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ORIGINAL EMPIRICAL RESEARCH

The local environment matters: Evidence from digital healthcare services for patient engagement

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Abstract

The creation and delivery of healthcare services are being transformed through patient-engaging digital services. However, their effects on hospital performance are unclear. We build on the theoretical foundations of resource dependency and environmental munificence to identify two characteristics of the hospital's regional environment, the population's access to digital computing resources (computing access) and health insurance coverage (service access), that condition the effects of hospitals' patient-engaging digital services on patient satisfaction and readmissions. We argue that these omitted environmental contingencies may help explain the inconclusive findings reported in prior empirical studies on digital services. Analysis of data collated from a national sample of 941 hospitals nested within 157 regions shows that computing access in the environment strengthens the effect of a hospital's digital services on readmissions and patient satisfaction. By contrast, service access dampens the moderated effect of digital services and computing access on readmissions, but the effect is not the same for patient satisfaction. Our study offers theoretical and practical implications underscoring the role of environmental heterogeneity in the value hospitals realize from patient-engaging digital services.

Keywords Digital services · Consumer engagement · Patient satisfaction · Readmissions · Munificence · Computing access · Service access · Healthcare insurance

Introduction

Propelled by both cost pressures and a pressing need for higher quality, hospitals are increasingly seeking to transform themselves through greater use of digital technologies (Agarwal et al., 2020). To illustrate, the average cost of unplanned hospital readmission is $15,200 (Weiss & Jiang, 2021). Further, operating margins for hospitals in 2022 continued their negative trend, falling by 44% (Kaufman Hall & Associates, 2022). Digital technologies offer one potential solution to these challenges; industry projections indicate an expected growth in the U.S. health information technology market from $163 billion in 2019 to over $441 billion in 2025 (Ugalmugle & Swain, 2021). Health information technology is being utilized across a range of different activities, including digital capture of health data in electronic health records systems, computerized physician order entry, and medication management (Agarwal et al., 2010). An emerging area of growing investment is patient-engaging digital services, i.e., electronic initiatives that involve patients in the process of healthcare service creation and delivery (Agarwal et al., 2020). Indeed, investments in these services are increasing, in anticipation of their potentially transformative influence on healthcare (Volpp & Mohta, 2017). However, empirical evidence related to the effects of such services on hospital performance is scant and limited to a handful of studies (see, for example, Bao et al., 2020; Essén et al., 2016; Gardner et al., 2015; Zainuddin et al.,

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2016). Therefore, an important and unasward research question is: do patient-engaging digital services enhance a hospital's performance?

Understanding the association between patient-engaging digital services and hospital performance is crucial as the technologies that engage patients in care creation and delivery processes represent a paradigm shift in healthcare, from a model where patients were largely passive consumers, to one where they are potentially active participants.[1] Whether this shift enabled by the implementation of patient-engaging digital services creates value for hospitals is not well understood. On the one hand, there are reasons to believe that it would improve a hospital's performance. Digital services may contribute to value by enabling patient access to information, electronic engagement with healthcare providers, and enhanced monitoring, management, and sharing of health information on a more continual basis (Essén et al., 2016; Zainuddin et al., 2016). For example, with features that enable direct access to lab tests, patients can take an active role in managing their health and maintain a closer connection with their care providers (Kane, 2016). In turn, this can improve care outcomes and potentially yield higher patient satisfaction with the care experience.

Alternatively, it is plausible that rather than resulting in improvements, the burden imposed by the information-centric and continuous engagement model (e.g., tasks and responsibilities related to using technology) yields adverse effects on clinical performance. Fundamentally, engaging patients in care creation and delivery challenges the dominant centuries-old delivery model of an episodic and high-touch credence service, characterized by significant information asymmetry between patients and doctors (Agarwal et al., 2019). Patients have always relied on the expertise and experience of medical professionals for healthcare delivery. Further, patients may lack motivation, knowledge, and skills to manage their own health. Therefore, intentionally engaging patients may be detrimental to care outcomes and satisfaction. Which of the two effects of patient-engaging digital services prevail across different hospitals is unclear, and the key focus of this research.

