IMPROVING DIGITAL RESILIENCE IN THE HEALTHCARE DOMAIN VIA EFFECTIVE USE OF ONLINE HEALTHCARE COMMUNITIES

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CERTIFICATE OF ORIGINALITY

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ABSTRACT

Many entities apply information systems to bolster resilience to internal or external shocks, referred to as information technology resilience or digital resilience. Literature has suggested that resilience contains three dimensions—prevention, resistance, and recovery. This thesis focuses on the resistance and recovery dimensions of digital resilience of certified physicians who adopted an online healthcare community (OHC) to acquire patients and conduct telemedicine services under two types of shocks that healthcare entities may face—external shocks (e.g., the sudden outbreak of COVID-19), and internal shocks (e.g., outpatient price change).

Three empirical studies were conducted. The first study was conducted in a scenario where the COVID-19 pandemic (a significant external shock) underscored the urgent need for healthcare entities to develop resilient strategies to cope with disruptions caused by the pandemic. I synthesize the resilience literature and identify two effects of digital resilience—the resistance effect and the recovery effect. I 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. I further analyze the sources of physicians' digital resilience by distinguishing between new and existing patients from both online and offline channels. The subgroup analysis shows that 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.

The second study focuses on the joint effects of OHC use and the change of medical consultation price (a significant internal shock) on digital resilience. I synthesize the literature and identify two effects of physicians' use of OHC on increasing physicians' digital resilience: 1) amplifying the positive impact of increased outpatient consultation price on medication adherence, and 2) attenuating the negative impact of increased outpatient consultation price on outpatient visits. I construct a proprietary dataset that matches online and offline data sources. I run a difference-in-differences (DID) analysis to test these effects. Moreover, I analyze the moderating role of physician title on the amplifying and attenuating effects using a DDD analysis.

The third study focuses on digital resilience when shocks haven't occurred. I investigate the effects of physicians' use of OHC on patients' trust in physicians. Given the importance of trust in the healthcare domain, increasing patients' trust would improve physicians' digital resilience. I theorize that OHC use would increase physicians' trust in the physicians before the patients visit the outpatient. Two laboratory experiments were conducted to test these effects.

This thesis significantly contributes to research and practice. This thesis provides a broad and deep understanding of digital resilience in the healthcare context. Furthermore, this thesis investigates how healthcare entities can apply information systems to increase digital resilience. Another important contribution of this thesis is its exploration of the heterogeneous effects of physicians' use of OHC on their digital resilience, which bears implications for practitioners to effectively utilize information systems to build digital resilience.

Keywords: digital resilience, online healthcare community, physician resilience, COVID-19 pandemic, healthcare pricing, patient trust

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Chapter 1. INTRODUCTION

1.1 Problem Statement

Recent information systems (IS) studies have found that many entities apply digital technologies to absorb major shocks, adapt to disruptions, and transform to a new stable state, which the literature refers to as *information technology resilience* or *digital resilience* (Boh et al. 2023). For example, to address a typical shock in the healthcare management domain—outpatient overcrowding, hospitals encourage physicians to join telemedicine platforms (e.g., mdlive.com); such platforms enable physicians to conduct professional diagnoses and write prescriptions and give patients the ability to access competent online healthcare service.[1] In today's turbulent environment, healthcare entities are particularly susceptible to various internal and external shocks, such as healthcare supply chain disruptions, healthcare data breaches, and severe overcrowding in outpatient departments (e.g., Bhakoo and Choi 2013; Davis et al. 2020; Kwon and Johnson 2014). As such, developing resilient strategies to effectively manage and cope with shocks is of paramount importance for healthcare entities (Achour and Price 2010).[2]

1.2 Research Gaps and Questions

Existing IS studies have touched on digital resilience being conducted in *normal* circumstances where digital technologies are applied to build resilience against predictable disruptions—i.e., disruptions that happen regularly (e.g., Kwon and Johnson 2013). For example, during influenza season, physicians might increase their use of telemedicine platforms to cope with outpatient overcrowding (Metzger and

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[1] Please see https://pwcc.upenn.edu/en/hospital-overcrowding-a-global-problem/, accessed on November 2022.
[2] Please see https://www.mckinsey.com/business-functions/operations/our-insights/building-resilient-operations, accessed on November 2022.

Flanagin 2011). Information systems can improve resilience by reducing the reoccurrence probability of identical disruptions (Ambulkar et al. 2015).

Despite the recent advance in resilience literature, three major difficulties exist when investigating digital resilience in the healthcare settings. First, previous literature is insufficient in operationalizing and empirically investigating 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 an internal or external shock. 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 shock.

Second, as articulated, current digital resilience studies have mainly been conducted in normal circumstances. However, when facing disruptions caused by unpredictable and unprecedented shocks, such as the sudden outbreak of the COVID-19 pandemic (i.e., an external shock) or an internal decision of outpatient price change (i.e., an internal shock), the utility of digital technologies in building resilience remains a complicated open question that may go beyond the understanding established in the current IS literature.

Third, the understanding of heterogeneous factors that influence digital resilience is still unclear. For example, one important heterogeneous factor in IS study—effective use of the system, may affect the level of healthcare entities' 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 contributes to digital resilience remains unclear. For example, for a specific information system that may generate digital resilience—an online healthcare community (OHC), over 888,800 registered physicians use haodf.com—one of the largest OHCs in China.[3] 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. Therefore, there is an urgent need for investigating the heterogeneous factors (e.g., effective use) in influencing digital resilience.

Accordingly, the purpose of this thesis is to enhance the understanding of digital resilience in healthcare settings by exploring the following three research questions:

- To investigate the structure of digital resilience. Specifically, what is digital resilience in the healthcare setting? How to measure and quantify digital resilience?
- To examine the specific external and internal shocks that healthcare entities face in developing digital resilience. Under such shocks, whether and how healthcare entities develop their digital resilience?
- To explore the heterogeneous factors that may influence digital resilience. What are the key heterogeneous factors that healthcare entities need to take into consideration when developing digital resilience? How do these factors affect digital resilience?

1.3 Research Outline and Objectives

To fill the research gaps, this thesis focuses on individual physicians' digital

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

resilience in an online healthcare setting when facing external and internal shocks. This thesis also echoes previous literature of resilience to examine whether and how applying information systems build resilience in special circumstance. Specifically, I focus on a particular healthcare information system—an 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. I examine the effectiveness of this OHC in increasing physicians' resilient responsiveness against different types of shocks.

This thesis draws upon the resilience literature (e.g., Kouvelis and Li 2008; Tomlin 2006) and identifies three dimensions of digital resilience—resistance (i.e., to mitigate reductions of physicians' performance when facing shocks), recovery (i.e., to facilitate increases of physicians' performance aftershocks), and prevention (i.e., to prevent negative events from reoccurrence). Given the multi-dimensional nature of resilience and the different types of shocks healthcare entities face, I conducted three studies to solve the abovementioned research questions.

In Study 1, I investigate digital resilience under external shock—the first wave of the COVID-19 outbreak. Specifically, in line with previous healthcare management literature, I use a physician's patient caseloads to measure his/her performance when studying resilience (e.g., Aguinis and O'Boyle Jr. 2014; Joo et al. 2017). I empirically examine physicians' use of an OHC to achieve a *resistance effect* in the *immediate period* of the COVID-19 outbreak and a *recovery effect* in the *subsequent period* of the outbreak. I 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. I thus postulate and test whether the OHC enabled different forms of digital resilience across different time periods following the external shock.

On top of the general effect of digital resilience, I further 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. Moreover, I investigate the impact of physicians' online reputation on their digital resilience. In this study, online reputation is operationalized as the overall rating of a physician's online service quality (Li et al. 2019a)—a signal that may attract new patients and thus strengthen digital resilience. By exploring the two factors, Study 1's 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.

To empirically test the theorization, I exploit 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. I apply a difference-in-differences (DID) model and conduct 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 Study 2, I examine digital resilience under internal shock—the policy change of increasing outpatient fees. In this study, I use medication adherence as an indicator of a physician's resilience, which is in line with prior medical studies (e.g., Oh et al. 2018). Medication adherence is defined as "*the extent to which patients take medication as prescribed by their doctors*" (Ayer et al. 2016; Oh et al. 2018). I conjecture that the physicians can apply OHC to amplify the positive consequence of improving medication adherence (i.e., *an amplifying effect*) and mitigate the negative impact of decreasing outpatient visits (i.e., *an attenuating effect*). In addition, I further examine the heterogeneity of the effects of OHC. Particularly, a close examination of the literature reveals a major constraint to a healthcare entity's resilience is the entity's reputation in building a strategy to resist negative outcomes of an event (e.g., Liu et al. 2016; Tomlin 2006). Accordingly, recognizing the potential heterogeneity of physicians' utilization of OHCs, I identify that the physician's rank/title (hereafter *title*), which is operationalized of a physician's reputation in this research, will be the moderator of the proposed effects of OHC use on medication adherence.

Study 2 exploits a natural experiment following an increase of the outpatient consultation price in China by matching two longitudinal datasets from online and offline channels respectively. I apply a difference-in-differences (DID) model and a difference-in-difference-in-differences (DDD) model to investigate the effects postulated above. The empirical results support the proposed effects as well as the moderating roles of physician title.

In Study 3, I particularly examine digital resilience when shocks haven't occurred (i.e., at a normal age). Study 1 and Study 2 mainly focus on resilience when facing shocks, the other scenario of resilience—before the shocks occur, needs further examination. In this study, I use patients' trust in a physician as an indicator to study resilience. Trust is vital yet difficult to be built. If a physician is considered as trustworthy, he/she will remain high performance when facing shocks. Therefore, I conjecture that the physicians can apply OHC to increase patients' trust in them. In this study, I conducted two laboratory experiments to verify the theorization.

1.4 Significance of the Research

This thesis offers significant contributions to both theoretical developments and practical management. The findings of this thesis have the potential to enhance the healthcare entities to build resilient strategies to deal with external or internal shocks. Five major theoretical contributions can be derived from this research.

First, this thesis provides a deeper understanding of the digital resilience. The nature and the dimensions of digital resilience are identified by reviewing the literature from different academic fields, including Information Systems (IS), Operation Management (OM), and Organization Behavior (OB). The proxies of different dimensions of digital resilience are quantitatively tested in this thesis.

Second, this thesis investigates how healthcare entities can apply information systems to increase digital resilience. The boundary effects of building resilience are still unknown. An important contribution of this thesis is its exploration of the heterogeneous effects of physicians' use of OHC on resilience.

Third, Study 1 provides empirical support for the digital resilience in an understudied context—the sudden external shock of the COVID-19 outbreak. Existing studies have been primarily conducted in contexts where digital technologies are applied to build resilience to predictable disruptions. The research context of Study 1 differs from the existing literature in that the healthcare system was disrupted by an unpredictable and unprecedented external 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. Study 1 identifies the resistance effect in the immediate period and the recovery effect in the subsequent period. I estimate the magnitude of these two effects using a unique dataset matching online and offline data sources. To the best of my knowledge, this thesis is 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.

Fourth, Study 2 provides empirical support for the digital resilience in another understudied context—the internal shock of price change policy. Such shock is also unpredictable by the physicians but planned by the organization. Therefore, Study 2 enriches our theoretical understanding of digital resilience by extending the research context of Study 1 to a broader scenario in which the healthcare entities face internal shocks. This extension enables researchers to examine the boundaries of the power of information systems in building digital resilience. In particular, Study 2 reveals that information systems can amplify the positive effects and attenuate the negative effects of the internal shocks on physicians' performance. This finding extends the current literature on resilience theory by recognizing the influence of information systems on dealing with internal policy changes.

The practical contributions of this thesis are summarized as follows. First, the effects of information systems help healthcare entities understand what is digital resilience. Second, online healthcare communities have great potential in building resilience strategies for the healthcare entities. Third, the effectiveness of OHCs can be applied to different contexts that healthcare entities may face in the future.

1.5 Thesis Structure

This thesis consists of nine chapters.

Chapter 1 presents the problem, research questions, outline, objectives, significance, and structure of this thesis.

Chapter 2 reviews the general foundations of this research. First, previous studies on the resilience, that is, the dimensions/components of resilience, are reviewed. Second, the key functions and features of online healthcare communities are reviewed.

Chapter 3 introduces the Study 1. First, the research model and hypotheses of Study 1 are developed. Second, the methodological issues of Study 1 are reported. The data, analysis method, data analysis results and hypotheses tests are then explained in detail.

Chapter 4 introduces the Study 2. I first develop the hypotheses and then introduce the method of Study 2.

Chapter 5 introduces the Study 3. The hypotheses and the method are reported.

Chapter 6 summarizes the theoretical and practical implications of the results. The limitations and opportunities for extending the current project are then discussed.

CHAPTER 2. THEORETICAL BACKGROUND

2.1 Digital Resilience

Digital resilience is generally defined as the "*capabilities developed through the use of digital technologies to absorb major shocks, adapt to disruptions, and transform to a new stable state*" (Boh et al. 2023, p. 344). Building resilience to cope with the risks and consequences of disruptions is an essential theme in the literature from various fields, including information systems, organizational behavior, and operations management. 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 do not adopt the OHC or those with lower reputation ratings. High online reputation ratings may serve as a positive signal to attract more patients after a 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 and 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 and Johnston 2001). Current digital resilience research in the IS field devotes 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 and encryption (Kwon and 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 and Dolgui 2019). When a disruption occurs, entities immediately experience performance loss after the disruption; a low level of performance loss is considered an indicator of high resistance (Munoz and Dunbar 2015). Recovery is the attempt to minimize the amount of time the 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 and Kouvelis 2020). For example, Japanese companies with multiple suppliers (a typical resilient strategy of supply chain management) recovered their production more quickly after the massive 2011 earthquake than their competitors (Ambulkar et al. 2015; Olcott and 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 thesis adopts the above categorization of resilience.

