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The Impact of Geographic and Social Proximity on Physicians: Evidence from the Adoption of an Online Health Community

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Abstract. Although online doctor consultations are rapidly gaining popularity, physicians must actively participate in physician–patient interaction platforms to fully unlock their potential. Through a social influence lens, this study empirically investigates physician adoption behavior over time across regions in the diffusion of an online health community (OHC). We examined the impacts of geographically and socially close adopters and investigated the interaction of proximity influences and competition in adoption. We collected panel data on 21,654 physicians in 32 cities in three provinces in China from a large Chinese OHC. The results demonstrate that both geographic and social proximity facilitate adoption when local competition is low. However, as local competition increases, the impact of socially close prior adopters increases, whereas that of geographically close prior adopters decreases. This pattern becomes stronger for physicians with lower titles.

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Keywords: online health community • social influence • geographic proximity • social proximity • adoption • local competition

1. Introduction

Online health communities (OHCs) have rapidly gained popularity in recent years, revolutionizing healthcare delivery by facilitating physician and patient interactions (Wang et al. 2020) and supplementing traditional in-hospital services by linking physicians and patients online (Safavi and Dare 2018). However, the full potential of OHCs can only be realized if physicians and patients are willing to participate. Understanding the motivations behind user participation in online communities is an enduring question. Physicians, given their extensive professional knowledge, play a dominant role in physician–patient interactions (Siegel 2017). Whereas patients stand to gain significantly from physicians' presence in OHCs, physicians often grapple with limited time and a heavy workload, potentially hindering their online participation. Thus, gaining a deeper understanding of physician's participation decisions is crucial for promoting OHC adoption and ensuring its long-term success.

Physicians may choose to adopt and participate in OHCs because they find fulfillment in helping patients (Zhao et al. 2022), seek patients who align with their interests or expertise (Guo et al. 2017), or aim for recognition from patients (Khurana et al. 2019). Moreover, social influence from peer physicians is equally pivotal. This study examines the social determinants of physicians' participation decisions in OHCs. Social influence aids in overcoming the uncertainty associated with OHCs, creates heightened social pressure for physicians, and stimulates imitation among peers.

Prior literature shows that individuals tend to be influenced by those similar to them (Choi et al. 2010). This similarity can manifest in both geographic and social proximity, fostering trust, reducing transaction costs in knowledge exchange, and enhancing social interactions (Agrawal et al. 2008). Geographic proximity refers to the closeness in physical space, whereas social proximity indicates the closeness of social space, which may arise from similarities in sociodemographic characteristics, occupation, affiliated organization, interests, and more (Rosenblat and Mobius 2004, Agrawal et al. 2008, Angst et al. 2010, Choi et al. 2010). These lead to our first research question: how do geographic and social proximity generally impact physicians' OHC adoption?

Additionally, healthcare services are inherently localized, fostering competition in OHCs among physicians with similar expertise in the same local market. Local competition stems from the overlap of the resource niche in local areas, including patients and medical facilities. Despite the virtual nature of online communities, patients still prefer physicians in close areas because of social, informational, and geographical frictions and the anticipation of follow-up off-line visits (Hwang et al. 2022). The competitive environment differentiates physicians' adoption behavior from that of users adopting consumer goods or services for which no direct competition exists among individuals. Local competition affects the potential benefits a physician can derive from OHCs, influences the feeling of belonging to a particular group (Riketta and Sacramento 2008), alters the degree to which norms are enforced (Goette et al. 2006), and thus changes the impact of proximity. Our second research question examines the potential competition among adopters in the same local market: how does the impact of proximity change as local competition among physicians increases?

Furthermore, user heterogeneity, including personal traits, status, and susceptibility to social influence, ultimately determines whether and when to adopt OHCs (Wejnert 2002). Given that professional titles serve as major indicators of expertise and status, physicians with different titles are likely to exhibit varying susceptibility to influence from geographically and socially close peers as well as the effects of local competition. Therefore, we propose our third research question: how do the interaction effects of proximity influence and competition on physicians' OHC adoption differ based on their professional titles?

Using longitudinal data collected from a leading OHC in China, we empirically investigate the impact of geographic and social proximity on the adoption behavior of physicians. Identifying proximity influence can be challenging as geographically and socially close individuals often make similar decisions because of shared preferences. To address this problem, we employ accelerated failure time models with instrumental variables (Terza et al. 2008, Atiyat 2011).

Our research yields three primary findings. First, in settings with low local competition, geographic and social proximity to prior adopters significantly accelerate the adoption of OHCs by nonadopting physicians. Second, the impact of proximity is contingent on the level of local competition faced by the nonadopter. As competition intensifies, the crowding-out effect surpasses the social influence emanating from an increasing number of geographically close adopters. In response, physicians become more inclined to conform to the adoption behaviors of socially close peers. Third, compared with high-title physicians, low-title physicians are more likely to be crowded out by geographically close peers and tend to conform more to the adoption behaviors of socially close peers as competition increases.

Our research contributes to the literature by empirically investigating heterogeneous social influence at the individual level in the OHC adoption process. By shedding light on the relationship between proximity and adoption in a professional service community, our study contributes to the growing evidence regarding the effects of social influence on adoption. Moreover, by integrating understandings of proximity influence and competition, our results reveal the nuanced influence of geographically and socially close adopters in a competitive environment. We also find that different subsets of the population, characterized by the distributions of individual status (i.e., professional titles), display varying susceptibilities to potential proximity influence and competition.

2. Related Literature

2.1. OHC Adoption

OHCs (e.g., RateMDs, PatientsLikeMe, MedHelp, and ZocDoc) provide a platform on which physicians and patients interact with each other around health-related topics, such as disease treatment and wellness promotion (Yan and Tan 2014, Wang et al. 2020). These OHCs offer various functions, including health information searches, appointment booking, online consultation, patient education, patient forums, and physician forums (Goh et al. 2016, Wang et al. 2020).

Prior literature suggests that physicians may adopt OHCs for intrinsic (Zhao et al. 2022), extrinsic (Liu et al. 2020, Huang et al. 2021), and internalized extrinsic motivations (Guo et al. 2017, Khurana et al. 2019). Intrinsic motivation, such as altruism, refers to the fact that physicians enjoy the fulfillment of helping patients (Zhao et al. 2022). Extrinsic motivation refers to work-related benefits or economic returns (Liu et al. 2020, Huang et al. 2021). For example, via rich media and synchronized online and off-line services, OHCs enable physicians to educate patients (Huang et al. 2021), facilitate patient management (Liu et al. 2020), and better match physicians' abilities with patient needs. Internalized extrinsic motivation (e.g., self-image considerations) stems from extrinsic reasons but transforms into self-regulating motivations after assimilation (Deci and Ryan 2002). Self-image concerns suggest that physicians may join OHCs to signal their benevolence and commitment to patients' health conditions (Guo et al. 2017, Khurana et al. 2019). Moreover, participation in these communities can be socially rewarding as it garners recognition from patients (Guo et al. 2017).

However, OHCs are complex platforms. For physicians, adopting OHCs may raise concerns about the effectiveness of online services, the reliability of online patient ratings (Gao et al. 2015), and the balance between online and off-line activities (Wang et al. 2020). When the perceived value of participating in OHCs is uncertain, physicians tend to seek more information and peer approval via social interactions (Coleman et al. 1959, Turner 1991).

2.2. Social Influence, Proximity Influence, and Homophily

Social influence involves changing an individual's attitudes or behaviors via social interactions (e.g., communication and observation) with another person or group (Turner 1991). Physicians' decisions to adopt OHCs can be affected by peers' adoption behaviors through two mechanisms: informational and normative social influence (Turner 1991). The former, often referred to as social learning, occurs when information acquired from peers via social interactions allows individuals to assess the technology's value and overcome uncertainties regarding adoption (Coleman et al. 1959). The latter arises from the desire to conform to others' expectations about what is appropriate, providing adopters with social utility (Iyengar et al. 2015).

The impact of social influence is stronger when it originates from individuals who are geographically or socially close because interactions among similar individuals offer more exposure and exert stronger influence (Agrawal et al. 2008, Meyners et al. 2017). We define proximity influence as the impact exerted by geographically or socially close peers on other users' decisions through social interactions. Proximity influence is social influence arising from either geographic or social proximity. According to prior literature (Angst et al. 2010, Choi et al. 2010, Li and Koizumi 2021), the propensity to interact with and imitate others is dependent on both physical closeness and social closeness. Geographic and social proximity capture different dimensions of "neighborhood" that makes social influence come into force.