The effects of digital services in the broader marketing literature are equivocal as well, with studies reporting both positive as well as negative impacts (Haumann et al., 2015; Scherer et al., 2015; Zolfagharian et al., 2018). We argue that these contradictory findings may indicate that performance is influenced by missing contingencies. Using this reasoning, we examine the role of the hospital's environment as a moderating contingency influencing the performance effects of digital services for engaging patients. We ground our study in the conceptual foundation of resource dependency and environmental munificence, which underlines the role of scarcity or abundance of environmental resources as an influence on the organization's ability to pursue its goals (Castrogiovanni, 1991; Pfeffer & Salancik, 1978; Staw & Szwajkowski, 1975).

Using this perspective, we highlight that engaging patients requires enabling both their learning and their motivation to participate. We focus on the availability of resources in the hospital's regional environment as key enablers of learning and motivation, to argue that the hospital's local region (operationalized as the Metropolitan Statistical Area MSA[2] in our study) offers resources that help patients become effective participants and satisfied consumers of healthcare services. We use this logic to identify how regional heterogeneity in the abundance of two environmental resources––computing access, reflected in the percentage of MSA's households owning different computing technologies and service access, indicated by the percentage of households in the MSAs with insurance coverage–influences the effects of patient-engaging digital services on critical performance outcomes–hospital readmissions and patient satisfaction.

Using a rich data set compiled from four different sources, the American Hospital Association (AHA), Center for Medicare and Medicaid Services (CMS), Healthcare Information and Management Systems Society (HIMSS) analytics, and the U.S. Census Bureau with a lag-effect empirical specification, we report novel findings related to the effects of digital patient-engaging services in healthcare. Results show that the performance effects of these services on readmissions and patient satisfaction are amplified for hospitals operating in regions with abundant computing access. We further find that the joint effect of digital services and computing access on hospital readmissions is contingent upon the region's service access.

Our study sheds light on the performance dynamics underlying a new and emerging paradigm of healthcare services creation, triggered by patient-engaging digital services. The growth of these services is accelerating in response to changing consumer expectations and needs, as well as the evolving regulatory environment that emphasizes greater patient engagement in health, such as those emphasizing shared decision-making with medical providers (Barry et al., 2017). Several studies that have been conducted at the consumer level in other domains suggest that customer characteristics such as perceived ability (e.g., Dong et al., 2008, 2015) and self-efficacy (e.g., Yim et al. 2012) are

[1] Patients do not necessarily need deep expertise or clinical knowledge about medical services to become active participants in care. They can be engaged in care through straightforward features of digital services that support a) clinical (i.e., viewing medical records, downloading medical records, transmitting care/referral summaries, requesting updates to health records, requesting prescription refills, and submitting patient-generated data) or b) administrative (i.e., scheduling appointments and paying bills) service processes.

[2] We use the terms local or external environment of the hospital, region, and MSA interchangeably.

critical for understanding the value of interactions between consumers and service providers. We offer an alternative, multilevel perspective that emphasizes two macro-level (i.e., region and hospital) determinants rather than micro-level (i.e., consumer or patient) determinants, suggesting that ability or know-how at the region level changes across regions depending on the availability of computing resources.

While focused at the macro level, our analysis also provides a granular assessment of the cross -level interaction effects. Specifically, we unravel if the hospital's outcomes are influenced by two-way interactions (i.e., between digital services and MSA's computing access) and three-way interactions (i.e., between digital services, MSA's computing access, and MSA's service access). Hence, we extend an emerging yet nascent marketing literature investigating digital services that are created in close contact with consumers (see Kopalle et al., 2020) and consumed at local levels (Shukla et al., 2021). To the degree that hyper-digitized environments are becoming increasingly commonplace across a range of service industries (e.g., Kopalle et al., 2020), understanding the value of digital interactions in healthcare–a critical societal sector–is timely. For practice, our findings deepen knowledge of optimal healthcare environments that balance the interests of multiple agents (e.g., patients, doctors, and insurance providers). Today, hospitals are increasingly competing in more open markets for consumers reflecting a growing trend in healthcare (Dyrda, 2021; Landi, 2021). In these contexts, our research contributes by offering nuanced recommendations regarding where to invest scarce organizational resources, in terms of investments in patient-engaging digital services.

Theoretical background

Distinct but related streams of literature inform our study and are briefly reviewed below. First, we review the marketing and healthcare literature studying patient (consumer) engaging digital services and associated impacts. Second, we describe the relevance of resource dependency and environmental munificence theoretical perspectives for our work. Finally, we identify two relevant service outcomes and discuss why they are consequential for hospitals.

