *Production and Operations Management*, *23*(12), 2178-2190. https://doi.org/10.1111/poms.12236

Bakshi, N., & Kleindorfer, P. (2009). Co-opetition and investment for supply-chain resilience. *Production and Operations Management*, *18*(6), 583-603. https://doi.org/10.1111/j.1937-5956.2009.01031.x

Barrett, M., Oborn, E., & Orlikowski, W. (2016). Creating value in online communities: The sociomaterial configuring of strategy, platform, and stakeholder engagement. *Information Systems Research*, *27*(4), 704-723. https://doi.org/10.1287/isre.2016.0648

Bartel, A. P., Chan, C. W., & Kim, S.-H. (2020). Should hospitals keep their patients longer? The role of inpatient care in reducing postdischarge mortality. *Management Science*, *66*(6), 2326-2346. https://doi.org/10.1287/mnsc.2019.3325

Bartlett, Y. K., & Coulson, N. S. (2011). An investigation into the empowerment effects of using online support groups and how this affects health professional/patient communication. *Patient education and counseling*, *83*(1), 113-119. https://doi.org/10.1016/j.pec.2010.05.029

Bennis, W. (2013). Leadership in a digital world: Embracing transparency and adaptive capacity. *MIS Quarterly*, *37*(2), 635-636.

Bhakoo, V., & Choi, T. (2013). The iron cage exposed: Institutional pressures and heterogeneity across the healthcare supply chain. *Journal of Operations Management*, *31*(6), 432-449. https://doi.org/10.1016/j.jom.2013.07.016

Boh, W. F. (2007). Mechanisms for sharing knowledge in project-based organizations. *Information and Organization*, *17*(1), 27-58. https://doi.org/10.1016/j.infoandorg.2006.10.001

Boh, W., Constantinides, P., Padmanabhan, B., & Viswanathan, S. (2023). Building Digital Resilience against Major Shocks. *MIS Quarterly*, *47*(1).

Burton-Jones, A., & Grange, C. (2013). From Use to Effective Use: A Representation Theory Perspective. *Information Systems Research*, *24*(3), 632-658. https://doi.org/10.1287/isre.1120.0444

Burton-Jones, A., & Volkoff, O. (2017). How can we develop contextualized theories of effective use? A demonstration in the context of community-care electronic health records. *Information Systems Research*, *28*(3), 468-489. https://doi.org/10.1287/isre.2017.0702

Cao, X., Liu, Y., Zhu, Z., Hu, J., & Chen, X. (2017). Online selection of a physician by patients: Empirical study from elaboration likelihood perspective. *Computers in Human Behavior*, *73*, 403-412. https://doi.org/10.1016/j.chb.2017.03.060

Catena, R., Dopson, S., & Holweg, M. (2020). On the tension between standardized and customized policies in health care: The case of length-of-stay reduction. *Journal of Operations Management*, *66*(1-2), 135-150. https://doi.org/10.1002/joom.1016

Cayirli, T., & Veral, E. (2003). Outpatient scheduling in health care: a review of literature. *Production and Operations Management*, *12*(4), 519-549. https://doi.org/10.1111/j.1937-5956.2003.tb00218.x

Chen, H. Y., Das, A., & Ivanov, D. (2019). Building resilience and managing post-disruption supply chain recovery: Lessons from the information and communication technology industry. *International Journal of Information Management*, *49*, 330-342. https://doi.org/10.1016/j.ijinfomgt.2019.06.002

Clark, J. R., & Huckman, R. S. (2012). Broadening focus: Spillovers, complementarities, and specialization in the hospital industry. *Management Science*, *58*(4), 708-722. https://doi.org/10.1287/mnsc.1110.1448

Cohen, M. A., & Kouvelis, P. (2020). Revisit of AAA excellence of global value chains: robustness, resilience and realignment. *Production and Operations Management*, *forthcoming*. https://doi.org/10.1111/poms.13305

Colin, J., Martens, A., Vanhoucke, M., & Wauters, M. (2015). A multivariate approach for top-down project control using earned value management. *Decision Support Systems*, *79*, 65-76. https://doi.org/10.1016/j.dss.2015.08.002

Davis, Z., Zobel, C. W., Khansa, L., & Glick, R. E. (2020). Emergency department resilience to disaster-level overcrowding: A component resilience framework for analysis and predictive modeling. *Journal of Operations Management*, *66*(1-2), 56-66. https://doi.org/10.1002/joom.1017

Fahey, R. A., & Hino, A. (2020). COVID-19, digital privacy, and the social limits on data-focused public health responses. *International Journal of Information Management*, *55*, Article 102181. https://doi.org/10.1016/j.ijinfomgt.2020.102181