2.2 Online Healthcare Community

In the current 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. 2020b). 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 the OHC and potential patients select physicians for online consultations and/or outpatient visits based on this information (Xiao et al. 2014; Yan and Tan 2017). OHCs provide various informational cues allowing potential patients to judge physicians' service quality, such as physician reputation ratings on the OHC (Wu and 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. 2020a). Physicians can use the OHC 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. 2020c; Tan and Yan 2020) and the positive impacts of physicians' participation in OHCs on patient well-being and patient-physician relationships (Liu et al. 2020b).

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 and 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 and Majchrzak 2010), leading to suboptimal patient-physician interactions and thus decreasing patients' intention to engage in offline medical care (Rupert et al. 2014). However, these studies were all conducted in the contexts wherein no shocks are involved. In the current thesis, I focus on different contexts—physicians' digital resilience following an external or internal shock.

CHAPTER 3. STUDY 1: DIGITAL RESILIENCE AND EXTERNAL SHOCKS

3.1 Theory and Hypotheses

In this study, I investigate the effects of physicians' use of digital technologies to improve their resilient responsiveness across different time periods following an unpredictable external shock. In particular, I contextualize digital resilience as enabled by an OHC in *the first wave of the COVID-19 outbreak*. As I focus on the impacts of the OHC on digital resilience, I 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*. In the specific context of Study 1, 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*. I then develop hypotheses for these two effects and the heterogeneity of the two effects related to the sentiment of physicians' online consultations and online reputations.

3.1.1 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 and Veral 2003; Salzarulo et al. 2011). These consultations can be outpatient visits in a clinical setting or telemedicine services conducted in the OHC. Given that the COVID-19 pandemic represents a major exogenous shock to physicians' production, I 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, I 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 and Chughtai 2020). OHCs are built on a digital infrastructure that is robust to disruptions such as the COVID-19 pandemic (Hollander and 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 on 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 use the 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 and Chan 2011).

I postulate that acquiring new online patients was the primary source of OHC physicians' *resistance* in the immediate period after the COVID-19 outbreak because they were able to replace their losses in offline outpatient visits with online consultations. By contrast, I 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, I 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.*

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

In the subsequent period after a disruption, affected entities need to take actions to restore their production to normal levels (Gupta et al. 2016). In the context of the COVID-19 pandemic, the offline outpatient channel became less constrained and was gradually restored in the subsequent period (Fahey and 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 through transferring patients from the online channel to the offline channel. Thus, in the subsequent period, I 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 in 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* were those who had visited OHC physicians via *only* the online channel before or during the immediate period; they needed further in-person treatments or examinations in the subsequent period (Li et al. 2016). These patients contributed to OHC physicians' offline consultations in the subsequent period. Second, the OHC may have generated *totally new offline patients* for OHC physicians—those who had not visited the 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 and Deng 2021). Given these likely positive impacts of the OHC on offline patient acquisition, I anticipate that OHC physicians attained normal-level production more quickly than that of non-OHC physicians in the subsequent period. Therefore, I hypothesize:

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

3.1.3 The Heterogeneous Treatment Effects of the OHC on Digital Resilience

In this subsection, I further develop the hypotheses regarding the heterogeneous treatment effects of the OHC on physicians' digital resilience. Since the effective use of information systems can lead to better performance (Burton-Jones and Grange 2013), it is necessary to investigate how physicians' individual use of the OHC affects their digital resilience. In this study, I 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 on 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 and Ridings 2002). In the current 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 had 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, I 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.*

I also investigate the impact of physicians' online reputation on their digital resilience. I 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 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 on the OHC would have relied on the same signal, whether for offline or online consultations. Therefore, I argue that OHC physicians with a high online reputation rating likely attained stronger resistance and recovery effects. In sum, I hypothesize:

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

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

3.2 Empirical Methodology and Results

3.2.1 Empirical Context and Data

The COVID-19 outbreak in China offered a natural experiment to test our hypotheses. I exploited the COVID-19 outbreak as the exogenous shock that created plausible variations in online and offline healthcare consultation behaviors among physicians and patients. I 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. I then analyzed the resistance and the recovery effects of OHC physicians compared with non-OHC physicians in the immediate and the subsequent periods following the outbreak.

The Immediate Period and the Subsequent Period

To generate credible causal evidence for our hypotheses, I exploited two events to divide the time period after the first outbreak of COVID-19 into the immediate and the subsequent periods to analyze the resistance and the recovery effects, respectively. The *first event* was the *initial COVID-19 outbreak*. On January 20, 2020, the Chinese government announced that the 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. I consider these two official announcements of COVID-19 to be signals of the 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, I 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 the research purposes, the second event occurred on February 23, 2020. I 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

I collected offline and online data of physicians working at a leading hospital located in a city in northern China (Hospital A hereafter).[4] 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 International Classification of Diseases, Tenth Revision, Clinical Modification (ICD codes hereafter).[5] 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 and Huckman 2012; Kuntz et al. 2019). Therefore, in this study, I also adopt ICD codes to control for patient heterogeneity and physician specialization. I conducted the data collection process under the supervision of professional physicians, who provided guidance regarding the ICD system.

[4] In the 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 no-acceptance 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 the normal life and work in the subsequent period.

[5] 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).

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. 2020b). As of April 2022, more than 888,800 certified physicians from 10,001 hospitals across China had registered with the platform.[6] The platform maintains a homepage for each certified physician, showing biographies, specializations, reputation ratings, and the contents of their online consultations (Figure 3.1). 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 the online consultations on the OHC platform.

Physicians mainly use the OHC to provide online consultations (i.e., telemedicine services).[7] These online consultations are paid services that involve formal and publicly accessible one-to-one communications between patients and physicians (Wang et al. 2020a). I collected data about physicians' profiles (e.g., reputation ratings) and their online consultations. I 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, I matched the online dataset with the offline dataset of each OHC physician to investigate the physicians' online and offline behaviors at the individual level.

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

[7] I have 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.

Figure 3.1 Screenshots of a Physician's OHC Homepage and Online Consultation

3.2.2 Empirical Strategy

I implemented a difference-in-differences (DID) model to examine the resistance and recovery effects. For the resistance effect, I ran the 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, I ran the DID model using the data in the subsequent period after the COVID-19 outbreak and a parallel period before the outbreak. Moreover, I examined the heterogeneous treatment effects using two factors: *the sentiment of physicians' online consultations* and *physicians' overall reputation on the OHC*. Figure 3.2 presents the timeline of our analysis.

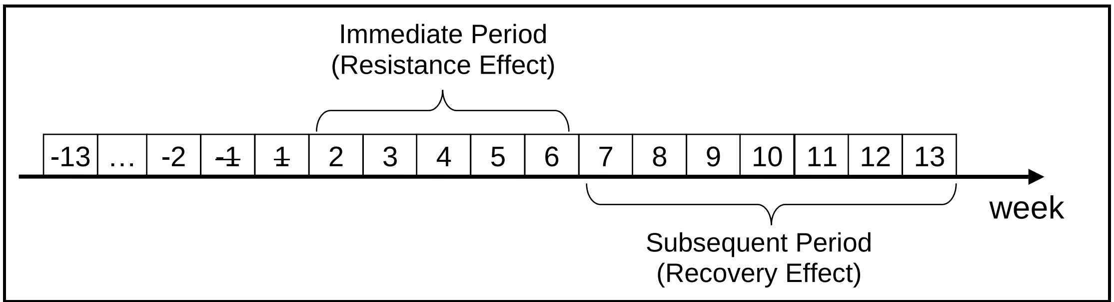

Figure 3.2 Timeline of the Analysis

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. I specify the week before and after the outbreak day (January 20, 2020) as the reference period of the 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, I 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). I 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).

3.2.3 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.[8] $\mathit{Total\_consultation}_{it}$ is

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[8] I 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

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.

I included 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), I 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, I set this ICD code dummy to 1 and 0 otherwise. In our dataset, there were 792 elements in each ICD code vector. I collected data to calculate physicians' average weekly offline consultations in the six months prior to Week -13. I 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).[9] Table 3.1 presents the list of variables and measures.

only use the focal OHC for telemedicine services. The number of consultations on the OHC thus sufficiently captures their online production.

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

Table 3.1 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"[10]	Hospital A
$education_i$	The educational qualification of physician *i*, which takes 1 for physicians with the "Clinical Medicine Postgraduate" 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

3.2.4 Data Analysis

I 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. I then ran DID models for the immediate period and the subsequent period, respectively, to analyze the resistance and the recovery effects of OHC physicians (i.e., H1 and H2). I also analyzed the sources of OHC physicians' digital resilience (i.e., the mechanisms of new patient acquisition). To investigate the heterogeneous treatment effects, I separated the OHC-physicians into two subgroups of high vs. low sentiment positivity

[10] 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.

of online consultations. I 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). I 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

I utilized PSM to match OHC physicians with non-OHC physicians who were similar on a set of observable characteristics. I 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 3.2.

Table 3.2 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: *** $p < 0.01$, ** $p < 0.5$, * $p < 0.1$	

I 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

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

statistics of all the variables after the PSM are reported in Table 3.3.

Table 3.3 Descriptive Statistics

Variable	*Mean*	*Std. Dev.*	*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%							

To verify the validity of the matching, I 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 3.4 reports the summary statistics of the comparisons.

Table 3.4 Comparisons of Matching Variables Before and After PSM

Variable		*Mean*		*t-value*
		Treatment (OHC physicians)	*Control (Non-OHC physicians)*	
$title_i$	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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$				

To further alleviate the concern of heterogeneity among different groups of physicians and consultations, I 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). I 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). I also compared the ICD codes used by OHC physicians for online vs. offline consultations for the entire time period. In particular, I 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 3.5 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.

Table 3.5 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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$		

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

The total consultations of OHC and non-OHC physicians and the offline consultations of OHC physicians are plotted in Figure 3.3. It can be observed 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 (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).

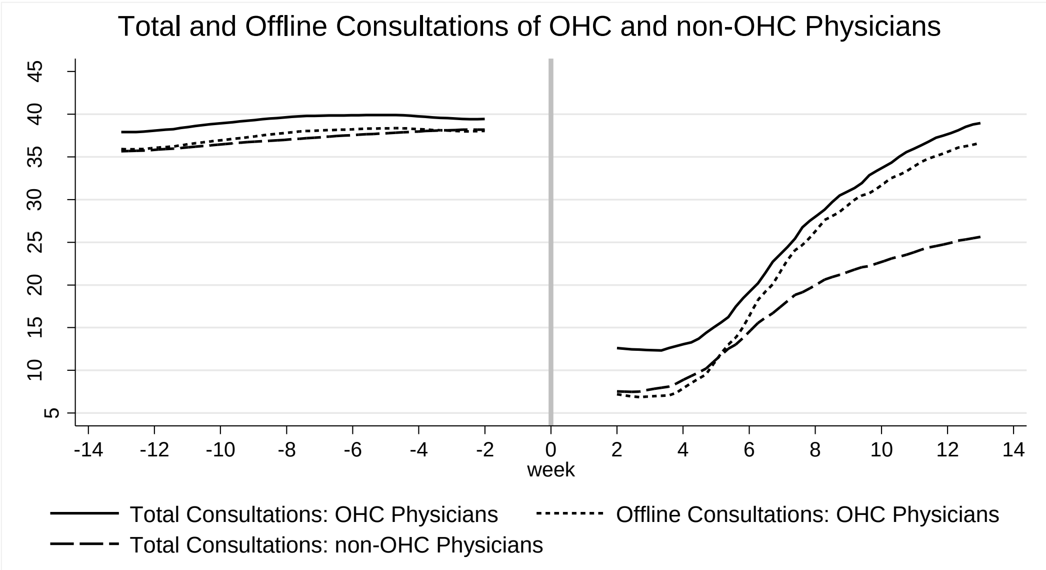

Figure 3.3 Physicians' Consultations

I also observed a decrease in the online consultations of OHC physicians in the subsequent period, as depicted in Figure 3.3 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 above model-free evidence, I employed the following DID specifications to examine and quantify the treatment effects:

$$total\_consultation_{it} = \beta_1 * OHC\_physician_i * outbreak_t + \beta_2 * OHC\_physician_i + \beta_3 * outbreak_t + \boldsymbol{\tau X} + \alpha_i + \delta_t + \varepsilon_{it} \quad (1)$$

$$offline\_consultation_{it} = \beta_1 * OHC\_physician_i * outbreak_t + \beta_2 * OHC\_physician_i + \beta_3 * outbreak_t + \boldsymbol{\tau X} + \alpha_i + \delta_t + \varepsilon_{it} \quad (2)$$

Existing literature suggests that physicians' production/performance follows the power law distribution (e.g., Aguinis and O'Boyle Jr. 2014). The current data follows the same pattern. Therefore, I 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 the physician fixed effects and δ_t captures the time fixed effects.

I ran the DID models to verify the resistance effect with data from the immediate

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

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, I 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 the recovery effects). Table 3.6 reports the results of the DID regressions.

Table 3.6 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The empirical results support H1 and H2. I 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) suggests 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 outbreak of COVID-19 decreased 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.

I 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) as well as 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 of OHC physicians was higher than that of 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, the findings are consistent with our observations from the model-free evidence and provide empirical support for H1 and H2.