Geographic proximity refers to the closeness between locations (Agrawal et al. 2008). Social proximity refers to similarities among social attributes of people, such as age, ethnicity, education, and socioeconomic status (Blau 1977). Unlike geographic proximity, social proximity has no universal definition, and its measurement depends on the research context. However, there is a consensus that individuals tend to interact more with those who share similar social attributes (Blau 1977, Conley and Topa 2002, Choi et al. 2010). Both Conley and Topa (2002) and Choi et al. (2010) suggest that region-level similarities (e.g., sociodemographic characteristics) reflect social network stratification. In the context of OHC adoption, social proximity likely stems from shared sociodemographic characteristics among physicians at the city and hospital levels. Physicians working in similar regions or hospitals are more likely to interact with one another compared with those who are not in close social proximity.

Geographically and socially close peers disproportionately influence an individual's attitudes or behaviors. However, identifying proximity influence can be challenging because of unobservable characteristics (e.g., homophily) that may induce similarities in behavior. Both proximity influence and homophily contribute to individuals' correlated behaviors (Ma et al. 2015). Homophily refers to the phenomenon by which individuals with similar characteristics or preferences tend to connect and make similar decisions (McPherson et al. 2001, Aral et al. 2009). Homophily can lead to correlated behaviors without involving influence from social interactions (Aral et al. 2009). On the other hand, proximity influence impacts behaviors through social interactions among individuals (Centola 2011). In our context, both proximity influence and homophily may lead to correlated OHC adoption behaviors among geographically and socially close physicians. For example, physicians from geographically close areas or similar cities may make similar adoption decisions without knowing other physicians' adoption behaviors (i.e., homophily) or as a result of social interactions with geographically or socially close prior adopting physicians (i.e., proximity influence). Our study utilizes instrumental variables to identify proximity influence on top of homophily.

2.3. Proximity Influence on Technology Adoption

Scholars have made substantial efforts to identify the influence of geographic or social proximity on the purchase decisions of physical goods, including iPhone 3G (Matos et al. 2014), solar panels (Bollinger et al. 2022), and products purchased by Twitter friends (Todri et al. 2022). There are also studies examining the role of proximity in the adoption of digital services, such as business-to-business (B2B) trading platforms (Barrot et al. 2008), online grocery retailing (Choi et al. 2010), electronic medical records (Angst et al. 2010), video-on-demand service (Nam et al. 2010b), caller ring-back tones (Ma et al. 2015), and cellular service (Meyners et al. 2017). However, these studies primarily focus on consumer goods or services for which there is no direct competition among users.

Three studies most relevant to our research examine both geographic and social proximity in technology innovation adoption (Angst et al. 2010, Choi et al. 2010, Meyners et al. 2017). Angst et al. (2010) find that spatial proximity (the distance between two hospitals) and social proximity (within the same healthcare system) positively affect the adoption of electronic medical records (EMR) with adoption rates varying across age, size, and prominence of hospitals. Their study was conducted at an aggregate hospital level, preventing them from observing individual adopters' statuses and behaviors. Using zip code–level data on the adoption of an e-tailer, Choi et al. (2010) find that individuals are more likely to imitate geographically close and demographically similar neighbors with the effect of demographic similarity strengthening over time. Meyners et al. (2017) demonstrate that living close to adopters positively affects the potential adopter's adoption of a cellular service provider. Neither Choi et al. (2010) nor Meyners et al. (2017) examine different users' susceptibility to proximity influence.

Our research distinguishes itself in several ways. First, we use individual-level adoption data, allowing us to obtain the exact adoption sequence among physicians. Second, we identify proximity influence from correlated preferences using instrumental variables and matching techniques. Third, we adopt a more nuanced perspective on proximity influence within a competitive environment. In typical consumer contexts, users usually do not compete for the benefits of a new technology or service adoption. One user's gain from adoption does not typically diminish others' benefits. Competition primarily exists among providers, such as e-tailers or mobile phone companies rather than users. In contrast, physicians in OHCs face local market competition from peers offering similar services, leading to uncertain benefits, such as low online patient visits. Physicians may be concerned about wasting valuable time or damaging their reputations. Hence, in addition to social influence, competition among physicians can lead to different adoption decisions by nonadopters who observe the adoption activities among peers. Table 1 summarizes the research investigating the impact of proximity on adoption decisions and illustrates the unique features of our paper.

3. Theoretical Framework and Hypotheses

To understand the nuanced influence of proximate adopters in a competitive environment, we first examine the overall impacts of geographically and socially close prior adopters on nonadopters' decisions (Hypothesis 1). We then explore whether proximity influences vary based on different levels of local competition (Hypothesis 2). Finally, we investigate the heterogeneous effects of proximity influences and competition effects on nonadopters with different statuses (Hypothesis 3).

3.1. Geographic Proximity, Social Proximity, and Their Impacts

OHCs show great potential in connecting physicians and patients across diverse locations, improving health capabilities for patients (Goh et al. 2016), and bolstering the professional reputation of physicians (Khurana et al. 2019). However, the complexity and uncertainty of using OHCs may impede their adoption (Gao et al. 2015, Wang et al. 2020). Similar to the adoption of a new product or trial, the uncertainties of OHCs make physicians more susceptible to social influence, particularly from geographically close prior adopters (Bell and Song 2007). First, geographically close prior adopters serve as credible information sources that affect nonadopters' perceived risks and benefits of innovations (Bell and Song 2007). Geographic proximity enhances social interactions by facilitating face-to-face communication and observational learning. Therefore, it reduces psychological distance and instills trust (Agrawal et al. 2008). In this sense, physicians in nearby cities have increased opportunities for interaction and exert informational social influence. By sharing firsthand user experiences, the growing adoption rate among geographically close physicians serves as critical social proof in diminishing uncertainties associated with OHCs.

Second, geographic proximity engenders social pressure toward conformity because of enhanced communication, exposure, and interactions. Geographic location plays an essential role in social identification (Twigger-Ross et al. 2003). Norm conformity is more substantial when the group is more relevant, immediate, and socially present, for example, when group members are close in space (Latané 1981). Forman et al. (2008) find that, when prior reviewers are from the same location as the focal member, their disclosure of social identity significantly affects the member's disclosure decision. Similarly, physicians are likely to be exposed to and engage with geographically close colleagues, thereby facilitating stronger normative social influence.

Hypothesis 1a. *The geographic proximity of prior adopters positively affects physicians' adoption behavior.*

Prior literature suggests that shared sociodemographic characteristics (e.g., education, income, age, ethnicity, and their subcategories) across two regions can lead to imitation between the regions (Conley and Topa 2002, Alstyne and Brynjolfsson 2005, Choi et al. 2010). Socially close individuals, who may have common interests and possess similar socioeconomic or demographic characteristics, are more likely to interact with each other because of lower communication costs and conscious efforts compared with dissimilar individuals (Fischer 1978, Rosenblat and Mobius 2004). Trust is engendered by social proximity because of the common foundation for effective communication. For example, social proximity enhances interpersonal interactions and familiarity, engendering bond-based attachment (Ren et al. 2012). Lower communication costs and increased trust facilitate informational social influence. Also, individuals prefer to identify with groups whose characteristics are more similar to their own (Trajfel and Turner 2004).