Fakhruddin, B., Blanchard, K., & Ragupathy, D. (2020). Are we there yet? The transition from response to recovery for the COVID-19 pandemic. *Progress in Disaster Science*, *7*, Article 100102. https://doi.org/10.1016/j.pdisas.2020.100102

Galbusera, L., Cardarilli, M., & Giannopoulos, G. (2021). The ERNCIP survey on COVID-19: Emergency & business continuity for fostering resilience in critical infrastructures. *Safety Science*, *139*, Article 105161. https://doi.org/10.1016/j.ssci.2021.105161

Gao, G. G., Greenwood, B. N., Agarwal, R., & McCullough, J. S. (2015). Vocal minority and silent majority: how do online ratings reflect population perceptions of quality? *MIS Quarterly*, *39*(3), 565-589. https://www.jstor.org/stable/26629621

Gao, G. G., McCullough, J. S., Agarwal, R., & Jha, A. K. (2012). A Changing landscape of physician quality reporting: Analysis of patients' online ratings of their physicians over a 5-year period. *Journal of medical Internet research*, *14*(1), Article e38. https://doi.org/10.2196/jmir.2003

Gefen, D., & Ridings, C. M. (2002). Implementation team responsiveness and user evaluation of customer relationship management: A quasi-experimental design study of social exchange theory. *Journal of Management Information Systems*, *19*(1), 47-69. https://doi.org/10.1080/07421222.2002.11045717

Goh, J. M., Gao, G., & Agarwal, R. (2016). The creation of social value: Can an online health community reduce rural-urban health disparities? *MIS Quarterly*, *40*(1), 247-263. https://doi.org/10.25300/MISQ/2016/40.1.11

Gong, Y., Wang, H., Xia, Q., Zheng, L., & Shi, Y. (2021). Factors that determine a Patient's willingness to physician selection in online healthcare communities: A trust theory perspective. *Technology in Society*, *64*, Article 101510. https://doi.org/10.1016/j.techsoc.2020.101510

Guo, S., & Fraser, M. W. (2014). *Propensity score analysis: Statistical methods and applications: statistical methods and applications*. SAGE.

Guo, S., Guo, X., Fang, Y., & Vogel, D. (2017). How doctors gain social and economic returns in online health-care communities: A professional capital perspective. *Journal of Management Information Systems*, *34*(2), 487-519. https://doi.org/10.1080/07421222.2017.1334480

Gupta, S., Starr, M. K., Farahani, R. Z., & Matinrad, N. (2016). Disaster management from a POM perspective: Mapping a new domain. *Production and Operations Management*, *25*(10), 1611-1637. https://doi.org/10.1111/poms.12591

Hollander, J. E., & Carr, B. G. (2020). Virtually perfect? Telemedicine for COVID-19. *New England Journal of Medicine*, *382*(18), 1679-1681. https://doi.org/10.1056/NEJMp2003539

Homburg, C., Ehm, L., & Artz, M. (2015). Measuring and managing consumer sentiment in an online community environment. *Journal of Marketing Research*, *52*(5), 629-641. https://doi.org/10.1509/jmr.11.0448

Hotelling, H. (1951). A generalized t test and measure of multivariate dispersion. In *Proceedings of the Second Berkeley Symposium on Mathematical Statistics and Probability* (pp. 23-41). University of California Press.

Ivanov, D., & Dolgui, A. (2019). Low-Certainty-Need (LCN) supply chains: A new perspective in managing disruption risks and resilience. *International Journal of Production Research*, *57*(15-16), 5119-5136. https://doi.org/10.1080/00207543.2018.1521025

Jarvenpaa, S. L., & Majchrzak, A. (2010). Vigilant interaction in knowledge collaboration: Challenges of online user participation under ambivalence. *Information Systems Research*, *21*(4), 773-784. https://doi.org/10.1287/isre.1100.0320

Kananut, C., Natt, L., Jing, T., & Akira, K. (2020). Business continuity management: A preliminary systematic literature review based on ScienceDirect database. *Journal of Disaster Research*, *15*(5), 546-555. https://doi.org/10.20965/jdr.2020.p0546

Khern-am-nuai, W., Kannan, K., & Ghasemkhani, H. (2018). Extrinsic versus intrinsic rewards for contributing reviews in an online platform. *Information Systems Research*, *29*(4), 871-892. https://doi.org/10.1287/isre.2017.0750

Kim, Y., Chen, Y.-S., & Linderman, K. (2015). Supply network disruption and resilience: A network structural perspective. *Journal of Operations Management*, *33*, 43-59. https://doi.org/10.1016/j.jom.2014.10.006

Kouvelis, P., & Li, J. (2008). Flexible backup supply and the management of lead-time uncertainty. *Production and Operations Management*, *17*(2), 184-199. https://doi.org/ 10.3401/poms.1080.0015