Validation Tests for DID Analysis

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

In this section, I report the results of several robustness checks to validate our findings in the DID analysis. First, I ensured that the parallel-trend assumption is satisfied for our DVs. That is, before the COVID-19 outbreak, OHC physicians' and non-OHC physicians' consultations followed similar trends. I 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 (Table 3.7).

Table 3.7. Results of the ADF Test and the KPSS Test of Stationary

	ADF test	**KPSS test**
total_consultation$_{it}$	-5.26***	0.339
offline_consultation$_{it}$	-4.60***	0.157

Second, since the treatment impact may vary given the progression of COVID-19, I applied the *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), I ran the following DID analysis:

$$DV_{it} = \beta_1 * OHC\_physician_i * outbreak_t * New\_case_t + \beta_2 * OHC\_physician_i + \beta_3 * outbreak_t + \boldsymbol{\tau X} + \alpha_i + \delta_t + \varepsilon_{it} \quad (3)$$

where the DV is *total_consultation*$_{it}$ or *offline_consultation*$_{it}$. As I 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 3.7), thereby demonstrating that our findings are robust to this alternative specification.

Table 3.7 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, I performed two falsification tests to further establish the robustness of our findings. For the first falsification test, I created a placebo event (Week -6). The results show that this placebo event had no significant effects on the DVs (Table 3.8). In the second falsification test, I examined whether the resistance and the 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. I examined whether similar reduction and bounce-back in physicians' production also occurred during the 2019 Chinese New Year to rule out this possibility. I 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 (Table 3.8).

Table 3.8 Falsification Tests						
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

Table 3.8 Falsification Tests

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)
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: 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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, I 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 (Table 3.9).

Table 3.9 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)

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, I 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 the recovery effects (Table 3.10).

Table 3.10 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Finally, six physicians registered in the OHC after the COVID-19 outbreak, and I did not include them in our analyses reported above. I reran two additional PSMs by specifying the six physicians as either OHC physicians or non-OHC physicians. After each PSM, I reran the DID analyses. The results are consistent with the main findings regarding the resistance and recovery effects (Table 3.11). In sum, the DID analyses generated robust causal evidence.

Table 3.11 Robustness Check for Six Physicians who Joined OHC after 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

Table 3.11 Robustness Check for Six Physicians who Joined OHC after 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)

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)

Analyses of the Mechanisms of New Patient Acquisition

Utilizing the uniqueness and richness of the matched offline and online datasets, I further explored the new-patient-acquisition mechanism. I first identified different types of online patients. For each online consultation of an OHC physician, I assessed whether this was the first record of the patient's online consultation with the physician (see Figure 3.1: 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). I 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 3.1: 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, I 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. I 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), I applied three criteria to identify new offline patients as being 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 his/her 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 3.12, and the descriptive statistics of these variables are reported in Table 3.3.

Table 3.12 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

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

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

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

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 3.13 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).

Table 3.13 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Given that the primary mechanism underlying the digital resilience of OHC physicians was their acquisition of new patients, I further analyzed the different types of these new patients. I plotted the proportions of all four types of new patients for the OHC physicians in Figure 3.4—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 3.14 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 the recovery effects of OHC physicians.

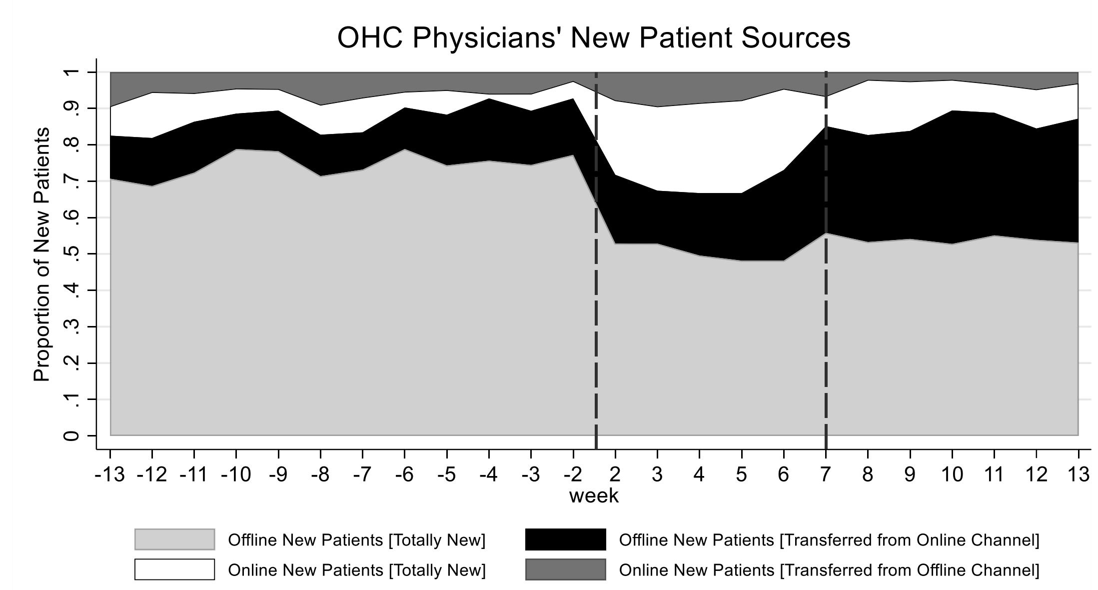

Figure 3.4 OHC Physicians' New Patients

Table 3.14 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]

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

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

I collected detailed physician-patient interactions of all online consultations for each OHC physician (see Figure 3.1). For each utterance within the physician-patient interactions, I 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), I 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 3.3 shows the descriptive statistics of $sentiment_i$. I split the OHC physicians into two subgroups using the median of $sentiment_i$, i.e., high and low positivity subgroups. After that, I included each subgroup of OHC physicians and the matched non-OHC physicians in the sample and reran the DID analyses.

Table 3.15 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, 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, 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.

Table 3.15 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

I also examined the effects of sentiment on physicians' new patient acquisition. I reran the analyses in Equations (4) and (5) for the high and low positivity subgroups. The results are presented in Table 3.16. 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.

Table 3.16 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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, I first generated a variable *reputation$_i$*, measured by physician *i*'s overall reputation rating on his/her OHC homepage (see Figure 3.1). I 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$_i$*. I then included each subgroup of OHC physicians and the matched non-OHC physicians in the sample and repeated the DID analyses. I compared the results.

Table 3.17 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 3.17 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$								

I 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 3.18) verify that OHC physicians with high online reputation ratings acquired more new patients, leading to stronger resistance and recovery effects[14].

Table 3.18 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$								

Given the importance of online reputation (e.g., Boh 2007; Ye et al. 2014) and its potential relationship with physician performance, I conducted the regression following

[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. I found a correlation of 0.24 ($p < 0.1$), which is not high.

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.

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

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. $\mathbf{X}$ 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 ($\widehat{\beta_2}$). I conducted two tests. In the first test, I 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, I 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 3.19.

Table 3.19 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: $offline\_new\_patient_{it}$

The results in Table 3.19 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 generate heterogeneous treatment effects. Therefore, I used the OHC physicians' date of registration in the OHC, $ohc\_registration_i$, to calculate their tenure with the OHC. I calculated their experience with the OHC using their aggregated number of online consultations, i.e., $aggregated\_patients_i$. I adopted the same approach of 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 3.20 and 3.21 report the results.

Table 3.20 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

Table 3.20 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
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 3.21 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The results show that neither OHC physicians' tenure nor their experience on 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, and digital resilience is driven by service quality rather than quantity.

3.3 Discussion of Study 1

This study focuses on digital resilience in the context of healthcare facing an unpredictable external shock—the COVID-19 pandemic. The contextualization provides an in-depth understanding of how physicians use OHCs to enhance their resilient responsiveness against exogenous shocks. In particular, I examined two forms of physicians' digital resilience—resistance and recovery effects—after the outbreak.

First, I found a *resistance effect* in the *immediate period* following the outbreak. While the sudden outbreak of COVID-19 rendered offline healthcare ineffective, I found that OHC physicians who conducted online consultations enjoyed significantly lower levels of production loss than non-OHC physicians. I identified the two major constituents of the resistance effect as *totally new online patients* and *those who switched from offline to online*. Second, I 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, I 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*. The 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.

CHAPTER 4. STUDY 2: DIGITAL RESILIENCE AND INTERNAL SHOCKS

In Study 2, I further investigate the possible effects of OHCs in building resilience when healthcare entities face internal shocks. The key feature of the research context of Study 2 is that the healthcare entities make some policy changes to try to improve their performance, but such changes are internal shocks to physicians and patients that may also generate disadvantages to their performance. Study 2 investigates whether information systems can extend their effects to improve the healthcare entities' resilience in such context, e.g., whether OHCs can strengthen the positive effects of the internal shocks and weaken the negative effects of the shocks.

Medication adherence is an essential part of the healthcare resilience strategy because poor medication adherence leads to severely poor clinical outcomes. Medication adherence is defined as "*the extent to which patients take medication as prescribed by their doctors*" (e.g., Ayer et al. 2016; Oh et al. 2018).[15] Improving patients' medication adherence has been a typical healthcare resilience problem. Healthcare sectors have tried several approaches to resolve this problem (e.g., Cutler et al. 2018; Oh et al. 2018; Suen et al. forthcoming). For example, some researchers suggest that policy change of increasing the price of healthcare services (e.g., outpatient consultation price) may increase patients' medication adherence. Such price change increases patients' perception of the quality of healthcare services, which, in turn, may increase patients' compliance with the healthcare services (e.g., medication adherence) (e.g., El-Shal et al. 2021; Qian et al. 2017). However, increasing healthcare service prices has been considered to cause some adverse effects, such as reducing outpatient

[15] Please also see https://www.fda.gov/drugs/fda-drug-info-rounds-video/transcript-medication-adherence.

visits (e.g., Ding et al. 2020). Therefore, developing strategies to improve medication adherence with increased healthcare service prices is of great importance for healthcare entities to build their resilience strategy (Achour and Price 2010).

The importance of increasing patient medication adherence highlights a need for a nuanced understanding of the conditions under the internal shock in which the outpatient consultation price is increased. For example, will OHCs increase patients' medication adherence and resist the reduced outpatient visits under the condition of increased outpatient consultation price? Theoretical and empirical understandings of the effects of information systems in such contexts are lacking. To fill the gap, this study focuses on individual physicians' healthcare performance in the online healthcare setting during an internal shock of increased outpatient consultation price. Given the importance of patients' medication adherence for physicians, the primary objective of Study 2 is to develop a fine-grained theory and conduct an empirical investigation to delineate whether and how physicians can use OHC to improve patients' medication adherence and mitigate the negative effect of decreased outpatient visits. I posit that the increased outpatient consultation price can increase patients' perception of healthcare service quality, resulting in their increased medication adherence. I argue that such increased outpatient consultation price would reduce healthcare demand, thereby reducing outpatient visits.

I conjecture that the physicians can apply OHC to amplify the positive consequence of improving medication adherence (i.e., *an amplifying effect*) and mitigate the negative impact of decreasing outpatient visits (i.e., *an attenuating effect*). This case is magnified when physicians use OHC to provide additional evidence to reveal their high service quality (e.g., their shared healthcare knowledge and interactions with potential patients). Patients may consider such evidence as persuasive content from a marketer (e.g., Gunaratne et al. 2018). As such, compared with physicians who do not use OHC (called non-OHC physicians in our study), patients are more willing to follow these OHC physicians' medical advice. In addition, the signal of high quality, which is indicated by physicians' OHC page, will increase patients' medical demand for these physicians. Therefore, physicians that use OHC can strengthen the positive effect of increased outpatient consultation price on patients' medication adherence while attenuating the negative effect of increased outpatient consultation price on decreased outpatient visits.

To better understand the role of OHCs in the context of building resilience under internal shocks, I further examine the heterogeneity of the effects of OHC. In particular, a close examination of the literature reveals a major constraint to a healthcare entity's resilience to shocks—namely, the entity's reputation in building a strategy to resist negative outcomes of an event (e.g., Liu et al. 2016; Tomlin 2006). Accordingly, recognizing the potential heterogeneity of physicians' utilization of OHCs, I identify a moderator of our proposed effects of OHC use on medication adherence. I argue that the physician's rank/title (hereafter *title*), which is operationalized of a physician's reputation in this research, will be the moderator. I postulate that a high-title OHC physician has a higher reputation than a low-title physician, resulting in a relatively stronger positive outcome (i.e., the increased medication adherence) and weaker negative outcome (i.e., the decreased outpatient visits) in response to the increased outpatient consultation price.

To empirically test our theorization, I exploit a natural experiment following an increase of the outpatient consultation price in China. I match two longitudinal datasets from online and offline channels respectively. I apply a difference-in-differences (DID) model and a difference-in-difference-in-differences (DDD) model to investigate the effects I postulate above. The empirical results support the proposed effects as well as the moderating roles of physician title.

4.1 Theoretical Background and Conceptual Extension

4.1.1 Medication Adherence

Medication adherence is an emerging topic of healthcare resilience. An appreciable number of patients (as many as 25%-40%) are non-adherent (Dunbar-Jacob et al. 2001), and adherence has been found to have significant effects on treatment outcomes (DiMatteo et al. 2002). Studies have shown that a high level of medication adherence enables patients to get the maximum benefit of medical treatment, resulting in better health outcomes, higher quality of life, and lower healthcare costs (Osterberg and Blaschke 2005; Sokol et al. 2005). For example, Roebuck et al. (2011) conducted a randomized controlled trial to evaluate the effect of medication adherence on healthcare use and cost and found that improved medication adherence produces substantial medical saving as a result of a reduction in hospitalization and emergency department use. Despite the importance of medication adherence, patients' nonadherence to medical treatment remains a persistent problem (van Dulmen et al. 2007). Both clinicians and researchers struggle to identify non-adherent patients, develop interventions to improve medication adherence, and predict patient medication adherence (McCoy and Eric Johnson 2014).