Patient-engaging digital services

While services, in general, have been studied extensively through different perspectives in diverse settings, such as physical environments or surroundings and frontline sales or service employees (e.g., Kidwell et al., 2020), our study addresses a gap that exists at the nexus of digital services, healthcare, and a patient-centered perspective. A review of relevant literature (see Web appendix A) shows that little previous research focuses on digital services, and even fewer studies explore patient-engaging digital services. Digital services are now becoming commonplace. Especially in hospitals, patient-engaging digital services represent a broader trend in the economy marked by consumer engagement across different economic sectors.

Conceptualizing engagement is complex. Brodie et al. (2011) suggest that consumer engagement is "a psychological state that occurs by interactive, co-creative customer experiences with a focal agent/object (e.g., brand) in focal service relationships" (p. 260). Consumer engagement has gained increased relevance and is being found to impact key organizational outcomes including customer retention, satisfaction, competitive advantage, and sales (Brodie et al., 2013). In prior work, researchers conceptualize consumer engagement as being unidimensional, multi-dimensional, or both, and with either behavioral, cognitive, or emotional dimensions (Brodie et al., 2011). A common theme among all the perspectives is the focus on interactions. Interactions involving customers are a key element underlying the definition of the engagement construct. Using this perspective, we conceptualize patient-engagement in terms of *interactions* between hospitals and patients.

In the healthcare setting, the consumption of care involves extensive service interactions between the hospital and the patient. These interactions pervade administrative and clinical processes. For example, during a medical visit, a variety of exchanges occur, such as the doctor eliciting information from patients, informing and educating them about their medical condition, offering expert advice and guidance, and recommending a treatment regimen. Patients also participate in various administrative activities, such as scheduling appointments and paying bills. According to Gruman et al. (2010), such interactions serve as a trigger for patient engagement behaviors that include follow-on actions, including gathering additional opinions, asking questions, assessing whether a facility can accommodate unique needs, and discussing treatment with the provider. Prior to the wave of digitization in healthcare, these exchanges occurred manually. Today, hospitals are implementing digital services to enable these interactions, i.e., the use of digital resources in the form of data and electronic communications to customize patient interactions (Sridhar & Fang, 2019). Using the interaction perspective, we define *patient-engaging digital services* as technology implementations involving patients in the creation or delivery of healthcare services.

Research suggests several prominent examples of patient-engaging digital services in hospitals, such as acquiring and exchanging information electronically through patient portals and secure messaging (Levinthal et al., 2014), and sharing electronic copies of health information, discharge instructions, or educational resources (Pye et al., 2014). Patients may also use digital services to schedule appointments, pay bills, view, and download electronic medical records and upload healthcare-related information such as vital signs (Demiris, 2016). Many such services (e.g., view records, download reports, upload vital signs) have the potential to positively impact outcomes. Indeed, when patients become active participants rather than passive recipients in the healthcare service system, it is likely that this will have a positive impact on hospital outcomes (Essén et al., 2016; Zainuddin et al., 2016). To illustrate, reduced cost or quality improvement may be realized when a population[3] of patients becomes more reliant on self-monitoring their healthcare, say by uploading their information, saving on costly and time-consuming hospital visits. However, it is unclear if all hospitals may realize similar effects of patient-engaging digital services, or if there are moderating environmental conditions that influence the extent and effectiveness of patient participation. Building on resource dependency arguments, we suggest that the munificence of the hospital's *regional environment* plays a critical role as an enabler.

Organizational environments and resource dependency

The central argument of the resource dependency perspective is that an organization's ability to realize value from internal resources, e.g., the services it offers, is contingent upon resources present in its environment (Chowdhury & Endres, 2021; Pfeffer & Salancik, 1978). Previous research has underscored the role of the environment in enabling the effective use of digital services (Kopalle et al., 2020; Wielgos et al., 2021). However, the role of the environment in healthcare is complex and distinct from its role in traditional business settings. In other sectors, the implementation of digital services, and associated automation, renders local environmental resources less important or even inconsequential, by reducing the level of face-to-face contact required. For example, online banking reduces reliance on local bank branches, dampening the role of regional resources (such as labor or facilities) on the bank's performance (Dallerup et al., 2018). In other words, as the customer base expands beyond local areas as a result of digital services, the regional environment's resources have lesser impacts on the organization's performance.