Kuntz, L., Scholtes, S., & Sülz, S. (2019). Separate and concentrate: Accounting for patient complexity in general hospitals. *Management Science*, *65*(6), 2482-2501. https://doi.org/10.1287/ mnsc.2018.3064

Kwon, J., & Johnson, M. E. (2013). Health-care security strategies for data protection and regulatory compliance. *Journal of Management Information Systems*, *30*(2), 41-66. https://doi.org/ 10.2753/MIS0742-1222300202

Kwon, J., & Johnson, M. E. (2014). Proactive versus reactive security investments in the healthcare sector. *MIS Quarterly*, *38*(2), 451-471. https://doi.org/10.25300/MISQ/2014/38.2.06

Li, H., Fang, Y., Lim, K. H., & Wang, Y. (2019). Platform-based function repetition, reputation, and sales performance of e-marketplace sellers. *MIS Quarterly*, *43*(1), 207-236. https://doi.org/10.25300/MISQ/2019/14201

Li, J., Wu, H., Deng, Z., Evans, R. D., Hong, Z., & Liu, S. (2021). Why online medical teams disband? The role of team diversity and leadership type. *Information Technology & People*, *34*(3), 1175-1199. https://doi.org/10.1108/ITP-10-2019-0534

Li, J., Zhang, Y., Ma, L., & Liu, X. (2016). The impact of the internet on health consultation market concentration: An econometric analysis of secondary data. *Journal of medical Internet research*, *18*(10), Article e276. https://doi.org/10.2196/jmir.6423

Lin, M., Liu, Y., & Viswanathan, S. (2018). Effectiveness of reputation in contracting for customized production: Evidence from online labor markets. *Management Science*, *64*(1), 345-359. https://doi.org/10.1287/mnsc.2016.2594

Liow, M. H. L., Tay, K. X. K., Yeo, N. E. M., Tay, D. K. J., Goh, S. K., Koh, J. S. B., Howe, T. S., & Tan, A. H. C. (2020). From "business continuity" to "back to business" for orthopaedic surgeons during the COVID-19 pandemic. *Bone & Joint Open*, *1*(6), 222-228. https://doi.org/10.1302/2633-1462.16.Bjo-2020-0036.R1

Liu, N., & Chan, H. (2011). A social identity perspective on participation in virtual healthcare communities. *Proceedings of the International Conference on Information Systems.*

Liu, Q. B., Liu, X., & Guo, X. (2020a). The effects of participating in a physician-driven online health community in managing chronic disease: Evidence from two natural experiments. *MIS Quarterly*, *44*(1), 391-419. https://doi.org/10.25300/MISQ/2020/15102

Liu, S., Zhang, M., Gao, B., & Jiang, G. (2020b). Physician voice characteristics and patient satisfaction in online health consultation. *Information & Management*, *57*(5), Article 103233. https://doi.org/10.1016/j.im.2019.103233

Lu, Y., Wu, Y., Liu, J., Li, J., & Zhang, P. (2017). Understanding health care social media use from different stakeholder perspectives: a content analysis of an online health community. *Journal of Medical Internet research*, *19*(4), e109. https://doi.org/ 10.2196/jmir.7087

Luo, X., Lu, X., & Li, J. (2019). When and how to leverage e-commerce cart targeting: The relative and moderated effects of scarcity and price incentives with a two-stage field experiment and causal forest optimization. *Information Systems Research*, *30*(4), 1203-1227. https://doi.org/10.1287/isre.2019.0859

Malgonde, O., Saldanha, T., & Mithas, S. (2023). Resilience in the Open Source Software Community: How Pandemic and Unemployment Shocks Influence Contributions to Others' and One's Own Projects. *MIS Quarterly*, *47*(1), 361-389. https://doi.org/10.25300/MISQ/2022/17256

Margherita, A., & Heikkilä, M. (2021). Business continuity in the COVID-19 emergency: A framework of actions undertaken by world-leading companies. *Business Horizons*, *64*(5), 683-695. https://doi.org/10.1016/j.bushor.2021.02.020

Metzger, M. J., & Flanagin, A. J. (2011). Using Web 2.0 technologies to enhance evidence-based medical information. *Journal of Health Communication*, *16*(1), 45-58. https://doi.org/10.1080/ 10810730.2011.589881

Munoz, A., & Dunbar, M. (2015). On the quantification of operational supply chain resilience. *International Journal of Production Research*, *53*(22), 6736-6751. https://doi.org/ 10.1080/00207543.2015.1057296

Olcott, G., & Oliver, N. (2014). Social capital, sensemaking, and recovery: Japanese companies and the 2011 earthquake. *California Management Review*, *56*(2), 5-22. https://doi.org/ 10.1525/cmr.2014.56.2.5