First, researchers have developed various measures of medication adherence (Lam and Fresco 2015). The most common methods of measuring medication adherence are patient self-report, electronic monitors, and pill count. Hansen et al. (2009) compared these three methods and found that all measures provide similar estimates of overall adherence. Patient self-report is the most common tool used to rate adherence to medication. The most common drawback of this approach is that patients tend to underreport nonadherence to avoid disapproval from their healthcare providers (Vik et al. 2004). Objective measures include pill count and electronic monitoring and are considered an improvement over subjective measures (i.e., self-report). While using an electronic device to monitor a dosing event is often considered the reference standard for medication adherence, electronic monitors may be impractical in clinical practice (Hansen et al. 2009). Using pharmacy data, pill count calculates the medication possession ratio to measure adherence (Choo et al. 1999). An advantage of using pill count to measure adherence is that it is scalable and is implemented into the clinical workflow since many health systems have linked their electronic health records with pharmacies. Lam and Fresco (2015) also found that using pill count to measure adherence contributes to a more precise record of patient medication-taking behavior. In this study, I follow the pill-count approach and operationalize medication adherence as the proportion of complied or executed prescriptions to the total prescriptions.

Second, innumerable intervention studies have been performed in the last decades to improve medication adherence (Boutilier et al. forthcoming). Roter et al. (1998) summarized the interventions that have been used to improve adherence and evaluate their effectiveness. Specifically, according to the mainstream theories, Roter et al. (1998) clustered adherence interventions into four categories: behavioral, educational, affective, and a combination of the above three. Researchers further analyzed the underlying theoretical principles and identified four theoretical approaches to adherence interventions: technical, behavioral, educational, and multi-faceted or complex interventions (van Dulmen et al. 2007). Previous studies also found that technical solutions, such as simplifying the regimen, can improve medication adherence (van Dulmen et al. 2007). Recently, Kini and Ho (2018) reviewed the literature on intervention strategies and identifies six categories of intervention strategies for enhancing adherence: patient education, medication regimen management, pharmacist-led interventions, cognitive-behavioral therapies, medication-taking reminders, and incentives to promote adherence. Although many interventions have been proposed to improve patient adherence, their effects are found to be modest at best (McDonald et al. 2002; Suen et al.). Therefore, it remains a critical issue to improve patients' medication adherence in healthcare practice (Ayer et al. 2016; Kini and Ho 2018).

Finally, some studies also investigated how cost factors affect medication adherence. Becker and Maiman (1975) summarized the most productive predictors of medication adherence and suggest that patient cost is a consistent predictor of adherence. Thomson et al. (2010) also argued that patient payment determines healthcare efficiency and may affect medication adherence. However, extant research mainly focuses on drug cost and argues that decreasing prescription drug expenditure may improve medication adherence (e.g., Etemadi and Hajizadeh 2022; Grepin 2009). Yet, little is known about how the change in medical consultation fees affect patient medication adherence. In this study, I empirically examine the effects of increased medical consultation price on medication adherence and explore how the adjustment of medical consultation fees can help improve adherence.

4.1.2 The Internal Shock: Change of Medical Consultation Price

Most healthcare systems require patients to pay fees at the point of usage. The consultation price serves two primary purposes related to getting better value from available healthcare resources (Thomson et al. 2010). The first purpose is that user charges can help make up for shortfalls in public funding (Lagarde and Palmer 2008). The second one is to make people more discerning in their choices of healthcare services (Moses et al. 1992). However, many researchers call for removing user fees because these fees create barriers for patients to access medical services (Masiye et al.

2016). Price adjustment decisions are thus in puzzle for healthcare providers and more investigations are needed on how a change in price affects the healthcare operations efficiency.

Therefore, a series of studies examining the effects of user fees on healthcare management have been conducted. Some studies have highlighted the negative effects of the increase of user fees on healthcare accessibility (Moses et al. 1992; Soumerai et al. 1994). For instance, Issifou and Kremsner (2004) measured the impact of increased user fees on the number of outpatient visits in the outpatient clinic of a privately funded hospital. They found a 74% reduction in outpatient visits occurred after increasing user fees. In contrast, Lagarde and Palmer (2008) found that the demand for healthcare is inelastic, and they believed that introducing or increasing fees leads to slight decrease in the use of health services. Litvack and Bodart (1993) conducted an experiment and found that increasing medical service price help increase income for the healthcare sectors without undermining healthcare demand. Moreover, a limited number of studies also argued that revenues raised through increasing user fees have positive impacts on healthcare quality (e.g., Etemadi and Hajizadeh 2022; Grepin 2009).

In summary, mixed findings are obtained from studies that examined the effects of medical price on healthcare services. An important limitation of these studies is that they do not distinguish the components of user fees for healthcare services. For example, Lagarde and Palmer (2008) defined user fees as the composite of drug costs, supply and medical material costs, and consultation fees. There is a need to examine the impact of each component on healthcare operations. That is, a fine-grained evaluation of the specific type of user fees on the utilization of healthcare services is needed. In this study, I focus on *outpatient consultation price,* which is levied for outpatient service appointments, and examine the effect of increased outpatient consultation price on the utilization of healthcare services. In addition, although prior studies suggest that medical service price have the potential to improve healthcare quality, empirical evidence is limited. Therefore, I also investigate the impact of a policy change—increasing consultation price on patients' medication adherence, which is an essential element of healthcare resilience.

4.2 Theory and Hypotheses

I investigate the effects of physicians' use of OHCs to build resilience, i.e., improve patients' medication adherence and mitigate the reduction of outpatient visits when the outpatient consultation price is increased. I postulate that physicians' use of OHCs exerts *an amplifying effect* on medication adherence and *an attenuating effect* on the reduction of outpatient visits under the increase of outpatient consultation price. In the following, I develop the hypotheses for these two effects and the heterogeneity of the two effects across physician rank/title. Note that both resilience outcomes—medication adherence and outpatient visits—are offline healthcare services.

4.2.1 Main Effects of Increased Outpatient Consultation Price

I conjecture that one of the manifestations of physicians' resilience is the effect of increasing outpatient consultation price on physicians' medical performance, which is captured by two major indicators of healthcare resilience—patients' medication adherence and physicians' outpatient visits. I posit that increased outpatient consultation price would increase patients' medication adherence. Patients' medication adherence is mainly driven by their perception of the medical service quality (Carter et al. 2021). However, in patients' eyes, it is difficult to judge a physician's medical service quality before finishing the treatment (Chang et al. 2013). Therefore, patients often rely on additional cues to predict a physician's medical service quality, such as the consultation price (Wang et al. 2020b). The extant literature on price-quality inference in the IS and marketing fields suggests that individuals often consider a product with high price of high quality (e.g., Abbey et al. 2015; Lin et al. 2014; Yan and Sengupta 2011). This is because high price is associated with high investments and a reputation for product performance (Cronley et al. 2005; Gardner 1971). In line with such arguments, in the healthcare settings, patients also rely on the physician's consultation price to infer his/her medical service quality. As such, when the outpatient consultation price is increased, patients would perceive the physician to have high medical knowledge and service quality, resulting in a high willingness to follow the physician's medical advice (i.e., increased medication adherence). The number of outpatient consultations per day/week is another important indicator of physician's performance (e.g., Cayirli and Veral 2003; Salzarulo et al. 2011). I postulate that physicians' outpatient visits will reduce after an increase of consultation price. When the price increases, the emerging high price barrier prevents patients with mild symptoms from paying outpatient visits, resulting in a significant reduction of the physicians' outpatient production. Therefore, I hypothesize:

H5*: Increased outpatient consultation price leads to (a) increased medication adherence of patients and (b) reduced outpatient visits for physicians.*

4.2.2 Effects of OHC Use on Physician Performance

An OHC is accessible to physicians and patients anytime and anywhere (Liu et al. 2020b). Unlike non-OHC physicians, OHC physicians can utilize the OHC to demonstrate their healthcare service quality—a positive signal to attract more patients than non-OHC physicians when the outpatient consultation price increases. This is because patients need more information about physicians' service quality to justify their medication adherence and outpatient visit decisions under price increase. The OHC can contribute to physicians' patient acquisition by signaling OHC physicians' service quality via online contents about OHC physicians' profiles and other patients' interactions with the physicians. First, patients can search for information about physicians on the OHC (Gong et al. 2021; Yuan and Deng 2021). Such information can help patients judge whether an OHC physician's expertise is suitable for his/her current health condition and whether the physician is available in outpatient before deciding outpatient visits (e.g., Li et al. 2019b; Maloney-Krichmar and Preece 2005; Wang et al. 2018; Yang et al. 2015). Second, patients can check other patients' interactions with physicians on OHCs, which contain personal and contextual details, such as the other patients' symptoms. Based on similar symptoms, the patients can further check how OHC physicians deal with the progression of symptoms and decide whether to see the physician on outpatient to receive additional offline treatments (Li et al. 2016; Yan et al. 2019). Therefore, OHC physicians can acquire outpatients by revealing their expertise and online interactions with the patients to help the patients judge whether they need offline treatments or examinations. Given these positive impacts of OHCs on patient acquisition, OHC physicians' outpatient visits will be higher than non-OHC physicians after the consultation price increases. That is, physicians' use of OHC can attenuate the negative effect of increased outpatient consultation price on decreased outpatient visits. In addition, if patients decide to visit the OHC physicians, albeit with the high consultation price after checking the OHC physicians' information online, they are likely to generate high trust in the physicians, which, in turn, improves the patients' medication adherence. Therefore, physicians' use of OHC also amplifies the positive effect of increased outpatient consultation price on increased patients' medication adherence. I hypothesize:

H6: *When outpatient consultation price is increased, (a) [the amplifying effect] the increase of medication adherence of patients will be higher for OHC physicians than non-OHC physicians; and (b) [the attenuating effect] the reduction of outpatient visits will be less for OHC physicians than non-OHC physicians.*

4.2.3 Moderating Effects of Physician Title

I further investigate the impact of physicians' official titles on the amplifying effect and the attenuating effect. I argue that a high title of an OHC physician, as the certification of his/her high reputation, enhances the credibility of his/her online signals—i.e., the profile, the expertise sharing, and the interactions with other patients, thus further strengthening medication adherence and mitigating the reduction of outpatient visits. In general, a physician's overall reputation is a reliable signal of his/her service quality (e.g., Bolton et al. 2004; Gao et al. 2015; Ye et al. 2014). Acquiring a high tile is even more difficult for an OHC physician (Guo et al. 2017) because it requires his/her long-term investment of time and effort to provide various high-quality information and medical services both online and offline (e.g., Lin et al. 2018; Liu et al. 2020b). As such, high-title OHC physicians' online signals about their service quality have higher credibility for patients when they make decisions about medication adherence and outpatient visits. Moreover, an OHC physicians' official rank/title increases the comparability across OHC physicians to facilitate patients' choice when online signals are similar. Therefore, I argue that OHC physicians with a high title attain stronger amplifying and attenuating effects because of signal credibility and comparability (Dineen and Allen 2016). Thus, I hypothesize:

H7: *(a) the positive effect of increased outpatient consultation price on medication adherence of patients will be stronger for high-title OHC physicians compared with low-title OHC physicians; (b) the negative effect of increased outpatient consultation price on outpatient visits will be weaker for high-title OHC physicians compared with low-title OHC physicians.*

4.3 Empirical Methodology and Results

4.3.1 Empirical Context and Data

The increase in the outpatient consultation price in 2018 in the focal hospital I collected our data rendered a natural experiment to test our hypotheses. I exploited the change in outpatient consultation price as an exogenous shock that created plausible variations in outpatient consultation behaviors among physicians (OHC and non-OHC ones) and patients. I collected a proprietary outpatient dataset that covers a time window of 104 weeks before and after the change of outpatient consultation price in China.

The Increase in Outpatient Consultation Price

To consult a physician in the hospitals in China, patients need to pay an outpatient consultation fee. The outpatient consultation price is positively related to the physicians' titles. There are three physician titles: a) attending physician; b) associate chief physician; c) chief physician. Chief physician is the most renowned title which is endowed to the most experienced physicians. Consequently, the outpatient consultation price for chief physicians is the highest. Before the change of the outpatient consultation price, it cost 3, 5, and 8 RMB to consult an attending physician, an associate chief physician, and a chief physician, respectively. In early 2018, a policy was issued that increased the outpatient consultation price to enhance the payoff for physicians' professional services. The outpatient consultation price was increased to 15, 20, and 30 RMB for attending physicians, associate chief physicians, and chief physicians, respectively (Table 4.1).[16] The policy took effect on 25 July 2018. I examine the impacts of such a shock on healthcare resilience at the level of individual physicians. I also examine the role of the OHC in such impacts. The haodf.com is adopted as the OHC platform in Study 2.

Table 4.1. Outpatient Consultation Price (Unit: RMB)

	Old Outpatient Consultation Price	New Outpatient Consultation Price
Attending Physician	3	15
Associate Chief Physician	5	20
Chief Physician	8	30

[16] The price of the online consultations on the focal OHC remained unchanged in the time window of the study.

The Outpatient Dataset

I collected the data of physicians' consultation records from Hospital A. The outpatient records are generated from traditional medical consultations where the patients go to Hospital A to consult physicians and receive prescriptions or medical treatments. Similar to Study 1, the data includes outpatient consultations of all physicians (both OHC and non-OHC ones) and their profiles in Hospital A. Specifically, for each offline consultation record, I have the physician's information, the date of the consultation, and the primary diagnoses identified by the International Classification of Diseases, Tenth Revision, Clinical Modification codes (ICD codes hereafter).