However, for healthcare services, the patient catchment area for hospitals tends to be predominantly regional. Therefore, the dynamics for healthcare services are likely distinct, and the role of regional environmental resources is likely to be substantial in this sector. This is because the essential nature of healthcare services is that they require close contact to facilitate their creation and delivery. Underscoring the regional dependence, research studying healthcare markets indicates that patients may only travel for about 15 miles to get specialized services or seek higher quality services in local or nearby areas (Welch et al., 1993). Given the "localness" of healthcare consumption and considering prior research that has underscored the role of the environment, it is plausible that the effective use of patient-engaging digital services is contingent upon environmental resources. To conceptualize the resources that are likely to be relevant to the hospital, we draw upon the theoretical notion of environmental munificence and empirical literature that has examined its facets.

Resource munificence in organizational environments

Researchers have viewed environmental munificence in three different ways, examining it as a capacity, conceptualizing munificence in terms of growth or decline, or equating munificence to opportunity and threat (Castrogiovanni, 1991). Web Appendix B includes a sample of exemplar research on environmental munificence. In this study, we view munificence from the resource-dependency lens and we utilize the perspective of munificence as a "capacity" that indicates the availability of and access to resources (Chowdhury & Endres, 2021; Vadakkepatt et al., 2021), together with the relative scarcity or abundance of resources within the macro-environment (Castrogiovanni, 1991).

In the specific context of patient-engaging digital services, we identify two environmental resources that are likely to condition their effectiveness. The first, computing access, relates directly to the population's knowledge and skills. These may help consumers effectively leverage digital services by providing the know-how or resources that are transferrable across different digital contexts. The second resource, service access, reflects the population's financial wherewithal to avail of healthcare services and captures the incentives for patients to participate in service interactions through digital services. Following from the resource dependency perspective, differences in these two environmental resources may explain the effect of patient-engaging digital services on service outcomes. As suggested in prior work, a core characteristic of an organization's environment, munificence exerts a transitive influence through its effects on tasks or processes at lower levels (Castrogiovanni, 1991). That is, macro environments—characterized by socioeconomic indicators—may support or hinder an organization's ability to pursue its goals—such as increasing sales and expanding the customer base in a typical retail firm, or decreasing readmissions and increasing patient satisfaction in a healthcare context.

[3] We refer to a population of patients at the MSA level. We use MSA's population and MSA's population of patients interchangeably because healthcare is an elementary service that applies to every individual in the MSA.

Service outcomes in healthcare

Studies that examine the influence of digital services (Web Appendix A) and studies that do not focus on digital services in healthcare contexts (Web Appendix C) have considered different healthcare or service outcomes. Two major categories of performance metrics are used in previous healthcare research: clinical care quality (e.g., mortality rates, complications, readmissions, adherence to protocols, etc.) and relational care quality (e.g., emotional value, social value, patient satisfaction, etc.). Consistent with studies that examine digital services for engaging patients (see Web Appendix A), we focus on both categories of service outcomes. We examine readmissions as a clinical outcome and patient satisfaction, representing inpatient assessment of their stay within the hospital (Gardner et al., 2015), as a relational outcome.

Readmissions Readmissions is a hospital performance outcome that refers to a patient returning to the hospital after being discharged within a specified period of time. Higher rates of readmissions may indicate breakdowns in hospital processes, including discharge instructions, inadequate communication with and information provided to the patient and caregivers, and limited post-discharge follow-up (Kripalani et al., 2014). Thus, the level of readmissions represents the overall clinical quality of care provided by the hospital, often adjusted for the medical complexity of patients treated by the hospital. Readmissions constitute a large proportion of healthcare costs and affect the reputation of the hospital due to mandated public reporting (Axon & Williams, 2011). Hospitals also have a financial incentive to reduce readmissions because of penalties imposed by the government (Rau, 2014). Consistent with the Center for Medicare and Medicaid Services (CMS), we define readmission as risk-standardized unplanned readmission of patients within a specified time (thirty days of the discharge date).

Patient satisfaction Our second performance outcome, patient satisfaction assesses the hospital's performance from the perspective of the patient, reflecting the consumer's overall assessment of their healthcare experience (Gardner et al., 2015; Pye et al., 2014). We assess patient satisfaction during a hospital stay. Patient satisfaction is critical for loyalty and positive word-of-mouth (Ferguson et al., 2007) and affects willingness to recommend the hospital to family and friends (Gardner et al., 2015). As with readmissions, patient satisfaction also has financial implications: hospital reimbursements from the government for services provided to certain types of patients such as those subsidized through Medicare and Medicaid include consideration of patient satisfaction (CMS, 2010; NEJM-Catalyst, 2018). We hypothesize how heterogeneity in the focal environmental resources shapes patients' participation in care creation and delivery within a hospital, influencing the effects of digital services on a hospital's readmissions and patient satisfaction.