PaddlePaddle. (2021). *PaddlePaddle*. Github. https://github.com/ PaddlePaddle

Pamuru, V., Khern-am-nuai, W., & Kannan, K. (2021). The impact of an augmented-reality game on local businesses: A study of pokémon go on restaurants. *Information Systems Research*, *32*(3), 950-966. https://doi.org/10.1287/isre.2021.1004

Pan, X., Dresner, M., Mantin, B., & Zhang, J. A. (2020). Pre-hurricane consumer stockpiling and post-hurricane product availability: Empirical evidence from natural experiments. *Production and Operations Management*, *29*(10), 2350-2380. https://doi.org/10.1111/poms.13230

Park, I., Sharman, R., & Rao., H. R. (2015). Disaster experience and hospital information systems: an examination of perceived information assurance, risk, resilience, and HIS usefulness. *MIS Quarterly*, *39*(2), 317-344.

Park, J., Son, Y., & Angst, C. (2023) The Value of Centralized IT in Building Resilience During Crises: Evidence from U.S. Higher Education's Transition to Emergency Remote Teaching. *MIS Quarterly*, *47*(1). https://doi.org/10.25300/MISQ/2022/17265

Paton, D., & Johnston, D. (2001). Disasters and communities: vulnerability, resilience and preparedness. *Disaster Prevention* *and Management*, *10*(4), 270-277. https://doi.org/10.1108/EUM0000000005930

Pirkkalainen, H., Salo, M., Tarafdar, M., & Makkonen, M. (2019). Deliberate or instinctive? Proactive and reactive coping for technostress. *Journal of Management Information Systems*, *36*(4), 1179-1212. https://doi.org/10.1080/07421222.2019.1661092

Qiao, D., Lee, S.-Y., Whinston, A. B., & Wei, Q. (2020). Financial incentives dampen altruism in online prosocial contributions: A study of online reviews. *Information Systems Research*, *31*(4), 1361-1375. https://doi.org/10.1287/isre.2020.0949

Redinger, R. (2011). Multivariate analysis of variance. In J. N. Sheth (Ed.), *Multivariate methods for market and survey research*. Marketing Classic Press.

Rupert, D. J., Moultrie, R. R., Read, J. G., Amoozegar, J. B., Bornkessel, A. S., O'Donoghue, A. C., & Sullivan, H. W. (2014). Perceived healthcare provider reactions to patient and caregiver use of online health communities. *Patient Education and Counseling*, *96*(3), 320-326. https://doi.org/10.1016/j.pec.2014.05.015

Sahebjamnia, N., Torabi, S. A., & Mansouri, S. A. (2015). Integrated business continuity and disaster recovery planning: Towards organizational resilience. *European Journal of Operational Research*, *242*(1), 261-273. https://doi.org/10.1016/j.ejor.2014.09.055

Sakurai, M., & Chughtai, H. (2020). Resilience against crises: COVID-19 and lessons from natural disasters. *European Journal of Information Systems*, *29*(5), 585-594. https://doi.org/10.1080/0960085X.2020.1814171

Salzarulo, P. A., Bretthauer, K. M., Côté, M. J., & Schultz, K. L. (2011). The impact of variability and patient information on health care system performance. *Production and Operations Management*, *20*(6), 848-859. https://doi.org/10.1111/j.1937-5956.2010.01210.x

Sanchis, R., Canetta, L., & Poler, R. (2020). A conceptual reference framework for enterprise resilience enhancement. *Sustainability*, *12*(4), 1464. https://doi.org/10.3390/su12041464

Sauleau, E. A., Paumier, J.-P., & Buemi, A. (2005). Medical record linkage in health information systems by approximate string matching and clustering. *BMC Medical Informatics and Decision Making*, *5*(1), Article 32. https://doi.org/10.1186/1472-6947-5-32

Shin, J., Taylor, M. S., & Seo., M.-G. (2012). Resources for change: The relationships of organizational inducements and psychological resilience to employees' attitudes and behaviors toward organizational change. *Academy of Management Journal*, *55*(3), 727-748. https://doi.org/10.5465/amj.2010.0325

Tan, H., & Yan, M. (2020). Physician-user interaction and users' perceived service quality: Evidence from Chinese mobile healthcare consultation. *Information Technology & People*, *33*(5), 1403-1426. https://doi.org/10.1108/ITP-01-2019-0039

Tang, T., Huang, L., & Chen, Y. (2020). Evaluation of Chinese Sentiment analysis APIs based on online reviews. *Proceedings of the 2020 IEEE International Conference on Industrial Engineering and Engineering Management.*

Tomlin, B. (2006). On the value of mitigation and contingency strategies for managing supply chain disruption risks. *Management Science*, *52*(5), 639-657. https://doi.org/10.1287/mnsc.1060.0515