Table 1. Summary of Studies of Proximity Influence on Technology Adoption

Author	Findings	Study level	Context	Geographic proximity	Social proximity	Moderator
Proximity influence on the adoption decision of typical consumer goods or services						
1 Geographic proximity						
Bell and Song (2007)	Geographic proximity has a positive effect on the adoption decision of nonadopters.	Zip code	Internet grocery retailing	First-order geographical contiguity		
Barrot et al. (2008)	Adopters within 0–4 km of a user significantly impact the user's adoption decisions.	Firm	A B2B trading platform	Distance		
Nam et al. (2010b)	The adoption rate of neighbors within a circle of a 0.5-mile radius positively affects the adoption decision of the focal household.	Household	Video-on-demand service	Colocation in a circle of 0.5-mile radius		Signal quality
Bollinger and Gillingham (2012)	Geographic proximity increases the probability of adopting solar photovoltaic panels.	Household	Solar photovoltaic panel	Colocation based on zip code-street		
Bollinger et al. (2022)	The visibility of geographically close peers' adoptions produces stronger social influence.	Household	Rooftop solar panels	Distance		Visibility
2 Social proximity						
Aral et al. (2009)	Both proximity influence and homophily positively affect the adoption decisions of potential adopters.	Individual	A mobile service application		Instant message network	
Goldenberg et al. (2009)	Individuals with many social ties (i.e., hubs) have significantly larger impacts than others on the adoption decisions of nonadopters.	Individual	A social networking site		Online social network on the basis of activities	
Katona et al. (2011)	Prior adopters who are from a densely connected group have a positive impact on the adoption decision of nonadopters in the group.	Individual	A social networking site		Friendship network data	
Aral and Walker (2012)	Individuals of different characteristics (e.g., age, gender, and relationship status) display different susceptibility and infectiousness in proximity influence.	Individual	A commercial Facebook application		Online friend	Age, gender, relationship status
Matos et al. (2014)	A user is more likely to adopt when the percentage of adopting friends increases.	Individual	iPhone 3G		Call records–based social network	

Table 1. (Continued)

Author	Findings	Study level	Context	Geographic proximity	Social proximity	Moderator
Risselada et al. (2014)	Proximity influence from social ties on adoption decisions decreases with time, whereas proximity influence from recent adopters remains constant.	Individual	Mobile telecommunication operator		Call records–based social network	
Ma et al. (2015)	Socially close adopters have a significant positive effect on the time of purchase and choice of product decisions, whereas latent homophily affects product tastes and the susceptibility to influence.	Individual	Caller ring-back tone		Call records–based social network	
Zhang et al. (2018)	Both direct (i.e., one-hop neighbor) and indirect peer influences (i.e., two-hop neighbor) positively impact the adoption decision of nonadopters.	Individual	Caller ring-back tone		Call records–based social network	
3 Geographic and social proximity						
Angst et al. (2010)	Geographic and social proximity positively affect the diffusion of EMR among hospitals.	Hospital	Electronic medical records	Distance	Within the same healthcare system	
Choi et al. (2010)	Geographic proximity has a strong effect in the early diffusion stage, whereas demographic similarity becomes more important over time.	Zip code	Internet retailer	Distance and contiguity	Demographic similarity	
Meyners et al. (2017)	Geographic proximity triggers social influence through perceived homophily.	Individual	Mobile phone service	Colocation and distance	Call records–based social network	
Proximity influence on adoption decisions in a competitive environment						
Present study	Our research studies proximity influence in a competitive environment. We consider not only the social influence, but also the competition among close physicians in adopting an online health community.	Individual	Online health community	Distance	Similarity in city-level sociodemographic attributes and hospital class	Local competition, physician status

Therefore, norm conformity is stronger when individuals feel socially close to other group members.

Angst et al. (2010) observe that hospitals refer to prior adopters from the same healthcare system when making adoption decisions regarding EMR. Similarly, healthcare services require extensive domain knowledge that shapes the informational content of social interactions among physicians. Thus, a physician's social space is defined by the physician's region and affiliated hospital class. Through increased social interaction and exposure, the adoption of OHCs by physicians in similar cities or hospitals helps nonadopters infer the value of OHCs and strengthens their inclination to conform to the behaviors of their peers.

Hypothesis 1b. *The social proximity of prior adopters positively affects physicians' adoption behavior.*

3.2. Proximity Influence and Local Competition

Traditionally, healthcare services involve a high degree of inseparability, by which both the delivery and consumption of services are inseparable from the service provider's location (Nam et al. 2010a). As a result, physicians compete with each other within the local market. Even for OHCs, local competition among physicians still persists. First, for patients exclusively seeking online consultations, when they consult with one physician in a specific region (e.g., Shanghai), the chance of consulting with other physicians in the same region significantly diminishes. Second, although online platforms transcend physical boundaries, patients may still prefer physicians who are geographically closer for potential in-person visits or because of local familiarity. Hwang et al. (2022) discover that language and cultural differences, limited media coverage, physical distance, jurisdiction difference, and mobility restriction can limit patients' choices of teleconsultations toward those in proximity. Moreover, the anticipation of follow-up offline visits may lead patients to prefer consulting nearby physicians (Hwang et al. 2022). Third, competition is intensified by the degree of overlap of resource niches, encompassing both the pool of patients and medical facilities (Hannan and Freeman 1989). Physicians engaging in OHCs must actively cultivate reputations (e.g., receiving high ratings and more appreciation gifts from online patients) to stand out among local competitors. Thus, physicians face competition from peers in OHCs offering similar or substitute services in the same markets.

The increasing adoption rate of geographically close physicians serves as credible social proof of the OHC's value and as a social norm for physicians (Goette et al. 2006). However, the informational and normative social influence exerted by geographically close peers weakens in the presence of stronger competition. As competition increases, a higher adoption rate of geographically close physicians results in higher entry barriers and uncertain benefits for newcomers. Prior adopters may have built their reputation in the OHCs. The accumulation of positive reviews and virtual gifts from patients demonstrate their popularity and attract more patients online. Thus, potential adopters must exert substantial efforts to compete with and outperform prior adopters of close areas in the OHCs. This adverse situation potentially dilutes the informational social influence of geographically proximate peers. Moreover, competition also changes the extent of norm enforcement (Goette et al. 2006) by altering the sense of group belonging (Riketta and Sacramento 2008). As local competition increases, physicians are likely to perceive peers from geographically close areas as competitors and outgroup members, which ultimately decreases the positive impact of geographic proximity.

Hypothesis 2a. *As competition increases, the impact of prior adoption by geographically close physicians decreases.*

Meanwhile, physicians may endure the opportunity cost if they do not adopt OHCs. The adoption decision is contingent on the trade-off between the potential benefits of adoption (e.g., connecting and educating patients efficiently) and the cost of participating online (Gao et al. 2015, Wang et al. 2020). As competition increases, the increased opportunity cost and uncertain benefits make physicians more prone to seek available information and social cues, facilitating their decision making (Hogg 2007).

Individuals tend to perceive people with similar status as in-group members and evaluate them more positively with stronger trust (Chen and Li 2009). The in-group cohesion also leads to cooperative and supportive relationships among similar people (Turner 2010). As local competition increases, the influence of social proximity increases because of the strengthened feeling of belonging to the same group. Competition among socially close physicians is less intense than that among geographically close physicians. Thus, nonadopters are more willing to identify themselves as similar to socially close peers rather than geographically close peers when the local competition is strong. Moreover, the heightened tension between the benefits and costs of adoption because of competition makes nonadopters more likely to rely on the adoption decision of socially close physicians for credible evidence to infer the value of OHC as they are less inclined to refer geographically close peers as social referents.

Hypothesis 2b. *As competition increases, the impact of prior adoption by socially close physicians increases.*

Research finds that personal characteristics can interact with social influence (Centola 2011, Aral and Walker 2012). It is natural to wonder whether physicians of different titles respond differently to proximity influence and competition. We expect that physicians with a high title exhibit less susceptibility to the interplay of geographic proximity influence and competition for two reasons.

First, healthcare services have a strong nature of credence goods (Darby and Karni 1973), so a physician's professional title is a crucial signal of competence and experience (Hao 2015, Khurana et al. 2019). High-title physicians usually have more experience and hold esteemed positions in healthcare, affording them better control over resources (Simcoe and Waguespack 2011). Similar to the adoption decision among hospitals with different statuses (Angst et al. 2010), high-title physicians face less uncertainty and feel more secure in adopting innovations such as the OHCs as they can leverage their social capital to navigate potential postadoption challenges. So they exhibit greater confidence in the OHC adoption decision and are less susceptible to proximity influence regardless of the intensity of local competition. In contrast, low-title physicians exhibit lower confidence levels. In the absence of local competition, they are more inclined to observe geographically close peers' OHC adoption to gather information regarding the OHCs. However, when facing increased competition, low-title physicians tend to perceive prior adopters from geographically close areas as potential competitors in the OHCs and are less likely to emulate their adoption behaviors.

Second, high-title physicians typically experience a heightened sense of security within their professional organizations. Therefore, high-title physicians derive fewer social benefits from imitating others. This expectation aligns with the findings of Hollander (1958), which suggest that high-status individuals enjoy greater leeway to deviate from group norms. Compared with high-title physicians, low-title physicians are more susceptible to normative social influence and the effect of competition. When competition is low, they are more likely to refer geographically close adopters as social proof. However, as their perception of local competition intensifies, their desire to conform to the behaviors of geographically close physicians weakens.