Research model

Drawing on the theoretical foundations discussed above, the research model underlying our study is shown in Fig. 1, and construct definitions are summarized in Table 1. The research model builds upon resource-dependency theory and environmental munificence to depict the proposed conceptualization at two levels: the external environment of the hospital–macro-level (i.e., computing access and service access) and internal environment of the hospital–hospital-level (i.e., digital services and hospital outcomes). We explicitly hypothesize the interaction between the two levels using the resource-dependency theory which suggests that the impact of internal resources on hospital outcomes is contingent on external resources within the external environment.

Prior research indicates that digital services should have positive impacts on hospital outcomes (lowering readmissions and amplifying patient satisfaction in our study) (Bao et al., 2020; Gardner et al., 2015; Wagner et al., 2012; Zainuddin et al., 2016). We include these relationships in the research model and our empirical tests; but do not develop hypotheses for these main effects. Rather, our focus is on the environmental resources that moderate these relationships. We expect the abundance of computing access, reflecting knowledge resources in the hospital's environment, to reinforce the effects of digital services on readmissions and patient satisfaction. Further, we hypothesize that this conditional or two-way effect is weakened by greater accessibility to service, i.e., health insurance coverage, in the population.

Computing access and service access

In a healthcare context, two resources are noteworthy–computing and service access in the hospital's region. Prior research has highlighted the role of computing resources (Awang et al., 2009; Castrogiovanni, 1991), noting, that the rate at which technology changes is an important characteristic of the external environment (Wielgos et al., 2021). Researchers have examined various aspects of computing resources including the average bandwidth and speed of the Internet (Vieira et al., 2019). For example, Vieira et al. (2019) discuss the importance of the Internet infrastructure for realizing value from digital services, across developing and developed countries.[4] Service access captures the economic conditions of the environment and is especially critical for healthcare consumption activities as access to healthcare is largely a function of the availability of health insurance. Opoku-Agyeman et al. (2020) draw upon the resource

[4] From a munificence perspective, an MSA with 1000 households and 300 households with computing resources has a computing access percentage of (300/1000) * 100 (i.e., 30%); here, computing resources are less abundant relative to another MSA with the same number of households but where 600 have access to computing resources.