Tong, Y., Tan, C.-H., & Teo, H.-H. (2017). Direct and indirect information system use: A multimethod exploration of social power antecedents in healthcare. *Information Systems Research*, *28*(4), 690-710. https://doi.org/10.1287/isre.2017.0708

Trang, S., Trenz, M., Weiger, W. H., Tarafdar, M., & Cheung, C. M. K. (2020). One app to trace them all? Examining app specifications for mass acceptance of contact-tracing apps. *European Journal of Information Systems*, *29*(4), 415-428. https://doi.org/10.1080/0960085X.2020.1784046

Tremblay, M. C., Kohli, R., & Rivero, C. 2023. Data is the New Protein: How Commonwealth of Virginia Built Digital Resilience Muscle and Rebounded from Opioid and COVID Shocks. *MIS Quarterly*, *47*(1). https://doi.org/10.25300/MISQ/2022/17260

Waizenegger, L., McKenna, B., Cai, W., & Bendz, T. (2020). An affordance perspective of team collaboration and enforced working from home during COVID-19. *European Journal of Information Systems*, *29*(4), 429-442. https://doi.org/10.1080/0960085X.2020.1800417

Wang, L., Yan, L., Zhou, T., Guo, X., & Heim, G. R. (2020). Understanding physicians' online-offline behavior dynamics: an empirical study. *Information Systems Research*, *31*(2), 537-555. https://doi.org/10.1287/isre.2019.0901

Wani, D., Malhotra, M., & Clark, J. (2020). Strategic service design attributes, customer experience, and co-created service choice: Evidence from Florida hospitals. *Production and Operations Management*, *30*(1), 210-234. https://doi.org/10.1111/poms.13264

Wein, L. M., Wilkins, A. H., Baveja, M., & Flynn, S. E. (2006). Preventing the importation of illicit nuclear materials in shipping containers. *Risk Analysis*, *26*(5), 1377-1393. https://doi.org/10.1111/j.1539-6924.2006.00817.x

Wosik, J., Fudim, M., Cameron, B., Gellad, Z. F., Cho, A., Phinney, D., Curtis, S., Roman, M., Poon, E. G., Ferranti, J., Katz, J. N., & Tcheng, J. (2020). Telehealth transformation: COVID-19 and the rise of virtual care. *Journal of the American Medical Informatics Association*, *27*(6), 957-962. https://doi.org/10.1093/jamia/ocaa067

Wu, H., & Deng, Z. (2019). Do physicians' online activities impact outpatient visits? An examination of online health communities. *Proceedings of the Pacific Asia Conference on Information Systems.*

Xiao, N., Sharman, R., Rao, H. R., & Upadhyaya, S. (2014). Factors influencing online health information search: An empirical analysis of a national cancer-related survey. *Decision Support Systems*, *57*, 417-427. https://doi.org/10.1016/j.dss.2012.10.047

Yan, L., & Tan, Y. (2017). The consensus effect in online health-care communities. *Journal of Management Information Systems*, *34*(1), 11-39. https://doi.org/10.1080/07421222.2017.1296742

Yan, L., Yan, X., Tan, Y., & Sun, S. X. (2019). Shared minds: How patients use collaborative information sharing via social media platforms. *Production and Operations Management*, *28*(1), 9-26. https://doi.org/10.1111/poms.12895

Ye, S., Gao, G. G., & Viswanathan, S. (2014). Strategic behavior in online reputation systems: Evidence from revoking on eBay. *MIS Quarterly*, *38*(4), 1033-1056. https://www.jstor.org/stable/26627961

Yuan, H., & Deng, W. (2021). Doctor recommendation on healthcare consultation platforms: an integrated framework of knowledge graph and deep learning. *Internet Research*, *32*(2), 454-476. https://doi.org/10.1108/INTR-07-2020-0379

Zhang, X., Liu, S., Deng, Z., & Chen, X. (2017). Knowledge sharing motivations in online health communities: A comparative study of health professionals and normal users. *Computers in Human Behavior*, *75*, 797-810. https://doi.org/10.1016/j.chb.2017.06.028

Zobel, C. W. (2011). Representing perceived tradeoffs in defining disaster resilience. *Decision Support Systems*, *50*(2), 394-403. https://doi.org/10.1016/j.dss.2010.10.001

About the Authors

Yinghao Liu is an assistant professor in the SILC Business School, Shanghai University. She received her Ph.D. in information systems from The Hong Kong Polytechnic University. Her research interests include judgment and decision-making in healthcare and the use and impact of information systems in healthcare. Her research work has been published at top-tier IS journals such as MIS Quarterly.