Hypothesis 3a. *As competition increases, the impact of prior adoption by geographically close physicians decreases more for low-title physicians than for high-title physicians.*

Similarly, regardless of competition levels, high-title physicians are less influenced by socially close peers' adoptions. Conversely, individuals with low status are more prone to imitate the adoption behavior of socially close others because of concerns about risk and social identity (Burt 1987). This tendency becomes more pronounced as competition intensifies. Increased local competition raises opportunity cost and uncertainty for low-title physicians. Faced with elevated uncertainty, individuals are more inclined to turn to similar others to inform their decisions and reduce uncertainty (Hogg 2007). Because geographically close physicians' adoption may signal higher competition rather than value of OHC, low-title physicians look for alternative social cues, particularly the decisions of socially close peers. Moreover, faced with uncertainty and perceived pressure, low-title physicians are more likely to seek socially close adopters who are away from competition as social proof. Consequently, low-title physicians are more inclined to conform to socially close physicians' behaviors as competition increases.

Hypothesis 3b. *As competition increases, the impact of prior adoption by socially close physicians increases more for low-title physicians than for high-title physicians.*

4. Research Method

4.1. Research Setting

In China, hospitals are classified into six hierarchical levels within three tiers: levels 1, 1A, 2, 2A, 3, and 3A (the highest), based on their functions, missions, facilities, technical equipment, quality of care, and administration level (National Health and Family Planning Commission 1998). Public hospitals provide more than 90% of inpatient and outpatient services in China (Yip et al. 2012) with high-quality hospitals (i.e., levels 3 and 3A) having more than 500 beds handling the most patients (Liu et al. 2017). In the public hospital system, physicians are evaluated and assigned professional titles, ranging from junior to senior positions: resident, attending, associate chief, and chief physicians. On average, physicians attain higher titles every five years after graduation and standardized training (Hao 2015).

Patients often seek medical attention without appointments, leading to long queues and brief physician–patient interactions, especially in high-quality hospitals. This challenge is exacerbated by healthcare disparities between coastal eastern and noncoastal western regions and between urban and rural areas. OHCs break geographic barriers, enabling patients in remote areas to access high-quality healthcare services. In this sense, OHCs facilitate the more efficient allocation of healthcare resources, alleviating overcrowding at high-level hospitals and addressing healthcare disparities.

4.2. Data

Our data were collected from a prominent OHC in China. Launched in 2006, this community has now become the largest Chinese OHC. As of August 18, 2022, it boasts 892,324 real name authenticated physicians from 10,164 hospitals and millions of active anonymous patients. This platform offers a range of services, including consultations (via text or telephone), appointment scheduling with physicians, and patient reviews about physicians. Additionally, patients can express their gratitude through various means, such as thank-you letters or virtual gifts to physicians.

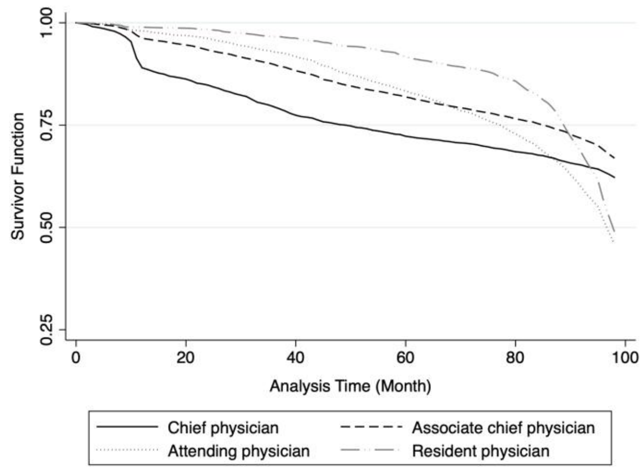
Initially, this OHC primarily focused on listing physicians' information and patient reviews after hospital visits. In March 2008, it added additional features such as physician–patient interactions (i.e., online consultation). Both adopting and nonadopting physicians have profile pages on the OHC, on which they can receive online patient reviews. However, only adopting physicians have home pages that allow them to respond to patient inquiries. Only after activating their home pages on the website can physicians access various products and services, such as text or telephone consultations.

We collected data using Python, extracting the physician-level information of 26,499 physicians in 32 cities across Shanghai, Anhui Province, and Gansu Province from March 1, 2008, to May 31, 2016. We started by selecting "search by hospitals" on the OHC platform and got to a page with hospitals by province, which lists hospitals by city. After clicking on the hyperlinks of a particular city, we can find each hospital's hyperlink within that city and navigate to the hospital page on the OHC. From these pages, we gathered hospital-level data, including the hospital's name, accreditation level (class), province, city, address, and URL link. From the hospital page, we visited each department page, which contains department information and physician listings with basic details.

Each physician's profile page, accessed from the department page, provided details such as the physician's name, affiliated hospital, department, professional title, online reviews (e.g., patient votes), personal information (e.g., age, gender, expertise, education, medical experiences, honors), available services (text consultation, telephone consultation, and online reservation), home page link (if adopted), and off-line appointment schedule. For privacy concerns, most physicians avoid sharing detailed personal information online, such as age, gender, and education. By clicking on the home page link, we collected information on the adopters, including the time of home page adoption, detailed physician–patient interaction records, and online votes from patients with time stamps.

We excluded observations from auxiliary medical departments (e.g., radiology) and focused only on clinical departments. As Chinese healthcare department names lack standardization, we constructed a table to map existing department names to unified ones (i.e., names of specialties). After excluding physicians who did not provide their professional titles, our final data set included 21,654 physicians from 18 specialties in 371 hospitals. In our final data set, 74.6% of the physicians came from level 3 or 3A hospitals. Our research focuses on the adoption behavior of physicians already listed on the OHC. The data are right-censored. Physicians

Figure 1. Kaplan–Meier Survival Curves by Professional Title



who did not adopt the platform before May 31, 2016, accounted for 62.8% of the total.

Figure 1 shows the Kaplan–Meier survivor curves, which depict the predicted unconditional survival probabilities across physicians' professional titles. The OHC adoption is treated as a failure event. As suggest by Figure 1, the initial adoption rate is higher in high-title physicians (i.e., chief and associate chief physicians); however, as more physicians adopt, the adoption rate among attending and resident physicians increases. Suppose physicians tended to adopt the OHC merely because of personal benefits or personality characteristics. In that case, the adoption should have spread among high-title physicians in the same ways as among the low-title physicians except earlier. The adoption rate of low-title physicians increases more than that of high-title physicians in later periods, suggesting that low-title physicians are more susceptible to social influences. Therefore, this study intends to examine how proximity influences physicians' adoption behavior.

Moreover, we gathered city-level data, including economic indicators (per capita gross domestic product), medical resources (e.g., medical institutions and physicians), education, and internet penetration, from the Chinese City Statistical Yearbook and Chinese Health and Family Planning Statistical Yearbook, available annually. We collected daily weather information at the city level for cities in Anhui and Gansu Provinces and district-level data for Shanghai, a municipal city in China, from a third-party website (tianqi.2345.com). We also crawled the city-level daily Baidu search index of the OHC through the Baidu application programming interface and aggregated them to a monthly level. As with Google Trends, the Baidu search index shows how frequently a search term is entered into the search engine over a given time period.

4.3. Measurements of Variables

Although individual adoption behavior is observable, the exact network ties that form social influence are not observable in our context. Following the literature (Leenders 2002, Bell and Song 2007), we approximated the network ties of neighborhoods using city-hospital level observations and weighting matrices. Specifically, we considered geographic and social proximity influences, which are the products of the geographic/social proximity matrix and the lagged cumulative adoption rate vector. We adopted the method proposed by Choi et al. (2010) to measure spatial and social proximity to consider the prevalence and concurrence of different entities.