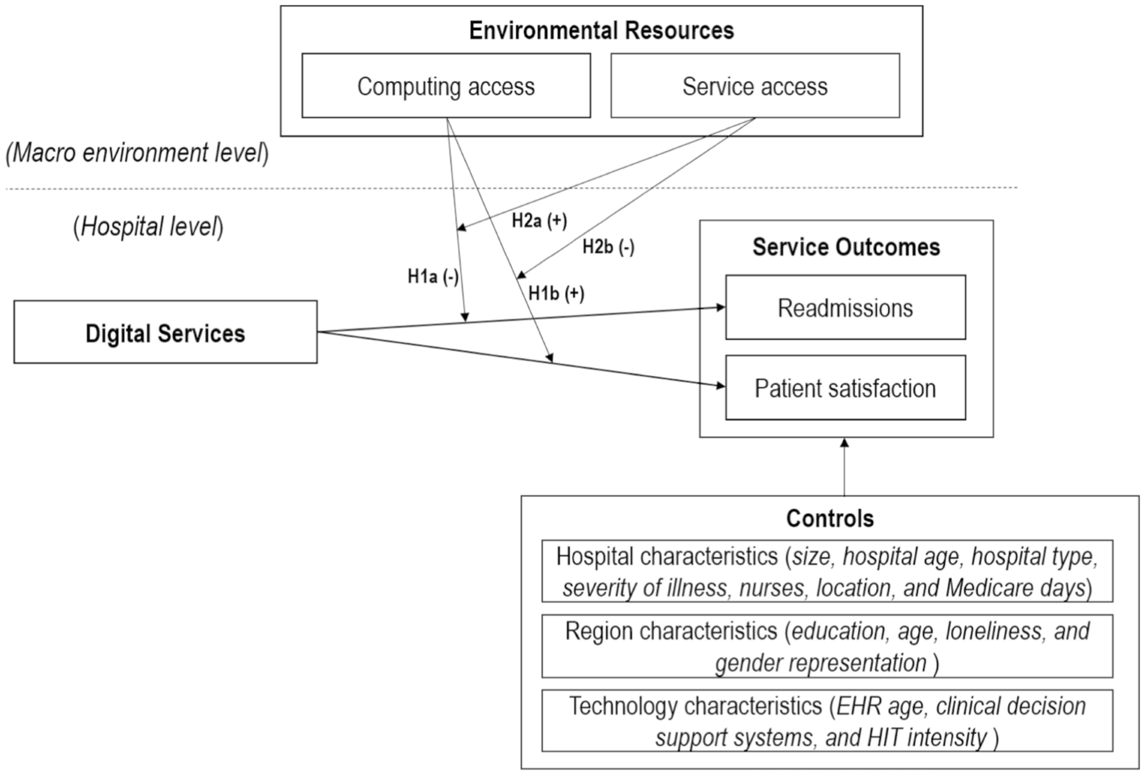

Fig. 1 Research model. Although the direct effects are not the focus of the study, we note signs of the direct effects for clarity

dependency perspective to identify health insurance as one characteristic of environmental munificence. These two resources thus represent key contingencies in our conceptualization.

Contingent impacts of computing access

Patient-engaging digital services and readmissions

Communication breakdowns and information gaps contribute to the root causes of readmissions (Kripalani et al., 2014). Digitally-enabled engagement of patients may help reduce these breakdowns and gaps. For example, implementing patient-engaging digital services may enhance healthcare providers' ability to determine whether discharge information and treatment follow-ups are communicated appropriately. These services also help monitor patient activity and healthcare progress. Similarly, by using up-to-date measures of vital signs that patients provide on a more frequent cadence than those gathered during an in-person visit, healthcare providers can accurately monitor levels of adherence to care processes and create personalized educational materials for patients, potentially influencing important service outcomes for the hospital (Agarwal et al., 2020). By using patient-engaging digital services, patients may also

Table 1 Construct definitions

Construct	Definition	Reference
Computing access	Abundance/scarcity of computing resources (e.g., computers) in the external environment of the hospital (i.e., MSA)	Adapted from Castrogiovanni, 1991
Service access	Abundance/scarcity of resources in the external environment of the hospital (i.e., MSA) that facilitate access to healthcare services (health insurance coverage)	Adapted from Castrogiovanni, 1991
Digital services for engaging patients	A technology that enables patients to be participants in their healthcare by giving them active control of their health and well-being	Adapted from Agarwal et al., 2020 and Bao et al., 2020
Patient satisfaction	Patients' overall ratings of the hospital including their willingness to recommend the hospital to family and friends	e.g., Gardner et al., 2015
Hospital readmissions	A risk-standardized unplanned readmission of patients within a certain period of the discharge date	e.g., Bardhan et al. 2015

get their questions answered by healthcare providers, follow up on test results or medications, and identify medical and administrative errors in billing or treatment (Chase, 2013). However, all of these exchanges require that patients engage actively, for example, by logging in regularly, accessing critical information relevant to their care, and providing or updating information.

What will enable patients to become engaged participants? We argue that computing access in the hospital's external environment acts as a catalyst: specifically, the abundance of computing resources in a hospital's external environment reinforces the effects of digital services for engaging patients on readmissions. Computing access represents a bundle of knowledge resources that patients draw on to exploit or harness technology. Indeed, to engage in digital healthcare services creation and to effectively leverage them, patients require the availability of technical expertise and prowess within their environment. For example, they may need help accessing digital portals and uploading vital signs. Regions with greater computing access have an abundance of relevant knowledge resources for patients to gain technical expertise, and populations with greater access to computing resources are more digitally savvy. As researchers have noted, the population's ability to assimilate and utilize new external knowledge increases with greater access to computing resources (Huang et al., 2018), and overall digital literacy is likely higher in regions with abundant computing access. Regional digital literacy has a spill-over effect on hospital patients, as it influences interactions of patients within a population, enabling them to engage in services through digital technologies more effectively.