Xin Xu is an associate professor in the Department of Management & Marketing, Faculty of Business at The Hong Kong Polytechnic University. He received his Ph.D. in information systems from the Hong Kong University of Science and Technology. His research interests include IT service innovation, social media analytics, human-AI interaction, digital transformation, decentralized finance & digital assets. His work has appeared in leading academic journals—e.g., *Management Science*, *MIS Quarterly*, *Information Systems Research*, *Journal of the Management Information Systems*, *Journal of the Association for Information Systems*, *Information Systems Frontiers*, and *IEEE Transactions on Engineering Management*. He served as associate editor for *MIS Quarterly* from 2015 to 2019. His works have received a total citation of over 10,000 by 2022 (Google Scholar). He has been ranked in the Top 10% of authors at SSRN by both annual and total downloads since 2018.

Yong Jin is an associate professor and assistant dean in the Faculty of Business, The Hong Kong Polytechnic University. He is also the co-director of the Center for Economic Sustainability and Entrepreneurial Finance and the deputy programme director of the Doctor of Management (HK) program at PolyU. He obtained his Ph.D. in Business Administration from the University of Florida, and his research interests include fintech, digital transformation, the economics of IS, IT strategies, and innovation and entrepreneurship. He served as an associate editor for *Decision Support Systems* and is an editorial board member for *Journal of the Association for Information Systems*. His works have appeared in *Decision Support Systems*, *Journal of the Association for Information Systems*, *Journal of the Management Information Systems*, *Production and Operations Management*, and other outlets.

Honglin Deng is an assistant professor at the Advanced Institute of Business, School of Economics and Management, Tongji University. He obtained his Ph.D. in information systems from City University of Hong Kong. His research interests include e-commerce, social media, e-healthcare, and human-AI interaction. His research work has appeared in top-tier IS journals such as *MIS Quarterly*.

Appendix A

Logit model for propensity score matching: We ran a logit model to evaluate the possibility that a physician adopts the OHC, in which the following physician-level variables were controlled: the physician's title, age, gender, work experience, overall medical service demand, educational qualification, and the physician's ICD codes. We then matched the OHC physicians and non-OHC physicians using the one-to-one nearest-neighbor matching method (Guo & Fraser, 2014). Table A1 reports the logit model results.

Table A1. Logistic Regression Result for PSM

DV	*OHC_physician$_i$*
title$_i$	0.50 (0.27)
gender$_i$	-0.58 (0.31)
age$_i$	-0.03 (0.06)
experience$_i$	0.01 (0.05)
overall_medical_demand$_i$	0.01 (0.01)
education$_i$	Yes
icd_codes$_i$ (1-digit)	Yes
constant	-1.19 (1.77)
Pseudo R^2	0.11
No. of Observations	454

Note: *** $p < 0.01$, ** $p < 0.5$, * $p < 0.1$

Table A2. Descriptive Statistics of the Variables

Variable	*Mean*	*SD*	*Min*	*25% percentiles*	*Median*	*75% percentiles*	*Max*
Total_consultation$_{it}$	30.39	41.81	0.00	4.00	14.00	40.00	282.00
Online_consultation$_{it}$	2.41	11.08	0.00	0.00	0.00	1.00	248.00
Offline_consultation$_{it}$	29.19	40.45	0.00	3.00	13.00	39.00	257.00
education$_i$	1.00	0.00	1.00	1.00	1.00	1.00	1.00
experience$_i$	17.45	9.88	3.00	9.00	15.00	24.00	48.00
overall_medical_demand$_i$	37.87	44.80	0.00	7.39	19.77	53.15	220.92
age$_i$	43.12	7.79	29.00	37.00	42.00	48.00	69.00
gender$_i$	0.44	0.50	0.00	0.00	0.00	1.00	1.00
new_case$_t$	27.22	37.09	0.00	0.00	6.00	33.00	93.00
cured_case$_t$	21.33	35.72	0.00	0.00	3.00	32.00	118.00
death_case$_t$	4.75	2.09	1.00	4.00	6.00	6.00	7.00
New_patient$_{it}$	11.24	15.55	0.00	3.00	8.00	12.00	256.00
Online_new_patient$_{it}$	2.34	11.03	0.00	0.00	0.00	1.00	248.00
Offline_new_patient$_{it}$	11.86	15.55	0.00	1.00	6.00	16.00	121.00
online_new_from_offline$_{it}$	0.89	3.54	0.00	0.00	0.00	0.00	38.00
online_totally_new$_{it}$	1.45	9.93	0.00	0.00	0.00	0.00	242.00
offline_new_from_online$_{it}$	3.57	8.06	0.00	0.00	0.00	3.00	74.00
offline_totally_new$_{it}$	8.29	10.55	0.00	2.00	5.00	8.00	112.00
sentiment$_i$	0.38	0.18	0.00	0.33	0.41	0.50	0.77
reputation$_i$	3.05	0.24	2.40	2.90	3.00	3.10	4.00
title$_i$: 1 attending physician: 41.56%; 2 associate chief physician: 29.87%; 3 chief physician: 28.57%							