4.3.1. Geographic Proximity Influence. Geographic proximity influence is the aggregate influence of geographic neighbors. It is operationalized as the product of the geographic proximity matrix and a vector of the lagged cumulative adoption rates of all hospitals. We measure the cumulative adoption rate as the ratio of cumulative adopters to the total number of physicians in each hospital at month t. The geographic proximity matrix G is a 371×371 matrix with the element $G_{h,l}$ defined as an inverse function of the distance between hospitals h and l:

$$G_{h,l} = \begin{cases} \exp(-d_{h,l}) & \textit{if } h \neq l, \\ 0, & \textit{if } h = l.; \end{cases}$$

here $d_{h,l}$ is the physical distance between hospitals h and l. To separate the within- and cross-hospital influences that shape information transmission, we isolated the focal hospital h from other hospitals to measure geographic proximity influence (Bell and Song 2007).

4.3.2. Social Proximity Influence. The social proximity influence is defined as the aggregate influence of social neighbors. Choi et al. (2010) use education, income, age, ethnicity, and their corresponding subcategories to construct a demographic similarity matrix, which they multiply by the adoption rate vector of all regions to capture the aggregate influence of demographic neighbors. In our context, we measure social proximity in the context of OHC adoption as the social similarity between physicians, taking into account city sociodemographic characteristics and hospital level. The social similarity first lies in city sociodemographic characteristics, such as age, education, income, and healthcare resources. Moreover, recognizing the significant differences in interactions among physicians across different classes of hospitals, we further measure hospital class similarity to consider the informational content of social interactions (Conley and Topa 2002). Therefore, a physician in a top-tier hospital located in Beijing is more likely to interact with someone from a top-tier hospital in Shanghai even if they may not know each other directly. We operationalize social proximity influence as the product of the social proximity matrix and a vector of the corresponding lagged cumulative adoption rate of physicians in each hospital at month t.

The social proximity matrix S is measured as a symmetric matrix with each element representing the cosine similarity between hospitals h and l in k attributes. They include city-level attributes (economy, medical resources, education, percentage of elderly persons, telephone usage) and the class of the hospital (see the base specification of Online Appendix Table A1, $k = 9$). We categorize each continuous attribute into quartiles and then convert the quartiles, along with categorical attributes such as hospital class, into indicator variables $v_{h,k',y-1}$. Subsequently, we measure the cosine similarity for vectors of $v_{h,k',y-1}$ and $v_{l,k',y-1}$ for hospitals h and l at year $y-1$ as follows:

$$S_{h,l,y-1} = \begin{cases} \dfrac{\sum_{k'}(v_{h,k',y-1} \cdot v_{l,k',y-1})}{\sqrt{\sum_{k'} v^2_{h,k',y-1}} \cdot \sqrt{\sum_{k'} v^2_{l,k',y-1}}}, & \textit{if } h \neq l, \\ 0, & \textit{if } h = l. \end{cases}$$

Similarly, we isolate the focal hospital from other hospitals to measure social proximity influence. It is important to note Aral et al. (2009) utilize cosine similarity to measure homophily. However, the cosine similarity only acts as a proximity weight on hospitals' lagged adoption rate in our measure.

To illustrate the difference between geographic and social proximity, we have chosen five cities: Hefei and Lu'an in Anhui Province, Lanzhou and Baiyin in Gansu Province, and Shanghai. The social proximities between a hospital in Shanghai and hospitals of the same class in Hefei, Lu'an, Lanzhou, and Baiyin in 2015 are 0.753, 0.155, 0.991, and 0.157, respectively. Although the social proximity between Lu'an and Shanghai (0.155) is similar to that between Baiyin and Shanghai (0.157), Lu'an is located 480 km away, whereas Baiyin is 1,721 km away from Shanghai. Moreover, although Lanzhou is geographically near Baiyin, it is more socially close to Shanghai than to Baiyin.

4.3.3. Competition. Given that healthcare services are localized in nature, physicians in nearby locations compete for patients and medical resources, especially for those physicians who offer similar services. Following Shukla et al. (2021), we define the local market as the same city and specialty. Similar to Hoberg and Phillips (2010), we measure competition as the summation of the cosine similarities between the expertise of physician m and all other adopting physicians in the local market (i.e., city-specialty cohort). According to the International Classification of Diseases–11[1] of the World Health Organization, we first classified physicians' expertise in diseases into 28 categories ($c = 1, \ldots, 28$) and defined a vector $\boldsymbol{u_m}$ with zero or one assigned to each category based on physician m's expertise listed in the OHC. Second, we calculated the cosine similarity between every pair of physicians. Third, for physician m, we summed the cosine similarities between physician m and all other physicians n_t who had adopted the OHC before month t and who belong to the same city-specialty cohort as follows:

$$Competition_{m,t} = \sum_{n_t} \frac{\sum_c (u_{m,c} \cdot u_{n_t,c})}{\sqrt{\sum_c u_{m,c}^2} \cdot \sqrt{\sum_c u_{n_t,c}^2}}.$$

Geographic proximity influence, social proximity influence, and competition are standardized with a mean of zero and a standard deviation of one.

4.3.4. The Number of New Patients. Given that the OHC is a multisided platform, physicians' adoption decisions may be influenced by patients. We used the number of new patients to measure the indirect network effect (i.e., more incoming patients on the platform will attract physicians to adopt because of positive externality). The number of new patients is the count of new incoming patients who consult physicians in city i at month t. We lagged one period to alleviate the simultaneity problem within the same period. We then added one and took the logarithm.

4.3.5. Local Marketing Efforts. Local marketing efforts can contribute to physicians' adoption by increasing the level of awareness. We used the Baidu search index of the OHC in city i at month t to capture the local awareness generated by localized marketing efforts. The search item of the OHC was available after 2011. Following Egger et al. (2019), we employed the cubic polynomial method to compute missing values of the search index prior to 2011 before taking the logarithm.

4.3.6. Weather Condition. Weather conditions impact patients' commuting costs and the allocation of off-line and online workloads for physicians. We measured weather conditions as the percentage of days that are not rainy in city i at month t. For Shanghai, we measured weather conditions at the district level.

4.3.7. Internet Penetration Rate. Internet penetration rate affects the way people search for information. A higher internet penetration rate increases physicians' exposure to online service channels, making them more likely to adopt the OHC. We measured the internet penetration rate as the ratio of individuals with internet access to the population of city i at year y.

4.3.8. Professional Title. Because of the significant information asymmetry in the healthcare industry, patients often have little knowledge about a physician's competence, rendering the professional title a strong indicator of service quality. Therefore, we included professional titles in our estimations and categorized them into high-title and low-title groups for easy interpretation.[2] The former includes chief and associate chief physicians, whereas the latter comprises attending and resident physicians.

4.3.9. Class of Hospital. Public and nonprofit hospitals play a dominant role in China. Moreover, physicians are usually employed by only one hospital and are perceived as hospital employees rather than independent practitioners. Therefore, a hospital's reputation significantly impacts a physician's popularity. We captured this effect using the four broad classes generally accepted in China, levels 3A, 3, 2A, and 2 and below.

Table 2 presents the measurements of proximity influences and local competition, and Online Appendix Table A2 reports the descriptive statistics of the key variables.

4.4. Empirical Model

Given that physicians can self-select into adoption (e.g., tech-savvy and more socially inclined physicians tend to adopt OHCs earlier), the physician composition may change over time, potentially accelerating or slowing

Table 2. Measurements of Key Variables

Variable	Definition	Measurement
The cumulative adoption rate of physicians	The ratio of cumulative adopters to the total number of physicians in hospital h at time t	$CAR_{h,t} = \frac{Cumulative\ adopters_{h,t}}{Total\ number\ of\ physicians_h}$
Geographic proximity influence	The influence of geographic neighbors	$GPI_{h,t-1} = \sum_l G_{h,l} * CAR_{l,t-1}$
Social proximity influence	The influence of social neighbors	$SPI_{h,t-1} = \sum_l S_{h,l,y-1} * CAR_{l,t-1}$
Competition	The sum of similarity scores between physician m and all other adopting physicians' expertise in the city-specialty market before time t	$Competition_{m,t} = \sum_{n_t} \frac{\sum_c (u_{m,c} \cdot u_{n_t,c})}{\sqrt{\sum_c u_{m,c}^2} \cdot \sqrt{\sum_c u_{n_t,c}^2}}$

down the speed of adoption. Therefore, we applied an accelerated failure time (AFT) model with time-varying covariates to estimate the effects of geographic and social proximity influences on the adoption time of the OHC. We converted a physician's adoption data (single line) into multiple lines with each corresponding to a specific level of covariates and adoption status. We assumed that the time to adoption followed the Weibull distribution conditional on the covariates, a commonly used parametric model in research (Allison 2010, Gao et al. 2022).