As environmental resources, greater knowledge and experience amongst populations help patients discern how and where digital technologies may be used to enhance their convenience, time savings, and ease of use associated with engagement in service creation. Research shows that digitally literate patients are likely to utilize digital services or transactions more extensively (Akhter, 2014; Van Beuningen et al., 2009) in a variety of ways. A patient may learn about using a patient portal after discharge, to confirm a medication regimen or review any recommended lifestyle changes. She may leverage the environment's computing resources within her environment to learn about ways to securely message her provider if she experiences a concerning symptom after discharge. This potentially avoids further deterioration of her medical condition and obviates the need for readmissions. Thereby, patients become more capable of engaging in services and providing input and feedback to the hospital, because they have a deeper understanding of the capabilities of digital services and higher levels of self-efficacy (Perzynski et al., 2017; Wagner et al., 2012). In summary, an abundance of computing access in the hospital's external environment provides relevant knowledge resources to leverage digital technologies for engaging patients in service creation, as it facilitates broader adoption, use, and learning. Therefore, we test:

H1a Regional computing access complements the negative effects of a hospital's digital services on readmissions, such that this effect is stronger in hospitals operating in regions with abundant computing access.

Patient-engaging digital services and patient satisfaction

Because patient-engaging digital services facilitate interactions with care providers, hospitals serving populations with higher levels of computing access are in a better position to accrue relational benefits from these services. These benefits manifest as patient satisfaction with hospital stays. Gwinner et al. (1998) define relational benefits as "the benefits customers receive from long-term relationships above and beyond the core service performance (e.g., reduced anxiety as opposed to on-time package delivery)" (p. 102). Because healthcare creation and delivery is a localized activity that relies on close contact between care providers and patients, it is likely that such relational benefits will be amplified when patients participate effectively. Care providers are often busy with care provisioning and are typically strapped for time, limiting their ability to engage in relational interactions. Greater access to computing resources within the external environment offers an alternate or complementary channel through which healthcare providers have more time to build and maintain closer relationships with the hospital's patients, reducing the constraints that inhibit the accrual of relational benefits.

To effectively engage patients in service creation, both care providers and patients need to understand service dynamics and work as a team. Abundant computing access in their external environments offers knowledge required for patients and providers to improve their skills at working together, as they learn from the population experience. That is, when computing resources are abundant in the population, both providers and patients tend to draw on knowledge resources to learn from their day-to-day experiences. Indeed, many non-healthcare examples of consumer participation in service creation are now commonplace (Rangaswamy et al., 2020). Customers are increasingly participating in the creation of traditional services, such as ordering food and ridesharing, by providing order details through apps and websites, checking delivery status on their own, and making payments online. In environments with greater computing access, the utilization of digital services in such non-healthcare contexts is likely to be higher (Vieira et al., 2019). In turn, this enables patients and care providers to transfer learning from other contexts, improving their ability to effectively engage in services within clinical settings.

As some activities are relegated to digital channels, relational benefits increase as providers are able to dedicate more time and effort to patients, building trust and confidence and reducing their anxieties about treatments. Further, patient-engaging digital services may enhance the personalization of care (Agarwal et al., 2020). Because digital services enable patients to take an active role (e.g., by uploading vital signs), healthcare providers can more effectively customize their services to patients' preferences (Agarwal et al., 2020). In turn, this customization may trigger positive effects on patients' perceived relational benefits during their hospital stays. That is, computing access within the external environment helps care providers relate more effectively with admitted patients and create more positive relational–and affective–experiences, driving satisfaction. Following these arguments, we propose:

H1b Regional computing access complements the positive effects of a hospital's digital services on patient satisfaction, such that this effect is stronger in hospitals operating in regions with abundant computing access.

Contingent impacts of service access

Patient-engaging digital services and readmissions

We propose that the moderating effect of computing access on readmissions (H1a) is stronger when health insurance coverage is low. In MSAs with low health insurance coverage, the paucity of access to healthcare services in the environment may stimulate a scarcity mindset wherein the population develops greater incentives to participate in the creation and delivery of healthcare services, resulting in better hospital outcomes. Low levels of health insurance coverage[5] are associated with costly access to healthcare services (Kerr & Ayanian, 2014; Oakes et al., 2019). In such scenarios, patient-engaging digital services can act as a viable and efficient supplement to traditional healthcare services. This amplifies the importance of computing resources that build the knowledge patients need for effectively exploiting digital services. In MSAs with low health insurance coverage, we expect the hospital's patients to be more motivated to leverage the hospital's patient-engaging digital services for self-management or preventive care as they are influenced by a population-level mindset that leans towards efficient use of healthcare services through participation in the creation and delivery of these services. For example, patients may conduct personal research to become informed about diseases and treatments (Agarwal et al., 2019). Similarly, the feature to upload vital signs allows patients to self-monitor their condition, hence reducing unnecessary or costly medical visits. Further, this feature may create value by enabling providers to identify at-risk patients and personalize their healthcare services.