Appendix B

Validation Tests for the DID Analysis

Testing parallel-trend assumption: One potential concern with our main DID model is the parallel-trend assumption. To further alleviate this concern, we utilized different unit root tests to examine whether the DVs in the treatment and control groups follow the same trend before the outbreak (e.g., Khern-am-nuai et al., 2018; Pamuru et al., 2021). We employed the augmented Dickey-Fuller (ADF) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. Note that the null hypothesis of the ADF test indicates that a unit root is present in a time series or the time series is nonstationary, while the null hypothesis of the KPSS test indicates that a time series is stationary. Hence, we expect the ADF test to reject the null hypothesis and the KPSS test to accept the null hypothesis if the DVs in the treatment and the control groups followed similar trends before the outbreak.

Table B1. Results of the ADF Test and the KPSS Test of Stationarity

	ADF test	KPSS test
$total\_consultation_{it}$	-5.26***	0.339
$offline\_consultation_{it}$	-4.60***	0.157

Table B1 reports the results from two different unit root tests—ADF test statistics reject the null hypothesis for total consultations and offline consultations as the DVs, respectively, and shows that the DVs between the two groups are stationary. We found consistent results using the KPSS tests. The KPSS test statistics cannot reject the null hypothesis (i.e., the time series is stationary), which translates to accepting the parallel-trend assumption.

Falsification Test 1 (placebo test): We created a "placebo event" at Week -6 and then applied the dataset from Week -13 to Week -1 to rerun the DID models. We expect the placebo event not to have significant effects, as the pseudo-causal effects are zero. The results show that the placebo event (Week -6) has no significant effect on the DVs.

Table B2. Falsification Test: Placebo Analysis

Time window	**Week [-13,-1]**					
Placebo event week	**Week -6**					
DV	***$total\_consultation_{it}$***			***$offline\_consultation_{it}$***		
Column	(1)	(2)	(3)	(4)	(5)	(6)
$OHC\_physician_i$ * $Pseudo\_outbreak_t$	**-0.02 (0.10)**	**-0.02 (0.10)**	**-0.02 (0.10)**	**0.05 (0.10)**	**0.05 (0.10)**	**0.05 (0.10)**
$Pseudo\_outbreak_t$	-0.23 (0.23)	-1.23*** (0.14)	-0.17*** (0.03)	-0.35 (0.23)	-2.43*** (0.06)	-2.63*** (0.02)
$OHC\_physician_i$	0.07 (0.07)	0.07 (0.07)	0.24** (0.10)	0.07 (0.07)	0.07 (0.07)	0.26*** (0.10)
Control variables	No	Yes	Yes	No	Yes	Yes
Physician FE	No	No	Yes	No	No	Yes
Time FE	No	No	Yes	No	No	Yes
No. of physicians	154	154	154	154	154	154
Adj. R-squared	0.04	0.84	0.84	0.01	0.86	0.86

Note: Standard errors in parentheses are robust and clustered by time and physician. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Falsification Test 2 (Chinese New Year effect): We conducted an additional placebo test to rule out the concern that the findings were possibly driven by Chinese New Year effects. We utilized the Chinese New Year week in 2019 as the second "placebo event" and further collected 26 weeks of data around the 2019 Chinese New Year week to examine the treatment effect of the placebo event. Table B3 shows that the pseudo-causal effect is insignificant and we conclude that our findings are not driven by the Chinese New Year effect. Thus, our baseline analysis generates credible causal evidence.

Table B3. Falsification Test: Chinese New Year Effect				
DV	***total_consultation$_{it}$***		***offline_consultation$_{it}$***	
Time window	**[-6,-2] & [2,6]**	**[-13,-7] & [7,13]**	**[-6,-2] & [2,6]**	**[-13,-7] & [7,13]**
Column	**(1)**	**(2)**	**(3)**	**(4)**
OHC_physician$_i$ * festival$_t$	**-0.14 (0.14)**	**-0.37 (0.24)**	**-0.14 (0.14)**	**-0.34 (0.24)**
OHC_physician$_i$	-0.39*** (0.07)	0.58*** (0.12)	-0.62*** (0.07)	0.38*** (0.12)
festival$_t$	0.54** (0.26)	-0.36 (1.59)	0.49* (0.26)	-0.07 (1.46)
Control variables	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
No. of physicians	154	154	154	154
Adj. *R*-squared	0.88	0.83	0.88	0.83

Note: Standard errors in parentheses are robust and clustered by time and physician. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Different thresholds of recovery: We alternatively used Week 6 and Week 8 as thresholds for the subsequent period to run the DID models to examine whether our findings are sensitive to the thresholds for the immediate and subsequent periods. The results are presented in Table B4, and we observe similar patterns to our main findings. Thus, we conclude that our empirical findings are robust and insensitive to the choice of thresholds for resistance and recovery periods.