We treated the adoption of the OHC as a failure event. Geographic proximity influence, social proximity influence, competition, the number of new patients, local adoption rate, and local marketing efforts are time-varying variables. We followed Cleves et al. (2008) to structure the survival data and estimate AFT models with time-varying variables. The following models were used to test Hypotheses 1 and 2:

$$\begin{aligned}\ln\left(TimeToAdopt_m\right) &= \alpha_0 + \alpha_1 Geographic\ proximity\ influence_{h,t-1}\\ &\quad + \alpha_2 Social\ proximity\ influence_{h,t-1}\\ &\quad + \alpha_3 Competition_{m,t} + \alpha_m X + \delta\epsilon_m, \end{aligned} \tag{1}$$

$$\begin{aligned}\ln\left(TimeToAdopt_m\right) &= \beta_0 + \beta_1 Geographic\ proximity\ influence_{h,t-1}\\ &\quad + \beta_2 Social\ proximity\ influence_{h,t-1} + \beta_3 Competition_{m,t}\\ &\quad + \beta_4 Geographic\ proximity\ influence_{h,t-1} * Competition_{m,t}\\ &\quad + \beta_5 Social\ proximity\ influence_{h,t-1} * Competition_{m,t}\\ &\quad + \beta_m X + \delta\epsilon_m, \end{aligned} \tag{2}$$

where h represents the hospital in which physician m works; t and y identify the month and year. The vector $\boldsymbol{X}$ includes $HighTitle_m$ (an indicator variable that equals to one for high-title physicians and zero for low-title physicians), $NumberPatients_{i,t-1}$ (the log number of new patients in city i at month $t-1$), $LocalAdoptionRate_{h,t-1}$ (the cumulative adoption rate of hospital h at month $t-1$), $LocalMarketingEfforts_{i,t-1}$ (Baidu search index of the OHC in city i at month $t-1$), $WeatherCondition_{i,t-1}$, $InternetPenetrationRate_{i,y-1}$, three dummies for the level of affiliated hospital h (i.e., levels 3A, 3, and 2A), city fixed effects, and specialty fixed effects. Low-title physicians and hospitals below level 2A serve as base groups. ϵ_m follows the extreme value (Gumbel) distribution with scale parameter δ. To test Hypotheses 3a and 3b, we split our sample into two subsamples: high- and low-title physician samples. For a robustness check, we use the following model with three-way interaction terms:

$$\begin{aligned}\ln\left(TimeToAdopt_m\right) &= \gamma_0 + \gamma_1 Geographic\ proximity\ influence_{h,t-1}\\ &\quad + \gamma_2 Social\ proximity\ influence_{h,t-1} + \gamma_3 Competition_{m,t}\\ &\quad + \gamma_4 Geographic\ proximity\ influence_{h,t-1} * Competition_{m,t}\\ &\quad + \gamma_5 Social\ proximity\ influence_{h,t-1} * Competition_{m,t}\\ &\quad + \gamma_6 Competition_{m,t} * HighTitle_m\\ &\quad + \gamma_7 Geographic\ proximity\ influence_{h,t-1}\\ &\quad * Competition_{m,t} * HighTitle_m\\ &\quad + \gamma_8 Social\ proximity\ influence_{h,t-1}\\ &\quad * Competition_{m,t} * HighTitle_m\\ &\quad + \gamma_9 Geographic\ proximity\ influence_{h,t-1} * HighTitle_m\\ &\quad + \gamma_{10} Social\ proximity\ influence_{h,t-1} * HighTitle_m\\ &\quad + \gamma_m X + \delta\epsilon_m. \end{aligned} \tag{3}$$

4.5. Identification Strategy

A key source of endogeneity in identifying social influence arises from homophily. Scholars have made great efforts to identify proximity influence on top of homophily. Typical identification strategies involve propensity score matching (Aral et al. 2009), randomized experiments (Bramoullé et al. 2009, Bapna and Umyarov 2015), econometric manipulation (Zhang et al. 2018), instrumental variables (Tucker 2008, Matos et al. 2014), and quasi-experimental design (Wang et al. 2018). In this research, we cannot obtain physicians' social network data. The OHC does not provide social features for physician–physician interactions, such as following and messaging. Even if the platform provides these features, the online social network would not be able to capture a physician's off-line interactions.

To identify the impacts of proximity influence, we employed instrumental variables for geographic and social proximity influences. Given that the proximity matrices G and S are exogenous to the focal physician's adoption behavior, the endogenous part of proximity influence mainly comes from the lagged adoption rates. Therefore, we instrumented each proximity influence using the product of proximity matrices and two exogenous variables. The first exogenous variable is the internet penetration rate of other cities (for all $j \neq i$) in the previous period, a commonly used instrumental variable (IV) in the economics literature (Bhuller et al. 2013). The high internet penetration rate of city j ensures easy access and exposure to the platform, leading to a high adoption rate for the city. The internet penetration rates of other cities in the previous year are exogenous and can only affect the adoption behavior of the focal physician in the current period through social influences from physicians of other cities.

The second is weather conditions, which have been used as an IV in economics and management (Fichera and Savage 2015, Ghose and Todri-Adamopoulos 2016, Lind 2020). We measured weather conditions as the percentage of days that are not rainy in city j at month $t-1$. Weather conditions can affect physicians' allocation of off-line and online activities. Bad weather can deter off-line activities, prompting physicians to engage online. Adverse weather conditions are likely to lead physicians to adopt the platform. Also, the weather conditions of other cities in the previous month are exogenous to the focal physician's adoption behavior in the current month after controlling for other variables.

The IV estimation examines how the variations in proximity influence brought by the two exogenous shifts (weather conditions and internet penetration rates of other cities in the previous period) affect physician adoption. Following Atiyat (2011) and Terza et al. (2008), we applied a two-stage residual inclusion method for estimating the AFT model with IVs, which excels in obtaining statistically consistent estimates of nonlinear models.

We also combined the IV approach with the coarsened exact matching method. In our case, the professional title, education, overseas experiences, and administrative position reflect large amounts of the information of a physician that is unobservable to researchers. These unobservable characteristics may include values, interests, habits, capabilities, and social norms. Leveraging the coarsened exact matching method, we constructed the strata of matched physicians. Because all physicians are affected by proximity influence, we ran the *cem* command in Stata without defining the treatment variable (Blackwell et al. 2009). We matched physicians with professional titles, ages, genders, education levels, overseas experiences, and administrative positions.[3] We excluded the city and class of hospital in our matching to ensure variations in the social proximity matrix and unbiasedness in estimation. Our final data set included 118 strata consisting of 21,463 physicians. Some physicians were dropped because no matches were found. Following Dale and Krueger (2002), we included a set of strata fixed effects, denoting groups of physicians with similar individual characteristics. Using the matched sample, we ran the AFT model with IVs and strata fixed effects.

The first stage estimations of the regressions using IVs[4] show that the instruments are significantly associated with proximity influence. Moreover, the Lagrange multiplier (LM) statistics for the underidentification test strongly reject the null hypothesis that instrumental variables are weak. The overidentification test statistics (Sargan–Hansen test) cannot reject the null hypothesis that the excluded instrumental variables are uncorrelated with the error terms in Equation (1).

5. Empirical Results

5.1. Effect of Proximity

Table 3 summarizes the IV estimation results of Equation (1). Model 1 lists the coefficient estimates and the related statistics. Model 2 uses the matched sample with strata fixed effects for Equation (1).

As shown in Table 3, geographic proximity influence extends a physician's time to adoption ($b = 0.368$, $p < 0.05$). On average, a standard deviation increase in adoption by geographically close physicians leads to a 44.5% increase in time to adoption of a nonadopting physician.[5] We also calculated the hazard ratio, which is 0.667, indicating that the chance of adopting the OHC is 33.3% lower with one standard deviation increase in geographic proximity influence. Hypothesis 1a does not seem to be supported by our results. Social proximity influence significantly reduces a physician's time to adoption ($b = -0.326$, $p < 0.001$) with a standard deviation increase resulting in a 27.8% reduction in a nonadopting physician's time to adoption. The hazard ratio is 1.366. Therefore, Hypothesis 1b is supported. Our results also suggest that competition accelerates OHC adoption ($b = -0.148$, $p < 0.01$).