4.3.2 Variables

The unit of the analysis is each physician and the time unit is each week (52 weeks pre and after the change of the outpatient consultation price). $OutpatientVisit_{it}$ is the number of patients who seek offline outpatient medical consultations from physician i in week t. For a physician i, his/her patients' medication adherence is operationalized as whether the proportion of complied or executed prescriptions to the total prescriptions is over 95%. The threshold of 95% is widely adopted in the medical studies about medication adherence (e.g., Altice et al. 2019; Mills et al. 2006). The binary variable $Adherence_{it}$ indicates whether the proportion of complied or executed prescriptions to the total prescriptions of physician i in week t is over 95% or not (1 means the proportion is over 95% and 0 means not). The implementation of the change of outpatient consultation price is operationalized as a binary variable $priceChange_i$, with 1 indicating after the change and 0 indicating before the change. The binary variable $OHC\_physician_i$ indicates whether physician i has registered on the OHC or not (1 means physician i is an OHC user and 0 means not).

I employed several physician-level variables as controls, including a physician's

ICD codes, title, educational level, work experience, age, and gender. In line with previous studies (e.g., Anderson et al. 2014; Bartel et al. 2020; Wani et al. 2020), I generated a physician's ICD code vector by considering all the individual consultation cases during the time window of our study. If a physician had one consultation case with a particular 3-digit ICD code, I set this ICD code dummy to 1 and 0 otherwise. In our dataset, there are 211 elements in each ICD code vector. I included this variable to control physician *i*'s medical service demand one year before the price change, denoted as $overallMedicalDemand_i$. Table 4.2 presents the list of variables and measures.

Table 4.2 Variables and Measures	
Outcome Variables	**Measures**
$adherence_{it}$	A binary variable that indicates whether no less than 95% of the prescriptions provided by physician *i* in week *t* have been complied by patients, which takes 1 for yes and 0 for not.
$outpatientVisit_{it}$	The total number of patients who seek medical consultations from physician *i* in week *t*.
Independent Variables	**Measures**
$priceChange_t$	A binary variable that indicates whether the policy on the change of outpatient consultation price takes effect, which takes 1 after the change and 0 before the change.
$OHC\_Physician_i$	A binary variable that indicates whether physician *i* had registered on the OHC, which takes 1 for OHC physicians, and 0 for non-OHC physicians.
Control Variables	**Measures**
$title_i$	The medical title of physician *i* as a categorical variable: "attending physician", "associate chief physician", and "chief physician." [17]
$highTitle_i$	A binary variable that indicates whether the title of physician *i* is above "attending physician", which takes 1 for "associate chief physician" and "chief physician", and 0 for "attending physician."
$overallMedicalDemand_i$	Average weekly offline consultations provided by physician *i* in one year before the change of outpatient consultation price.
$overallExecutedProportion_i$	Average weekly proportion of executed prescriptions to total prescriptions of physician *i*.
$experience_i$	Years of work experience of physician *i* by 2018.
age_i	Age of physician *i* by 2018.

[17] The categorization of $title_i$ is widely adopted in IS and OM researches on Chinese OHC (e.g., Li et al. 2021).

$gender_i$	Gender of physician *i*, 0 for female and 1 for male.
$education_i$	The educational qualification of physician *i*, which takes 1 for physicians with "Clinical Medicine Postgraduate", and 0 for lower qualification.
icd_codes_i	A vector of ICD codes, if the physician *i* has a consultation with a particular ICD code, this ICD code dummy takes 1, and 0 otherwise.
Moderator	**Measures**
$highTitle_i$	A binary variable that indicates whether the title of physician *i* is above "attending physician", which takes 1 for "chief physician", and 0 for "associate chief physician" and "attending physician."

There are 585 physicians in total in the full dataset and 153 of them had registered OHC before the time window of our study. The overview of the panel data is reported in Table 4.3. I list the descriptive statistics in Table 4.4.

Table 4.3 Panel Data Overview

Parameter	**Value**
No. of total physicians	585
No. of weeks	104
Total observations	52,277
No. of OHC physicians	153
Total observations after PSM	27,117

Table 4.4 Descriptive Statistics

Variables	N	Mean	Std. Dev.	Min	Max	P25	Median	P75
$outpatientVisit_{it}$	52,277	38.07	47.81	1.00	591.00	8.00	20.00	49.00
$overallMedicalDemand_i$	585	37.89	45.95	1.40	292.2	9.20	19.24	48.50
$overallMedicalDemand_i$	585	0.88	0.04	0.70	0.98	0.85	0.88	0.91
$experience_i$	585	18.38	13.08	3.00	66.00	8.00	14.00	27.00
age_i	585	43.38	10.55	28.00	86.00	36.00	40.00	49.00
Categorical Variables								
$gender_i$	Female: 50.09%					Male: 49.91%		
$education_i$	Undergraduate: 31.11%					Postgraduate: 68.89%		
$title_i$	Attending physician: 38.46% Associate chief physician: 34.53% Chief physician: 27.01%							
$adherence_{it}$	Below 95%: 71.75%					Over 95%: 28.25%		

4.3.3 Empirical Model and Data Analysis

Main Effect of the Increased Outpatient Consultation Price

The first goal is to examine the baseline impact of increased outpatient consultation price on patients' adherence (H5a) and outpatient visits (H5b), and I adopt the following model to test them.

$$DV_{it} = \beta_1 * priceChange_t + \boldsymbol{\tau X} + \alpha_i + \delta_t + \varepsilon_{it} \quad (6)$$

where *i* is the physician index and *t* is the week index. DV varies depending on the hypothesis test (e.g., $adherence_{it}$ for H1a and $outpatientVisit_{it}$ for H5b). $PriceChange_t$ is the time dummy indicating whether the change in the outpatient consultation price has been implemented. **X** represents a group of control variables for physician heterogeneity, including physicians' title, age, gender, work experience, overall medical service demand, educational qualification, 3-digit ICD code vector, and whether a physician is an OHC physician or not. Finally, α_i captures the physician fixed effects and δ_t captures the time fixed effects. $\widehat{\beta_1}$ is the coefficient of our interest.

Medication Adherence. To test H5a, I regress whether or not over 95% of the prescriptions prescribed by physician *i* have been executed by his patients in week t. Since the dependent variable $adherence_{it}$ is binary, I apply the logistic regression. The regression results are reported in column 2 of Table 4.5. I find that the coefficient of $priceChange_t$ is 0.997 and statistically significant at the 0.01 confidence level. The coefficient implies that after controlling for physician characteristics, overall medical service demand, and expertise, the odds that over 95% of the prescriptions are complied by patients increases 1.71 ($e^{0.997}$ = 2.71) times after the change of outpatient consultation price. The findings provide empirical support for H5a that increased outpatient consultation price leads to increased medication adherence of patients.

Outpatient Visits. To test H5b, I run a linear regression on $outpatientVisit_{it}$, which denotes the number of patients seeking medical consultations from physician *i* in week *t*. From column 2 in Table 4.5, the coefficient of $outpatientVisit_{it}$ is significantly negative, which indicates that on average the number of weekly outpatient visits decreased by 3.259 for each physician after the increase of outpatient consultation price.

Thus, H5b is supported by this empirical result.

Table 4.5 Analysis Results on the Main Effect		
Regression	Logistic	OLS
DV	***$adherence_{it}$***	***$outpatientVisit_{it}$***
Column	(1)	(2)
$priceChange_t$	**0.997***** (0.160)	**-3.259**** (1.511)
Control Variables	Yes	Yes
Physician FE	Yes	Yes
Time FE	Yes	Yes
No. of Physicians	585	585
Observations	49274	52277
Adj. R-Squared	-	0.836
Pseudo R-Squared	0.198	-
Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.		

The Amplifying and Attenuating Effects of OHC

To test the amplifying effect (H6a) and attenuating effect (H6b) of OHC, I employed propensity score matching (PSM) to match OHC physicians (the treatment group) with non-OHC physicians (the control group) before conducting the DID analysis (Guo and Fraser 2014; Liu et al. 2020b). I then ran DID models for patients' medication adherence and outpatient visits, respectively, to analyze the variation of the main effects on patients' medication adherence (H6a) and outpatient visits (H6b) between OHC physicians and non-OHC physicians.

Propensity Score Matching

I applied PSM to match OHC physicians with non-OHC physicians based on a set of observable characteristics. I ran a logit model to evaluate the probability of a physician adopting the OHC. I controlled the following physician-level variables: the physicians' (1) title, (2) age, (3) gender, (4) years of work experience, (5) overall medical service demand before the price change, (6) overall proportion of executed prescriptions to total prescriptions before the price change, (7) educational qualification, and (8) ICD code vector. I then matched the OHC physicians with non-OHC physicians using the one-one nearest neighbor matching method (Guo and Fraser 2014; Pamuru et al. 2021). After matching, there are 153 OHC physicians and 153 non-OHC physicians in our sample. The result of the regression is reported in Table 4.6.

Table 4.6 Logistic Regression Result for PSM	
DV	***OHC_physician$_i$***
title$_i$	0.510*** (0.191)
gender$_i$	0.161(0.203)
age$_i$	-0.109**(0.047)
experience$_i$	0.046 (0.037)
overallMedicalDemand$_i$	0.0002 (0.002)
overallExecutedProportion$_i$	-4.048*(2.274)
education$_i$	0.395(0.283)
icd_codes$_i$	Yes
constant	4.092 (2.641)
Pseudo R^2	0.051
No. of Observations	585
Note: *** $p < 0.01$, ** $p < 0.5$, * $p < 0.1$	

The descriptive statistics of all the variables after the PSM are reported in Table 4.7.

Table 4.7 Descriptive Statistics after PSM								
Variable	N	Mean	Std. Dev.	Min	Max	P25	Median	P75
outpatientVisit$_{it}$	27,117	36.96	49.38	1.00	421.00	7.00	18.00	46.00
overallMedicalDemand$_i$	306	36.18	46.87	2.00	292.2	8.37	17.26	45.42
overallExecutedProportion$_i$	306	0.87	0.04	0.73	0.97	0.85	0.88	0.90
experience$_i$	306	16.15	10.29	3.00	59.00	8.00	13.00	21.00
age$_i$	306	41.45	8.19	31.00	81.00	35.00	39.00	46.00
Categorical Variable								
gender$_i$	Female: 46.08%				Male: 53.92%			
education$_i$	Undergraduate: 20.92%				Postgraduate: 79.08%			
title$_i$	Attending physician: 37.91% Associate chief physician: 34.31% Chief physician: 27.78%							
adherence$_{it}$	Below 95%: 72.87%			Over 95%: 27.13%				

To verify the validity of the matching, I applied paired *t*-tests to compare the seven matching variables between the treatment group and the control group before and after matching. The results indicate no significant differences in these variables between the treatment group and the control group. Table 4.8 reports the summary statistics of the comparisons.

Table 4.8 Comparisons of Matching Variables Before and After PSM				
Variable		***Mean***		*t-value*
		Treatment (OHC Physicians)	*Control (Non-OHC Physicians)*	
age_i	Before	41.68	43.98	-2.33
	After	41.68	41.22	0.49
$gender_i$	Before	1.53	1.49	0.87
	After	1.53	1.55	-0.34
$experience_i$	Before	16.50	19.06	-2.08
	After	16.50	15.79	0.60
$overallMedicalDemand_i$	Before	35.13	38.87	-0.87
	After	35.13	37.24	-0.39
$overallExecutedProportion_i$	Before	0.87	0.88	-1.90
	After	0.87	0.87	-0.01
$education_i$	Before	0.78	0.66	2.78
	After	0.78	0.80	-0.56
icd_codes_i	Before	Yes	Yes	All insignificant
	After	Yes	Yes	All insignificant
$title_i$	Before	Yes	Yes	All insignificant
	After	Yes	Yes	All insignificant
Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$				

Differences in Differences Analysis

To test the variation of the main effect on patients' medication adherence (H6a) and outpatient visits (H6b) between OHC physicians and non-OHC physicians, I employed the following DID model after PSM:

$$DV_{it} = \beta_1 * OHC\_physician_i * priceChange_t + \beta_2 * OHC\_physician_i + \beta_3 * priceChange_t + \boldsymbol{\tau X} + \alpha_i + \delta_t + \varepsilon_{it} \quad (7)$$

where i is the physician index and t is the week index. DV varies depending on the hypotheses I test (e.g., $adherence_{it}$ for H6a and $outpatientVisit_{it}$ for H6b). $OHC\_physician_i$ is the binary variable indicating whether physician i has registered OHC before the time window of our study. $PriceChange_t$ is the time dummy to measure whether the change of outpatient consultation price has been implemented. **X** represents a group of control variables for physicians' heterogeneity, including title, age, gender, work experience, the overall medical service demand, educational qualification, and the 3-digit ICD code vector. Finally, α_i captures the physician fixed effects, and δ_t captures the time fixed effects.

The coefficient of $OHC\_physician_i*priceChange_t$ (i.e., $\widehat{\beta_1}$) is of interest because it is the estimate of the difference in the dependent variables (DVs) between OHC and non-OHC physicians after the increase of outpatient consultation price. Therefore, $\widehat{\beta_1}$ captures the amplifying effect (attenuating effect) of OHC usage in the main effect of the consultation price change on physicians' healthcare outcome (i.e., medication adherence and outpatient visits). The results of the DID regressions are reported in Table 4.9.