Table B4. Different Thresholds of Recovery and Digital Resilience								
Threshold of recovery	**Week 6**				**Week 8**			
DV	***total_consultation$_{it}$***		***offline_consultation$_{it}$***		***total_consultation$_{it}$***		***offline_consultation$_{it}$***	
Time window	***1***	***2***	***1***	***2***	***1***	***2***	***1***	***2***
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OHC_physician$_i$ * outbreak$_t$	**0.26* (0.16)**	**0.29** (0.15)**	**0.04 (0.16)**	**0.30** (0.15)**	**0.30** (0.14)**	**0.26* (0.16)**	**0.14 (0.15)**	**0.29* (0.16)**
OHC_physician$_i$	4.65*** (0.08)	1.39*** (0.07)	3.06*** (0.08)	-1.45*** (0.07)	3.07*** (0.07)	1.88*** (0.08)	0.71*** (0.07)	-0.60*** (0.08)
outbreak$_t$	19.43** (7.72)	-3.65*** (1.22)	24.61*** (6.19)	-2.93** (1.15)	7.43* (3.82)	-3.63*** (1.24)	8.40** (3.59)	-2.92** (1.16)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of physicians	154	154	154	154	154	154	154	154
Adj. *R*-squared	0.77	0.75	0.79	0.77	0.75	0.75	0.77	0.78

Note: Standard errors in parentheses are robust and clustered by time and physician. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Time window: 1: [-6, -2] & [2, 6] (Resistance); 2: [-13,-7] & [7,13] (Recovery)

Physicians' overall medical service demand: We used physicians' average weekly total consultations from the six-month period prior to Week -13 to operationalize physicians' medical service demand before the pandemic. We reran the PSM and DID. The results are presented in Table B5 and are consistent with our main findings.

Table B5. Weekly Total Consultations as Physicians' Overall Medical Demand

DV	*total_consultation$_{it}$*		*offline_consultation$_{it}$*	
Time window	**[-6, -2] & [2, 6] (Resistance)**	**[-13,-7] & [7,13] (Recovery)**	**[-6, -2] & [2, 6] (Resistance)**	**[-13,-7] & [7,13] (Recovery)**
Column	**(1)**	**(2)**	**(3)**	**(4)**
OHC_physician$_i$ * outbreak$_t$	**0.36** (0.15)**	**0.36** (0.15)**	**0.16 (0.15)**	**0.36** (0.15)**
OHC_physician$_i$	-6.39*** (0.07)	-0.18 (0.22)	-7.04*** (0.08)	-6.39*** (0.07)
outbreak$_t$	-1.37*** (0.30)	-0.77*** (0.15)	-1.39*** (0.28)	-1.37*** (0.30)
Control variables	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
No. of physicians	154	154	154	154
Adj. *R*-squared	0.77	0.76	0.78	0.79

Note: Standard errors in parentheses are robust and clustered by time and physician. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Physicians who adopted the OHC after the outbreak: We included the six physicians who registered in the OHC after the outbreak in the sample as OHC physicians and non-OHC physicians, respectively, and reran the PSMs and DID models. The results are presented in Table B6 and are consistent with our main findings.

Table B6. Robustness Check for Six Physicians Who Joined the OHC after the Pandemic

The six physicians are considered as:	OHC physicians				Non-OHC physicians			
DV	*total_consultation$_{it}$*		*offline_consultation$_{it}$*		*total_consultation$_{it}$*		*offline_consultation$_{it}$*	
Time window	**1**	**2**	**1**	**2**	**1**	**2**	**1**	**2**
Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
OHC_physician$_i$ * outbreak$_t$	**0.40*** (0.14)**	**0.29** (0.15)**	**0.20 (0.14)**	**0.30** (0.14)**	**0.30** (0.14)**	**0.31** (0.15)**	**0.09 (0.15)**	**0.33** (0.14)**
OHC_physician$_i$	-21.48*** (0.07)	-19.71*** (0.07)	-21.40*** (0.07)	-19.71*** (0.07)	-6.45*** (0.07)	-3.08*** (0.07)	-3.03*** (0.07)	-0.23*** (0.07)
outbreak$_t$	-1.16*** (0.28)	-4.37*** (1.19)	-1.20*** (0.25)	-3.71*** (1.13)	-1.07*** (0.26)	-4.02*** (1.23)	-1.11*** (0.24)	-3.31*** (1.16)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of physicians	166	166	166	166	154	154	154	154
Adj. *R*-squared	0.74	0.74	0.76	0.77	0.74	0.76	0.77	0.79

Note: Standard errors in parentheses are robust and clustered by time and physician. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Time window: 1: [-6, -2] & [2, 6] (Resistance); 2: [-13,-7] & [7,13] (Recovery)