Overall, although social proximity influence is found to accelerate OHC adoption, our results suggest that the impact of prior adoption by geographically close physicians is negative. The result is counterintuitive and may well be attributed to local competition faced by nonadopters. To examine the role of competition in proximity influence, we run regressions of Equation (2).

5.2. Proximity Influence and Competition Effect

Table 4 summarizes the estimation results of Equation (2). Model 1 lists the coefficient estimates and the related statistics. Model 4 uses the matched sample with strata fixed effects for Equation (2).

The coefficient before *Geographic proximity influence* is -0.652 ($p < 0.001$), and that before *Geographic proximity influence* × *Competition* is 0.647 ($p < 0.001$). Therefore, the impact of geographic proximity is contingent on the level of competition. Specifically, when there is no competition, a standard deviation increase in geographic proximity influence reduces nonadopting physicians' time to adoption by 67.3%. However, its impact decreases with competition. Thus, Hypothesis 2a is supported. This result explains the negative impact of geographic proximity found in the previous section, suggesting a nuanced interaction between geographic proximity and competition. Moreover, the coefficient before *Social proximity influence* × *Competition* is -0.344 ($p < 0.001$), suggesting that the impact of social proximity increases with competition. Therefore, Hypothesis 2b is also supported.

Table 3. Proximity Effects on Adoption

	Full sample		Matched sample	
Variables	Model 1		Model 2	
Geographic proximity influence	0.443*	(0.185)	0.368*	(0.184)
Social proximity influence	−0.341***	(0.058)	−0.326***	(0.058)
Competition	−0.168***	(0.045)	−0.148**	(0.045)
High title	0.630***	(0.030)	18.914[a]	(4,024.8)
Lagged local adoption rate	−3.706***	(0.286)	−3.628***	(0.282)
Log(number of new patients + 1)	−0.421***	(0.023)	−0.410***	(0.023)
Local marketing efforts	0.049	(0.057)	0.058	(0.056)
Weather	0.032	(0.090)	0.061	(0.090)
Penetration rate	−1.422	(1.026)	−1.231	(1.022)
Level 3A hospital	−0.047	(0.090)	−0.073	(0.090)
Level 3 hospital	−0.253*	(0.101)	−0.270**	(0.100)
Level 2A hospital	0.011	(0.089)	0.006	(0.088)
City dummies	Yes		Yes	
Specialty dummies	Yes		Yes	
Strata fixed effects	—		Yes	
Observations	1,532,569		1,519,008	
Log-likelihood	−16,771		−16,228	
Under-ID test (LM statistics)	1.2 e+05		1.2 e+05	
Weak IV test (Wald F statistics)	3.3 e+04		3.3 e+04	
Over-ID test (Sargan statistics)	3.749		5.524	

Notes. Standard errors in parentheses. The under-ID, weak IV, and over-ID tests are obtained by estimating linear probability models.
[a]Highly insignificant because the professional title, a matching variable in *cem*, is highly correlated to strata fixed effects.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

To elaborate on the heterogenous interaction effects of proximity influence and competition on physicians' adoption across professional titles, we reran Equation (2) for low- and high-title groups separately. The results are reported in Table 4. The interaction effect of geographic proximity and competition is larger for low-title physicians (b = 0.728, $p < 0.001$) than for high-title physicians (b = 0.211, $p > 0.05$). The interaction effect of social proximity and competition is stronger for low-title physicians (b = −0.360, $p < 0.001$) compared with high-title physicians (b = −0.163, $p < 0.05$). Further, we incorporated the three-way interactions

Table 4. Proximity Influence and Competition

	Full sample			Matched sample		
Variables	Model 1 (all title)	Model 2 (low title)	Model 3 (high title)	Model 4 (all title)	Model 5 (low title)	Model 6 (high title)
Geographic Proximity Influence	−0.634**	−1.235***	0.243	−0.652***	−1.220***	0.195
	(0.199)	(0.254)	(0.263)	(0.197)	(0.249)	(0.261)
Social Proximity Influence	−0.316***	−0.160*	−0.204**	−0.304***	−0.153*	−0.191**
	(0.056)	(0.069)	(0.074)	(0.055)	(0.068)	(0.074)
Geographic Proximity Influence × Competition	0.660***	0.740***	0.229	0.647***	0.728***	0.211
	(0.083)	(0.091)	(0.123)	(0.082)	(0.089)	(0.123)
Social Proximity Influence × Competition	−0.347***	−0.354***	−0.180*	−0.344***	−0.360***	−0.163*
	(0.057)	(0.064)	(0.083)	(0.057)	(0.063)	(0.083)
Competition	−0.631***	−0.631***	−0.263**	−0.633***	−0.617***	−0.257**
	(0.064)	(0.064)	(0.094)	(0.058)	(0.067)	(0.093)
High Title	0.673***	—	—	19.435[a]	—	—
	(0.032)			(4,235.4)		
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Strata fixed effects	—	—	—	Yes	Yes	Yes
Observations	1,532,569	521,673	1,010,896	1,519,008	518,391	1,000,617
Log-likelihood	−16,397	−4,440	−11,453	−16,228	−4,237	−11,122

Notes. Standard errors in parentheses. Baseline controls include lagged adoption rate, log(new patients + 1), local marketing efforts, weather condition, internet penetration rate, class of hospital, city dummies, and specialty dummies.
[a]Highly insignificant because the professional title, a matching variable in *cem*, is highly correlated to strata fixed effects.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Table 5. Proximity Influence and Competition Effect over Different Statuses

	Full sample		Matched sample	
Variables	Model 1		Model 2	
Geographic Proximity Influence	−0.279	(0.210)	−0.325	(0.209)
Social Proximity Influence	−0.474***	(0.065)	−0.458***	(0.064)
Geographic Proximity Influence × Competition	0.864***	(0.095)	0.859***	(0.094)
Social Proximity Influence × Competition	−0.711***	(0.077)	−0.711***	(0.076)
Geographic Proximity Influence × Competition × High Title	−0.350***	(0.103)	−0.369***	(0.102)
Social Proximity Influence × Competition × High Title	0.615***	(0.098)	0.629***	(0.097)
Geographic Proximity Influence × High Title	−0.603***	(0.078)	−0.574***	(0.080)
Social Proximity Influence × High Title	0.379***	(0.058)	0.374***	(0.057)
Competition × High Title	0.045	(0.053)	0.025	(0.054)
Competition	−0.689***	(0.066)	−0.649***	(0.066)
High Title	0.294***	(0.038)	19.178[a]	(4,908.7)
Baseline controls	Yes		Yes	
Strata fixed effects	—		Yes	
Observations	1,532,569		1,519,008	
Loglikelihood	−16,311		−15,768	

Notes. Standard errors in parentheses. Baseline controls include lagged adoption rate, log(new patients + 1), local marketing efforts, weather condition, internet penetration rate, class of hospital, city dummies, and specialty dummies.
[a]Highly insignificant because the professional title, a matching variable in *cem*, is highly correlated to strata fixed effects.
***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

and ran Equation (3) (see Table 5). The results are consistent. As shown in Table 5, Model 2, as competition increases, the impact of geographically close prior adopters decreases less for high-title physicians than low-title physicians ($b = -0.369$, $p < 0.001$). Meanwhile, the increase in the impact of socially close prior adopters is less significant for high-title physicians than for low-title physicians ($b = 0.629$, $p < 0.001$). Therefore, Hypotheses 3a and 3b are supported.

5.3. Robustness Check

First, online quality signals might contribute to the adoption decision of physicians and confound our estimation of proximity influence as physicians may adopt to maintain or improve their reputation in the face of peer adoption. Therefore, we included the online quality signal measured as the log transformation of one plus the volume of online reviews (i.e., the number of patient votes) a physician received in the previous month in our model. The results, shown in column (2) of Online Appendix Tables A3–A5, are consistent with our main findings.

Second, we explored the robustness of our results to different measures of the social proximity matrix. We constructed the social proximity matrix using two alternative specifications (i.e., alternatives 1 and 2 in Online Appendix Table A1). The results are consistent and can be found in columns (3) and (4) in Online Appendix Tables A3–A5.