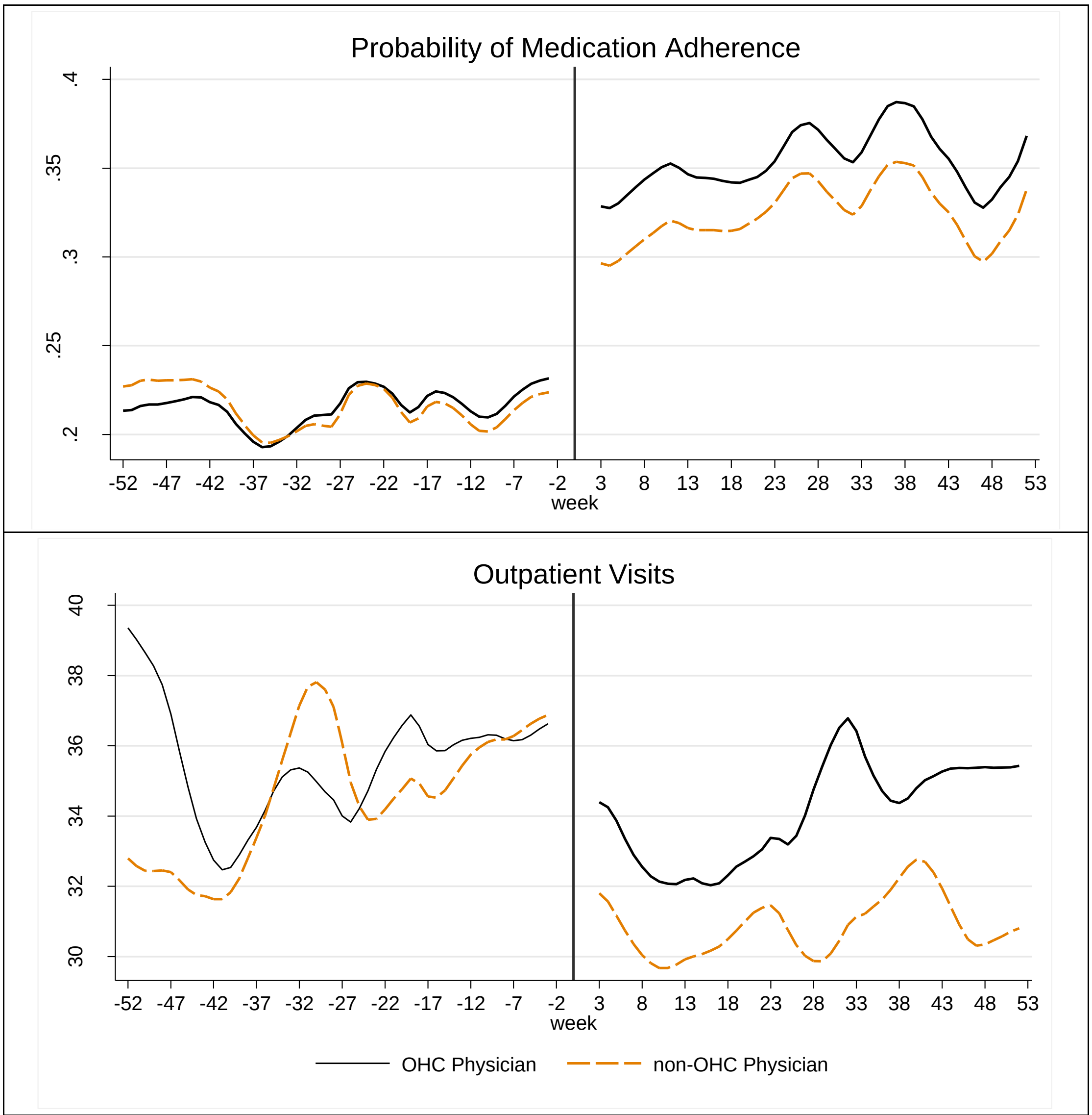

Figure 4.1 OHC and non-OHC Physicians' Medication Adherence and Outpatient Visits

Medication Adherence. To test H6a, I run regression model 7 on $adherence_{it}$. Since the dependent variable $adherence_{it}$ is binary, I apply the logistic regression. The results are provided in column 1 of Table 4.9. $\widehat{\beta_1}$ is 0.240 at the significant level of

0.01. This significantly positive $\widehat{\beta_1}$ implies that the odds of over 95% of the physician's prescriptions complied by patients increases 27.10% ($e^{0.240} = 1.271$) for OHC physicians compared to non-OHC physicians after the change of outpatient consultation price. This result provides empirical support for the H2a that the medical adherence of OHC physicians is higher than that of non-OHC physicians after the increase of outpatient consultation price.

Outpatient Visits. To test H6b, I run the regression model 7 on $outpatientVisit_{it}$. The results are reported in column 2 of Table 4.9. $\widehat{\beta_1}$ is 2.415 and significant at the confidence level of 0.01. This result indicates that on average the OHC physicians have 2.415 more medical consultation visits every week than non-OHC physicians after the change of consultation price. Although the increase of outpatient consultation price reduces the outpatient visits, the decrease in the outpatient visits of OHC physicians is smaller than that of non-OHC physicians. Thus, H6b is also supported by our empirical result.

Table 4.9 Analysis Results on the DID Model

Regression	Logistic	OLS
DV	***$adherence_{it}$***	***$outpatientVisit_{it}$***
Column	(1)	(2)
$priceChange_t \times OHC\_Physician_i$	**0.240*** (0.065)**	**2.415*** (0.480)**
$OHC\_Physician_i$	0.815** (0.396)	12.060*** (3.468)
$priceChange_t$	1.050*** (0.227)	-3.766* (2.133)
Control Variables	Yes	Yes
Physician FE	Yes	Yes
Time FE	Yes	Yes
No. of Physicians	306	306
Observations	26,048	27,117
Adj. R-Squared	-	0.849
Pseudo R-Squared	0.191	-

Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Validation Tests for DID Analysis

This section reports the results of robustness checks to validate our findings in the DID analysis. First, I ensure that the parallel-trend assumption is satisfied for our DVs. That is, before the change of the outpatient consultation price, the medication adherence and number of outpatient visits of both the OHC and non-OHC physicians followed similar trends. I 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; Pamuru et al. 2021). The results show no pre-treatment differences in the DVs of OHC physicians and non-OHC physicians, which supports our parallel-trend assumption. Table 4.10 reports the results from two different unit root tests. ADF test statistics reject the null hypothesis with both total consultations and offline consultations being the DVs, showing that the DVs between the two groups are stationary. I find similar results using the KPSS test. The KPSS test statistics cannot reject the null hypothesis (i.e., the time series was stationary), which supports the parallel-trend assumption.

Table 4.10 Results of ADF Test and KPSS Test of Stationary

	ADF Test	**KPSS Test**
$adherence_{it}$	-7.581^{***}	0.341
$outpatientVisit_{it}$	-6.344^{***}	0.053

Second, I performed a falsification test to further validate the robustness of our findings. In particular, I create a placebo event before the price increase (Week -25). The results show that the placebo event has no significant effects on the DVs (Table 4.11).

Table 4.11 Falsification Test: Placebo Analysis

Placebo Event	***Week -26***	
Regression	Logistic	OLS
DV	$\boldsymbol{adherence_{it}}$	$\boldsymbol{outpatientVisit_{it}}$
Column	(1)	(2)
$\boldsymbol{priceChange_t \times OHC\_Physician_i}$	**0.197** **(0.121)**	**0.652** **(0.682)**
Control Variables	Yes	Yes
Physician FE	Yes	Yes
Time FE	Yes	Yes
No. of Physicians	306	306
Observations	11,659	13,184
Adj. R-Squared	-	0.872
Pseudo R-Squared	0.179	-
Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.		

Analysis of Moderation Effect of Physicians' Title

In the above analysis, I find a significant difference in the medication adherence and outpatient visits for OHC physicians and non-OHC physicians after increasing the outpatient consultation price. To further examine how the difference is moderated by physicians' title (i.e., H7a and H7b), I adopt the following DDD model:

$$\begin{aligned} DV_{it} = {} & \beta_1 * highTitle_i * OHC\_physician_i * priceChange_t + \beta_2 \\ & * highTitle_i * OHC\_physician_i + \beta_3 * highTitle_i \\ & * priceChange_t + \ \beta_4 * OHC\_physician_i * priceChange_t \\ & + \gamma_1 * highTitle_i + \gamma_2 * OHC\_physician_i + \gamma_3 \\ & * priceChange_t + \boldsymbol{\tau X} + \alpha_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{8}$$

where DV varies depending on the hypotheses I test (e.g., $adherence_{it}$ for H7a and $outpatientVisit_{it}$ for H7b). Recall that $highTitle_i$ is a binary variable that takes the value of 1 for "associate chief physician" or "chief physician" and 0 for "attending physician." The coefficient β_1 is of our interest.

Medication Adherence. To test H7a, I ran model 83 on $adherence_{it}$. Since the dependent variable $adherence_{it}$ is binary, I apply the logit model. The results provided in column 1 on Table 4.12 shows that $\widehat{\beta_1}$ is 0.495 at the significant level of 0.01. This significantly positive coefficient implies that the odds of over 95% of the physician's prescriptions adhered by patients increases 64% ($e^{0.495}$=1.640) for OHC physicians with a high title vs. a low title after the change of outpatient consultation price. Thus, H7a is supported by this empirical result.

Outpatient Visits. To test H7b, I run the model 8 on $outpatientVisit_{it}$. The regression result shows that the coefficient $\widehat{\beta_1}$ is not significant, indicating that physicians' title has no significant effect on the outpatient visits for OHC physicians after the change of outpatient consultation price (column 2 of Table 4.12). Therefore, H7b is not supported by the empirical results. Our DID analysis (model 7) shows that the decrease of outpatient visits of OHC physicians is less than that of non-OHC physicians after the change of outpatient consultation price. The DDD result further demonstrates that this difference in outpatient visits of OHC and non-OHC physicians does not vary by their titles. In other words, the attenuating effect of OHC on outpatient visits is distributed evenly across physicians of all titles.

Table 4.12 Analysis Results on the DDD Model		
Regression	Logistic	OLS
DV	***$adherence_{it}$***	***$outpatientVisit_{it}$***
Column	(1)	(2)
$highTitle_i \times priceChange_t \times OHC\_Physician_i$	**0.495*** (0.154)**	**-0.922 (1.034)**
$priceChange_t \times OHC\_Physician_i$	0.113 (0.074)	2.889*** (0.569)
$OHC\_Physician_i \times highTitle_i$	-4.539*** (1.601)	205.674*** (32.635)
$priceChange_t \times highTitle_i$	-0.153 (0.114)	-1.155 (0.762)
$priceChange_t$	1.079*** (0.229)	-3.474 (2.134)
$OHC\_Physician_i$	0.540 (0.334)	11.734*** (3.462)
$highTitle_i$	4.502** (2.253)	-304.220*** (56.192)
Control Variables	Yes	Yes
Physician FE	Yes	Yes
Time FE	Yes	Yes
No. of Physicians	306	306
Observations	26,048	27,117
Adj. R-Squared	-	0.849
Pseudo R-Squared	0.192	-
Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.		

4.4 Discussion of Study 2

OHCs have been widely adopted by physicians to improve their healthcare resilience. Study 2 focuses on the joint effects of OHC use and digital resilience under internal shocks on two key healthcare performance outcomes—medication adherence and outpatient visits. I synthesize the literature and identify two effects of physicians' use of social technology: 1) amplifying the positive impact of increased outpatient consultation price on medication adherence, and 2) attenuating the negative impact of increased outpatient consultation price on outpatient visits. I construct a proprietary dataset that matches online and offline data sources. I run a difference-in-differences (DID) analysis to test these effects. Moreover, I analyze the moderating role of physician title on the amplifying and attenuating effects using a DDD analysis.

Study 2 offers an assessment of the influence of increased medical consultation price on healthcare resilience outcomes—i.e., outpatient visits and medication adherence. Existing studies focus on the total price of a composite of healthcare services such as consultation fees, drug costs, and material costs. Mixed findings have been obtained on the effect of the total price on healthcare service utilization. I provide an in-depth investigation of the effect of each specific component of the total price is needed. In this work, I focus on the effect of increased outpatient consultation price on the utilization of healthcare services. The results indicate that increased outpatient consultation price decreases outpatient demand and improves healthcare quality by making patients adhere more to prescriptions. Overall, I find an improvement in healthcare resilience in the research context when healthcare entities face internal shocks.

CHAPTER 5. STUDY 3: DIGITAL RESILIENCE AND PATIENT TRUST

Study 1 and Study 2 mainly focus on resistance and recovery of physicians' digital resilience under the contexts of external and internal shocks. As such, another scenario of building resilience—when shocks haven't occurred (i.e., at a normal age), needs further investigation in this thesis. Therefore, to enhance the understanding of digital resilience, Study 3 focuses on the digital resilience at the normal age (i.e., no shocks involved). Specifically, I use patients' trust in physicians to study physicians' digital resilience. This is because trust is vital in the healthcare settings and building high trust between patients and physicians can help physicians prevent loss of production when facing unexpected shocks (Goh et al. 2016). As such, the trust between physicians and patients can be an indicator when examining physicians' digital resilience. Yet, initial trust is difficult to build because patients are unfamiliar with physicians before visit the physicians. Patients may have concerns about the physicians' expertise or attitude (Ding et al. 2020). In offline contexts, to facilitate building patients' trust, healthcare entities often display the physician information in the frontend of the outpatient department. Given the information display function of OHCs, the first objective of Study 3 is to investigate whether OHCs can affect patients' trust building compared with the traditional offline information board.

Another difficulty in building trust between patients and physicians is that trust involves different dimensions, i.e., competence, benevolence, and integrity. Previous literature has suggested that different dimensions of trust need different information to increase (McKnight et al. 2002). Therefore, the second objective of this study is to examine how OHCs increase different dimensions of trust between patients and physicians.

Furthermore, on top of building initial trust, I investigate after visiting the physicians, how patients' trust changes given different information sources (i.e., offline information boards vs. OHCs) before patients visit the physicians. Applying the anchoring effect, I postulate that before visiting the physicians, using OHCs can build higher trust in the physicians than that when patients read offline information boards. However, after visiting the physicians, patients' trust will be increased only for the patients who read offline information boards.

To empirically test the theorization, I conducted two laboratory experiments in China. The empirical results support the proposed effects of OHCs on patients' trust in the physicians.

5.1 Theoretical Background and Conceptual Extension

5.1.1 Patient Trust

Patients' trust in physicians is an essential component of the physician-patient relationship. High trust between physicians and patients can prevent physician-patient conflicts—a typical type of negative event in the healthcare settings. The relationship with a low trust level would be characterized by more patient requests for diagnostic tests, referrals, or additional medical information, which may be a way of verifying their physicians' competency and commitment (Thom et al. 2002). Patients with a low trust level are also less likely to report detailed symptoms to physicians and follow the physicians' advice. In turn, the requests induced by low trust levels may be more likely to be denied by physicians if they are seen as motivated by a lack of confidence rather than a legitimate medical concern (Thom et al. 2002). As a result, patient trust has a significant extrinsic value because it has been linked to patient satisfaction, adherence to treatment, continuity of care with the same physician, and improved health (Fiscella et al. 2004). Thus, improving patient trust at a high level is pivotal for guaranteeing a smooth and effective office visit.

Patient trust generally includes three dimensions: perceived integrity, competence, and benevolence. It can be enhanced when physicians try to understand patients' experiences, communicate clearly and thoroughly, build partnerships, obtain referrals, and share power. Besides being affected by the above physician behaviors, patient trust is more significant when patients are allowed to select the physician of their choice (Balkrishnan et al. 2003). The information assisting patients in better realizing and choosing the physicians is essential for enhancing patient trust.

Patients' trust in physicians is affected by many physician characteristics, such as physician empathy (Wu et al. 2022), and some patient demographic characteristics, such as age, education level, annual income, and health insurance coverage (Zhao et al. 2016), and patient self-disclosure (Liu et al. 2022a). The most crucial reason for impeding patient trust is the information asymmetry between patients and physicians, which is a natural property of the physician-patient relationship (Zhao et al. 2016). With society and technology developing, health information has become widely available to the public through various sources, such as the online health community, social media platforms, traditional newspapers, and offline information boards (Liu and Jiang 2019). Many studies continuously explore how to provide which kinds of physician information to patients to enhance patient trust. The existing studies have found that patient trust can be improved if patients can read physicians' notes (Delbanco et al. 2012). The way physicians' information is conveyed to patients can be summarized into three types: seeking, discussing, and scanning (Liu and Jiang 2019). Obtaining sufficient physician information directly improves patient trust.

This study focuses on the three dimensions of patient trust and explores how physician information disclosed by OHC and offline information board affects patients' perceived integrity, competence, and benevolence before and after visiting the physicians.

5.1.2 Online and Offline Physician Information

Providing timely physician information is an excellent way to increase patient trust. The traditional physician information is disclosed on the offline information board at the hospital. In some hospitals, simple physician descriptions have been provided at the office door. Without any aforehand information, patients realize the physicians from the information board outside the consultation room. The limited information board includes the physician’s name, title, photo, area of expertise, and simple introduction. In the limited space of the offline information board, only some professionally-related physician information is presented in the offline information board.

As technology develops, the digitization of the information board enables physicians to put any information, such as the traditional test descriptions and the modern QR code. This physician information helps patients realize their physicians once again. Compared with an offline information board, OHC provides sufficient physician information for patients, thus assisting patients in more comprehensively learning physicians.

5.1.3 Anchoring effect

As a well-known decision bias, the anchoring effect refers to the initial irrelevant number (anchor) that can impact late estimation (Kuo et al. 2021). The anchoring effect can be explained as people starting from the anchor and stopping incremental adjustment too early. Anchoring and adjustment are one of the heuristics described by the study of Tversky and Kahneman (1974).

The anchoring process is initiated by asking participants to compare the anchor value to the targeted value. A high or low anchor was provided to two groups of subjects, respectively, and served as the foundation of their comparison. Then, participants conduct an adjustment process to produce the final estimation. Generally, the estimates made by participants in the high anchor group are higher than those in the low anchor group (Wu et al. 2012).

This study regards the perceived trust after the visit as the targeted value and hopes to provide adequate physician information to increase patient trust before the visit. The patients can read the physician information disclosed by OHC or offline board, regarded as the anchors.

5.2 Theory and Hypotheses

Most anchoring studies design two-stage experiments to have a comparative judgment (Wu et al. 2008). The patient can have a precise trust level for the physicians after going through the whole visiting process, so this study regards the patient trust after the visit as the targeted value. Before the visit, I provide physician information disclosed on OHC and offline board for patients and ask them to estimate their trust level in the physicians. This study also suggests and validates an alternative experimental design where no comparison process is needed to induce anchoring bias.

5.2.1 Patient Trust without Aforehand Information

According to the Commitment Trust Theory, patient trust in physicians is built and developed through physician-patient communications (Zhang and Liu 2021). Without any aforehand information, patients have little knowledge about physicians and do not wholly trust physicians. Therefore, if the patients have no pathways to read any physician's statement, they would have a low trust level in the physicians. Only after the patients visit the physician and experience a whole consultation process their trust in physicians is developed. In most cases, physicians help patients solve various problems during the visit, and patients would appreciate and trust physicians. Therefore, patient trust in the physician can be formed after the visit, and I hypothesize:

H8*: After visiting the physician, the patients' (1) perceived integrity (H8a), (2) perceived competence (H8b), and (3) perceived benevolence (H8c), will increase when patients did not read physician information disclosed on OHC or offline board before visiting the physician.*

5.2.2 Anchoring Effect of Physician Information Disclosed on OHC

The aforehand information exchange assists patients in realizing physicians before the visit. Participants can conveniently share information, experience, and feelings on health-related topics in OHC (Liu et al. 2022b). In addition to patients, physicians also contribute and provide detailed information in OHC (Yang et al. 2021). The sufficient physician information presented in OHC assists patients in realizing physicians before visiting a consultation. Physician information in OHC can cover various aspects. There is no doubt that patients can recognize physicians' professional levels from information disclosed on OHC, such as physician titles, self-introduction, and historical evaluations. Many physicians may post some healthy tips in OHC (Liu et al. 2020a), and patients can share their gratitude or send gifts to physicians (Wu et al. 2020), so the patients would increase perceived benevolence in the physicians. The mature Internet enables us to disclose unethical physician behaviors timely. If the patients cannot observe negative physician behaviors, they quickly increase the perceived integrity of physicians. Based on the above analysis, it can be seen that physician information disclosed on OHC has anchoring effects on patients' perceived integrity, perceived competence, and benevolence of the physicians. As OHC information is rich and comprehensive, patients hardly obtain extra physician information from a transitory consultation. Therefore, I hypothesize:

H9*: Before visiting the physician, physician information disclosed on OHC will: (1) increase the patients' perceived integrity (H9a), (2) increase the patients' perceived competence (H9b), and (3) increase the patients' perceived benevolence (H9c) on the physician.*

H10: *After visiting the physician, the patients' (1) perceived integrity (H10a), (2) perceived competence (H10b), and (3) perceived benevolence (H10c), will not increase when the patients read physician information disclosed on OHC before visiting the physician.*

5.2.3 Anchoring Effect of Physician Information Disclosed on Offline Broad

Unlike OHC, the offline board generally has limited space to present physician information (Guo et al. 2016). Patients typically realize simple physician names, photos, titles, and specialties from the offline board. From the simple information, patients increase perceived competence to certain degrees. As the offline board cannot provide extra behavioral details on physicians, patients cannot increase perceived integrity and benevolence from the offline board. From the simple physician information, patients may know that the physician is an expert in the area but still have little knowledge about his past successful experience. After experiencing a successful visit, the patients would further increase the perceived integrity and benevolence of the physicians. Therefore, I hypothesize:

H11: *Before visiting the physician, physician information disclosed on the offline board will: (1) not increase the patients' perceived integrity (H11a), (2) increase the patients' perceived competence (H11b), and (3) not increase the patients' perceived benevolence (H11c) in the physician.*

H12: *After visiting the physician, the patients' (1) perceived integrity (H12a) and (2) perceived benevolence (H12c) will, (3) but their perceived competence (H12b) will not increase when the patients read physician information disclosed on offline board before visiting the physician.*

5.3 Empirical Methodology and Results

To test the hypothesis, I conducted two experiments in Hospital A. Experiment 1 examines the effects of different information disclosing channels (OHC vs. information board) on the three trust dimensions (integrity, competence and benevolence) of the patient's trust before visiting the physicians. Experiment 2 examines how the effects of different information disclosing on patients' trust differ before and after visiting the physicians.

Manipulations of Information Disclosed Channels

Offline Information Board

The hospitals in China usually provide an information board that contains the basic information of the physicians in each department, such as the physician's name, specialty and title. The placement of the information board is often set in the most obvious position at the entrance of the hospital. The purpose of the information board is to facilitate the patients to get familiar with the physicians and choose a suitable physician for outpatient consultation. Figure 5.1 is an example of the information board in Hospital A. From the information board, patients can quickly observe the physicians' specialty and title.

Figure 5.1 Offline Information Board

Online Healthcare Communities (OHCs): Online Channel

The empirical context for the online information showcase channel in Study 3 is also the OHC platform of haodf.com. The platform maintains a personal homepage for each registered physician. On the personal homepage, there is plenty of useful information such as the physicians' online reputation, specialty, title, educational background, and historical online consultations.

Experiment 1

I employed an experiment with three groups of patients to test H9 and H11. The three groups include two treatment groups (Groups 1 and 2) and a control group (Group 3). The participants in the two treatment groups received the physicians' information through two different disclosed channels (OHC vs. information board) before visiting the physicians. The participants in the control group did not receive any physicians' information. Table 5.1 shows the experimental design of Experiment 1.

Table 5.1 Experimental Design of Experiment 1

Groups	Information Disclosed Channel
Group 1 (n = 25)	The participants read the physicians' information from the physicians' personal webpage of haodf.com.
Group 2 (n = 25)	The participants read the physicians' information board which is released by the hospital.
Group 3 (n = 25)	The participants do not read the physicians' information either from OHC or information board.

Experimental Participants, Task, and Procedure

Experiment 1 was conducted in two outpatient departments with the highest number of outpatient visits amount in Hospital A (i.e., otorhinolaryngology department and dermatology department). In the waiting room of the two departments, I recruited 48 participants, with 30 males and 15 females. These participants made an appointment with a physician for the outpatient consultation in one of the two departments. I only choose the patients who did not consult the physician before so that the readmission patients were excluded from our experiment. The ages of the participants ranged from 16 to 62 years old.

In the waiting room of the otorhinolaryngology department and dermatology department, I invited the patients who were waiting for the outpatient consultation. I briefly oriented them regarding the purpose and the procedure of the experiment. The participants first finish a background questionnaire and randomly being assigned to Group 1, 2 or 3.

Different sources of information were applied for participants in Groups 1 and 2. For Group 1, the participants were asked to surf the appointed physicians’ OHC homepage from haodf.com. For Group 2, I displayed the appointed physician’s information same as the hospital information board. For Group 3, I did not show any physicians’ information. Then, participants were asked to complete a questionnaire for the main and control variables. The entire experimental session lasted for approximately half an hour. The participants received RMB5 as compensation for their participation. The procedure of the Experiment 1 is shown in Figure 5.2 below.

For Group 1, the haodf.com website was displayed on an iPad and the participants were asked to search for the appointed physician. The participants were then asked to browse the webpage of their appointed physician. After the participants completed the surfing, they answered a questionnaire about the main variables. For Group 2, I printed a hardcopy for each physician of the two focal departments based on the information board. I showed the appointed physician’s information card to the participants and asked the participants to read the information card. The information on the card is the same as that shown on the offline information board of Hospital A. after reading the card, the participants were asked to answer the questionnaire about the main variables. For Group 3, I did not show any information to them. Participants in Group 3 were directly asked to answer the questionnaire.