Third, a physician may have been promoted to a higher title during our observation period (from March 2008 to May 2016), which may confound the moderating effect of professional title on physicians' dependence on proximity influences and competition. According to Hao (2015), a physician typically moves to a higher professional title every five years. Thus, we removed associated chief physicians from our sample because they were likely to be promoted from low to high titles in our time window. We redefined *HighTitle* as one for chief physicians and zero for resident and attending physicians and then reestimated our models. As shown in column (5) in Online Appendix Tables A3–A5, the results are consistent with our main hypothesis.

Fourth, we relaxed the definition of the local market from city-specialty cohort to city cohort when measuring competition to account for possible competition across specialties within a city. As shown in the last column of Online Appendix Tables A3–A5, the results remain consistent.

Fifth, given the potential heterogeneous effects of local marketing efforts on physicians with different titles, we included the interaction terms between the Baidu search index and professional titles. We also examined the robustness of our results by including the interaction terms between the Baidu search index and the hospital classes. The results shown in Online Appendix Tables A6(a), A6(b), A7(a), and A7(b) are consistent with our main results.

Sixth, to investigate the dynamic effects of proximity influence, we ran the AFT model in 10 different time periods by setting the ending time of our data set six months earlier in each step until November 2011. Consistent with Choi et al. (2010), the results (available upon request) show that geographic proximity influence gradually decreases over time, whereas social proximity influence becomes more important over time. More notably, our results show that the moderating roles of local competition exist with the same signs as in our main results during different time periods.

Finally, to address the possibility that the relevance between IVs and proximity influence measurements may arise from similar time trends, we followed the idea of Barron et al. (2021) and conducted a placebo test to rule out the concern. In each month, we randomly swapped the proximity influence measurements across hospitals. We repeated the randomization process 200 times. The randomized proximity influences preserve the time trend. If our results were mainly driven by similar time trends in proximity influences and IVs, we should get similar results when estimating the model using these randomized proximity influences. Online Figure A1 shows the normal-fitted distributions of estimates and z-statistics for the coefficients of the randomized proximity influences. The dashed lines represent the main estimates. As expected, most of the random draws yield statistically insignificant results with only four draws producing significant results at a 95% significance level.

6. Discussion and Conclusion

Taking a social influence perspective, we emphasize the mutual influence that physicians exert on each other, especially those who are socially and geographically close. We sought to quantify the influence of proximate adopters on the physician adoption of an OHC. Distinguishing proximity influence from homophily is critical in understanding the diffusion of OHCs. If homophily were the primary driver of diffusion, the focus should be on market segmentation and identifying specific target physicians. However, when social influence plays the leading role in imitation, we should devote more effort to identifying influential and susceptible individuals (Dewan et al. 2017).

We identified proximity influences by controlling for the homophily effect through instrumental variables and matched physicians. Our results indicate that prior adopters' social proximity significantly accelerates physician adoption of OHCs. The impact of social proximity is large as the internet facilitates the formation of social space based on shared interests and attitudes. Surprisingly, on average, geographic proximity has either no effect or even a negative impact on adoption decisions. An in-depth analysis reveals a more nuanced picture: the influences of proximity vary with competition. Without competition, geographically close prior adopters significantly expedite nonadopters' adoption. As competition increases, the impact of geographically close prior adopters weakens, whereas the influence of socially close prior adopters strengthens. Proximity matters because it facilitates communication, social proof, and norm conformity. However, local competition diminishes the influence of geographic proximity, reinforcing social proximity influence.

Moreover, the influence of prior adopters is heterogeneously experienced by nonadopters in the face of competition. As competition increases, the impact of geographically close prior adopters decreases more, and that of socially close prior adopters increases more for low-title physicians compared with high-title physicians.

6.1. Theoretical Contributions

In the realm of technological diffusion, researchers have produced abundant evidence highlighting the role of social influence (Choi et al. 2010, Risselada et al. 2014). Our study aims to examine the impact of social influence, weighted by the closeness in the population's geographic distance and sociodemographic composition, on physicians' adoption of an OHC. We empirically investigated whether geographically and socially close adopters affect the focal physician's decision to adopt an OHC. Our findings confirm the presence of proximity influence in the diffusion process of OHCs. We demonstrate that geographic and social proximity provide a significant foundation for social influence. Going beyond research in e-commerce contexts (Barrot et al. 2008, Choi et al. 2010), this study extends our understanding of social influence in the adoption of online professional service communities, an area that has received limited attention.

Furthermore, by directly measuring local competition, we examine whether these proximity influences are contingent on the level of competition. Our results verify that local competition discourages others from emulating the adoption behaviors of geographically close adopters. This negative effect can outweigh the positive social influence of the increasing number of geographically close adopters. However, we also observe that physicians tend to rely more on socially close prior adopters when local competition intensifies. To the best of our knowledge, this study is among the early efforts to empirically investigate how social influence affects individual users in a competitive environment in which the adoption behavior of other users diminishes one's benefits of adopting an innovation. Whereas proximity influence is generally influential, it can manifest differently as local competition changes. These findings have broader applications in contexts in which the internet continues to penetrate the service industry. For most online service platforms, such as those in the gig economy, users predominantly consist of individual service providers who benefit from the platform but face competition from fellow adopters as well.

Finally, our research offers fresh insights into the role of status in social contagion and technology adoption.

It suggests that proximity influences and competition effects are heterogeneous across personal characteristics. Different subsets of the population, characterized by distributions of physician professional titles, exhibit different susceptibilities to the interaction effects of potential proximity influence and competition. Low-title physicians are more susceptible than high-title physicians to their social network's composition and decision when it comes to adopting innovations such as OHCs, particularly in competitive environments. Overall, our findings imply that the low adoption levels of most health innovations could be attributed to the social environment rather than a baseline reluctance to adopt.

6.2. Managerial Implications

Our research offers practical insights. It reveals that shared traits between physicians, such as location and class of hospital, significantly increase the likelihood of adoption. In practice, online platforms can leverage proximity influence by incorporating information cues such as cumulative adoption rates in nearby hospitals, similar cities, or hospitals of the same class for nonadopters.

Moreover, our results suggest that proximity influence is contingent on the level of local competition. Therefore, the framing of information cues should consider both competition and social influence. When sharing information cues about the adoption behavior of socially close peers, online platforms can enhance the effect of proximity influence by facilitating the social identification process (e.g., emphasis on their similarities). For information cues related to geographically close prior adopters, however, platforms should find a balance between the beneficial direct impact of competition on the focal physician and the adverse moderating effect by which competition diminishes the influence of geographically close peers. Furthermore, we find that low-title physicians are more susceptible to the interplay of proximity influence and local competition. Therefore, online platforms can make more efforts to share adoption information about socially close peers with low-title physicians through different channels (e.g., social media, workshops, conferences), mitigating potential competition effects brought about by more adopters in local markets. For high-title physicians, who are more independent, content recommendations should emphasize the benefits and usefulness of online platforms.

6.3. Limitations and Future Research

Our study has certain limitations that present future research opportunities. First, we used a data set of three provinces instead of nationwide data: Shanghai, a first tier city and province-level municipality; Anhui, a province in the East; and Gansu, a province in the Northwest. They were intentionally selected, which no doubt simplified the social influences faced by the focal physicians. Expanding the data set to cover a wider geographical area may enhance our main results. Second, although we measured individuals' dynamic adoption behaviors in detail, the data may be incomplete because of potential privacy concerns. A more comprehensive analysis of heterogeneous social influences across personal characteristics could be achieved with a detailed data set of physicians' personal information, including education, medical experience, and off-line work schedules. Combining physicians' social network data could provide more insights into the moderating effects of network characteristics, such as tie strength and structural embeddedness, and better delineate the diffusion process of the OHC. Third, we measured social proximity at the hospital level to facilitate the construction of our IVs. However, a finer level measurement could help better represent social interactions. Fourth, further research could leverage randomized experiments to test the effectiveness of incentives given to different subsets and identify underlying contagion mechanisms.

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Endnotes

[1] See https://icd.who.int/browse11/l-m/en.

[2] The results with four professional titles based on Equations (1) and (2) provide consistent results (see Online Appendix Table A6a). The results with four professional titles based on Equation (3) are hardly tractable.

[3] Some physicians did not reveal their information, such as age and graduation year; we set an indicator variable to signify whether certain information is missing. We included a measure of gender derived from the physician's name using the naive Bayes classifier using the *ngender* package of Python.

[4] The first stage estimations of the regressions using IVs are available upon request.

[5] The effect is calculated as $exp(0.368) - 1$, which is approximately 0.445.

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