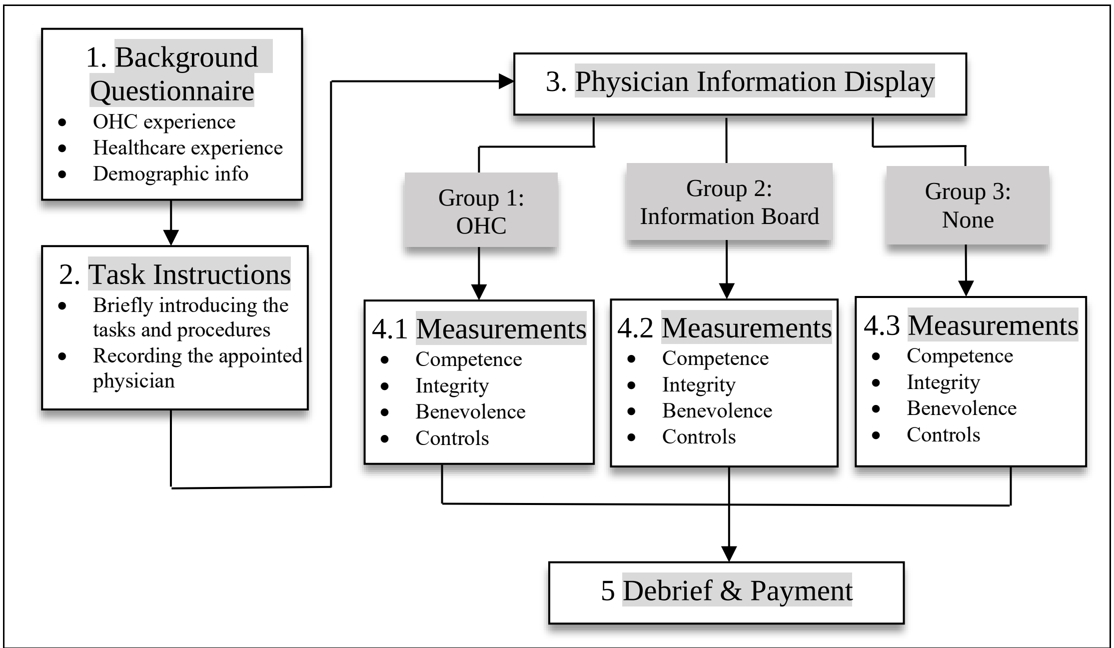

Figure 5.2 Flow of Experiment 1

<u>Measurements</u>

The dependent variables (DVs) include three trusting dimensions, competence, benevolence, and integrity. I also measure patients' perceived severity of the disease and their perceived reputation of Hospital A as controls. The measurement items are presented in Table 5.2.

Table 5.2 Measurement Items

Variables	Items	Sources
Dependent Variables		
Perceived Integrity	• This physician is truthful in his/her medical service. • I would characterize this physician as honest. • This physician would keep his/her commitments.	McKinght et.al. (2002)
Perceived Competence	• This physician is competent and effective in healthcare. • This physician performs his/her role of doctor very well. • Overall, this physician is a capable and proficient doctor. • In general, this physician is very knowledgeable about healthcare. • This physician has the skills and expertise in healthcare.	
Perceived Benevolence	• This physician is likely to be concerned about patients' welfare. • If patients require help, this physician is likely to do his/her best to help him/her. • This physician is interested in patients' well-being, not just his/her own.	
Controls		
Perceived Severity of the Disease	• I think my illness is serious. • My illness has a great impact on my life. • My illness has strongly influenced others' views on me. • My illness brings difficulties to the people around me.	Venkatesh et.al. (2016)
Perceived Reputation of Hospital A	• Hospital A has a good reputation. • Hospital A is reputable. • Hospital A has a good reputation in terms of diagnostic accuracy. • Hospital A has a good reputation in terms of service attitude. • Hospital A has a good reputation in terms of treatment effects.	

Results of Experiment 1

Table 5.3 reports the descriptive results of Experiment 1.

Table 5.3 Descriptive Results of Experiment 1

Variables	Group		
	1	2	3
Perceived Integrity	6.16 (1.11)	5.64 (1.31)	5.29 (1.24)
Perceived Competence	5.85 (1.14)	5.73 (1.19)	5.08 (1.16)
Perceived Benevolence	5.98 (1.14)	5.59 (1.17)	5.16 (1.07)
Perceived Severity of the Disease	2.44 (1.55)	2.67 (1.74)	3.17 (1.59)
Perceived Reputation of Hospital A	5.39 (1.59)	5.55 (1.17)	5.52 (1.41)

I first conducted a multiple analysis of covariance (MANCOVA) to check the overall effects of physician information disclosed channel on the participants' perceived integrity, competence, and benevolence of the physicians (two control variables were included). The significant main effect of the physician information disclosed channel (Wilks' $\lambda = 0.55$, $F = 18.87$, $p < 0.001$) is observed.

Then, I conducted three ANCOVAs to test the effects of the physician information disclosed channel with the following three trusting beliefs as DVs: integrity (H9a and H11a), competence (H9a and H11a), and benevolence (H9a and H11a). The results show that compared with no information shown before visiting the physicians, viewing physician information via OHC significantly increased participants' perceived integrity (M = 6.16 vs. 5.29, $p = 0.014$), perceived competence (M = 5.85 vs. 5.08, $p = 0.012$), and perceived benevolence (M = 5.98 vs. 5.16, $p = 0.023$). By contrast, viewing physician information via an offline information board only increased participants' perceived competence (M = 5.73 vs. 5.08, $p = 0.050$), but not perceived integrity (M = 5.64 vs. 5.29, $p = 0.319$) or perceived benevolence (M = 5.59 vs. 5.16, $p = 0.180$). Thus, H9 and H11 are supported.

Experiment 2

I employed Experiment 2 with 3 groups of patients to test H8, H10, and H12. Similar to Experiment 1, the participants in the treatment groups received the appointed physicians' information through two different disclosed channels (OHC vs. information board) before visiting the physicians. The participants in the control group did not receive any physicians' information. In Experiment 2, after visiting the physicians, all the participants were asked to answer again the questionnaire of the main variables (i.e., a repeated-measure approach). Each group contained 25 participants.

Similar to the Experiment 1, Experiment 2 was also conducted in the otorhinolaryngology department and dermatology department. Among the 75 participants, 36 are males and 39 were females. The ages of the participants ranged from 15 to 69 years.

<u>Results of Experiment 2</u>

Table 5.4 reports the descriptive results of Experiment 2.

Table 5.4 Descriptive Results of Experiment 2

Variables	**Time Period**	**Group**		
		1 (H10)	**2 (H12)**	**3 (H8)**
Perceived Integrity	Before visiting	5.99 (1.15)	5.53 (1.23)	5.31 (1.15)
	After visiting	6.12 (0.95)	6.03 (0.88)	6.15 (1.06)
Perceived Competence	Before visiting	6.04 (0.98)	5.52 (1.12)	5.18 (1.04)
	After visiting	5.99 (1.00)	5.81 (0.73)	5.70 (1.00)
Perceived Benevolence	Before visiting	5.99 (1.06)	5.42 (1.20)	5.10 (1.22)
	After visiting	5.83 (1.10)	5.56 (0.93)	5.71 (1.06)
Perceived Severity of the Disease		2.289 (2.25)	2.62 (1.60)	3.00 (1.70)
Perceived Reputation of Hospital A		5.93 (1.07)	5.76 (1.13)	5.75 (1.10)

To test H8 (i.e., trust changes before vs. after visiting the physicians without reading any physician information), I conducted repeated-measured ANCOVAs with the three trusting beliefs as DVs: integrity (H8a), competence (H8b), and benevolence (H8c). The results show that after visiting the physician, the patients' perceived integrity, competence, and benevolence were all increased all $p < 0.05$). Thus, H8 is supported.

Regarding H10 (i.e., trust changes before vs. after visiting the physicians when reading physician information via OHC), I found that as expected, patients' perceived competence and benevolence were not increased (both $p > 0.05$), while their perceived integrity was further increased (p = 0.088, marginally significant). Overall, H10 is largely supported.

In terms of H12 ((i.e., trust changes before vs. after visiting the physicians when reading physician information via an offline information board), a similar analysis was conducted. The results show that patients' perceived integrity and benevolence were increased (both $p < 0.05$), while their perceived competence remained unchanged (p = 0.138). Therefore, H12 is supported.

5.4 Discussion of Study 3

On top of Studies 1 and 2, Study 3 extends the investigation of digital resilience by focusing on the normal age (no shocks involved). I synthesize the literature and identify patients' trust in the physicians to study resilience in this scenario. Two experiments were conducted and the results reveal that before visiting the physicians, the physician information disclosed on OHCs can successfully build patients' initial trust (all trust dimensions) in the physicians, while such information disclosed by the offline board only helps patients recognize the physicians' competence. Yet, after visiting the physicians, patients' trust in the physicians generally increases even though patients do not receive any information about the physicians.

CHAPTER 6. CONTRIBUTIONS, LIMITATIONS AND FUTURE WORKS

6.1 Contributions

6.1.1 Theoretical Contributions

This thesis identifies three research questions, namely, in the healthcare settings, the structure of digital resilience and the specific external and internal shocks that healthcare entities face in developing digital resilience and the heterogeneous factors that may influence digital resilience. Through three studies, this thesis intends to solve these three research questions. By addressing these research gaps, this thesis enriches the existing knowledge on healthcare management by investigating the digital resilience from the perspectives of information systems usage (i.e., OHCs).

This thesis offers several contributions to IS research on digital resilience. First, this thesis provides empirical support for the digital resilience of physicians who adopt an OHC. Through three studies, I identify different forms of digital resilience after an external shock (i.e., the resistance effect and the recovery effect), after an internal shock (i.e., the amplifying effect and the attenuating effect), and in normal age (i.e., patients' trust in the physicians). I estimate the magnitude of these effects using a mix-method approach—unique dataset matching online and offline data sources as well as laboratory experiments. As such, this thesis achieves quantitative rigor through the different research designs. While there is emerging research on digital resilience 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 my knowledge, this thesis is among the first to provide in-depth empirical evidence demonstrating both the existence and the sources of different dimensions of digital resilience in the healthcare sector.

Second, this thesis examines digital resilience in different contexts when facing unpredictable shocks. Existing studies have been primarily conducted in contexts where digital technologies built resilience to predictable disruptions, such as supply chain disruptions (Bakshi and Kleindorfer 2009) and data theft (Kwon and Johnson 2014). In such cases, digital technologies increase resilience by reducing the probability of the reoccurrence of disruptions. The research context in this thesis differs from the existing literature in that the healthcare system was disrupted by unpredictable and unprecedented shocks, e.g., the outbreak of the COVID-19 pandemic or pricing policy change. Whether or not IT artifacts (the OHC in our case) can build digital resilience after such shocks has not been addressed in depth in the literature. Moreover, prior research has mainly examined the overall resilient effect of digital technologies with data aggregated across different time periods after a shock, thus offering a limited understanding of different digital resilience effects (e.g., Park et al. 2015).

Third, the subgroup analyses of Study 1 and Study 2 reveal that OHC physicians' use of the OHC platform enhanced digital resilience. I examined the role of various specific and direct metrics of physicians' online behavior, e.g., the sentiment of physicians' conversations with their patients during online consultations. I 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. I 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, I further uncovered the effects of online reputation on OHC physicians' resilience across different subgroups and under both external and internal shocks. 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 are positively associated with patient opinions about physician quality (Gao et al. 2012). I utilized the overall rating (Study 1) as well as the physicians' professional title (Study 2) as the metric for the reputation of an OHC physician and found that the highly rated group enjoyed significantly higher digital resilience than that of the group with a lower reputation. Moreover, I also found that patients' trust in the physicians varies across different information disclosed channels and different time periods. These findings not only reveal that the heterogeneous factors enhance resistance and recovery, but also shed light on the dynamics of digital resilience.

Fourth, this thesis 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 and Heikkilä 2021), critical infrastructure (Galbusera et al. 2021), and specific healthcare fields (Liow et al. 2020), most inquiries are *qualitative*. This 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 and policy changes. The subgroup analysis also suggests the effectiveness of IT use in building organizational resilience (e.g., Kouvelis and Li 2008) and maintaining business continuity until full disaster recovery (Fakhruddin et al. 2020). This thesis thus provides a solid stepping stone for both theorizing and empirical analysis in research on business continuity and disaster recovery.

6.1.2 Practical Contributions

This thesis has several practical implications. First, considering that some shocks such as COVID-19 and policy changes may exist in the long term and that there may be more outbreaks in the future, this thesis highlights the key role of digital technologies in enhancing the digital resilience of healthcare entities against new shocks. 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 the analysis across the three studies in this thesis, 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 information such as articles and share their knowledge with existing and potential patients. Physicians' utilization of OHC features can influence patients' decision-making and improve physician-patient trust, enhancing physicians' digital resilience.

Third, this thesis suggests that physicians' usage of different functions on OHCs e.g., information disclosing and online ratings, is an important signal that helps patients choose physicians across different contexts. OHC platforms should consider optimizing the algorithm that discloses physician information, e.g., calculating the 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.

6.2 Limitations and Future Works

This thesis has several limitations and also suggests directions for future research. First, in Study 1 and Study 2, I address the generalizability of our research findings. The two studies focus on unpredictable shocks (i.e., external shock of the first wave of the COVID-19 pandemic and internal shock of pricing policy change). There is a need to validate the application of the findings to subsequent outbreaks as well as other policy changes. However, I expect that the overall pattern of our results—e.g., the resistance and recovery aspects of digital resilience—would still apply. This thesis encourages future studies to validate the findings in other external shocks other than the COVID-19 pandemic and sectors beyond healthcare. Furthermore, while the focal hospital offers the full spectrum of medical services and thus the physicians in the sample represent physicians from different medical specialties, the results are based on data from a single hospital. I acknowledge the limitation regarding the generalizability of the findings and call for future research utilizing more representative samples.

Second, while this thesis demonstrates significant differences in digital resilience between OHC and non-OHC physicians and between subgroups of OHC physicians, I am 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 regarding the resistance and recovery dimensions. One of my 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 this thesis has incorporated ICD codes in our analysis to mitigate the issue of systematic differences between OHC and non-OHC channels, I cannot completely rule out the possible differences in the characteristics of demand between OHC and non-OHC channels. Also, I focused on the effects of online sentiment and online reputation on OHC physicians' digital resilience in Study 1 and Study 2. Other factors, such as physicians' sentiment in outpatient consultations and offline reputation, may have influenced our research findings. Thus, I 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 external or internal shocks.

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