In regions with limited health insurance coverage, as patients cope with scarcity and seek cost-effective ways to consume healthcare services, they develop a greater drive to exploit digital services and leverage the digital knowledge of the broader population, to participate in care creation. Anecdotal evidence supports this assertion: practitioners at the University of Southern California system note that digital services may provide the greatest advantage for patients for whom medical visits are financially challenging due to limited health insurance (Peden & Saxon, 2017). These patients are motivated to engage in healthcare services creation, such as by self-monitoring vital signs instead of a hospital visit, to reduce the overall cost of accessing healthcare services. Therefore, we expect that limited access to health insurance in a hospital's external environment will enhance the catalyst role of the environment's computing access on healthcare performance improvement through patient-engaging digital services. In other words, relative to the regions with greater health insurance coverage, hospitals in regions with limited health insurance coverage realize a stronger positive moderation through computing access:

H2a The moderating effect of computing access on the relationship between patient engaging digital services and lower readmissions is stronger in hospitals operating in regions with lower health insurance coverage.

Patient-engaging digital services and patient satisfaction

We propose that the moderating effect of computing access in the hospital's external environment on patient satisfaction (H1b) is stronger when service access or health insurance coverage is less abundant as well. As argued in H2a, because of a scarcity mindset in the population, patients in such regions have greater incentives to become participants in care creation/delivery and will likely prefer more efficient solutions by engaging through digital services rather than using traditional clinical services for cost considerations. Such a preference also raises the importance of computing access to harness the potential of digital services and ultimately, accrue relational benefits from these services. Digital services facilitate patients' self-management, reducing the volume of clinical services by delegating some tasks (e.g., health indicator tracking) to patients (Kao et al., 2018;

[5] In our context, a lack of health insurance coverage does not equate to a complete lack of access to healthcare services and associated digital services. For instance, federally qualified health centers and safety-net hospitals are legally obligated to provide healthcare for individuals regardless of their insurance status. However, access to care in these hospitals may still be challenging for patients given the financial and staff constraints that these hospitals face.

Mollard & Michaud, 2018). In turn, this reduces the need for doctor or nurse visits, and ultimately the need to go through lengthy reimbursements. By contrast, in regions where healthcare services are more accessible to the population due to abundant insurance coverage, the absence of a scarcity mindset in the population may lead patients to not consider the efficiency payoff from digital services as important.

Further, the technological burden of participating in care through patient-engaging digital services, i.e., tasks and responsibilities related to using the technology, vs. the financial burden of healthcare services may be weighed differently by patients across regions, based on insurance coverage. When the population has lower service access and perceives a paucity of healthcare services, patients may tend to avoid financial burdens. As a result, they value more tasks and responsibilities, perceiving care participation to be less burdensome and exhibiting lower resistance to leveraging digital services. With the technology being utilized more extensively, the need for care provider intervention reduces. In such settings when patients and providers are both armed with key information, the relational benefits accrue as care providers are free to be able to take on deeper or more relational roles that patients value such as dedicating more time to relating personally with patients. During hospital stays, the coordination between care providers and patients through patient engaging digital services may also be better in regions with less service access. Considering these arguments, we test:

H2b The moderating effect of computing access on the relationship between patient engaging digital services and enhanced patient satisfaction is stronger in hospitals operating in regions with lower health insurance coverage.

Data and measures

Data sources and sample

To test the proposed hypotheses, we compiled a dataset from three U.S.-based healthcare data sources and the U.S. Census Bureau. The healthcare data were extracted from the American Hospital Association (AHA) for the year 2013, the Center for Medicare and Medicaid Services for the year 2014, and the Healthcare Information and Management Systems Society (HIMSS) analytics for the year 2013.[6] The combined dataset comprises two major categories of variables: region and hospital characteristics.

In circumscribing a hospital's macro environment, we consider the "local" nature of healthcare consumption and draw upon health policy literature (e.g., Opoku-Agyeman et al., 2020). We define a region, i.e., a hospital's external environment, using the U.S. Office of Management and Budget (OMB) delineation of a Metropolitan Statistical Area (MSA) that is utilized by the Census Bureau for reporting regional characteristics. An MSA is a "…. core area containing a substantial population nucleus, together with adjacent communities having a high degree of economic and social integration with that core" (Census, 2021). Thus, a region (MSA) may contain more than one hospital, e.g., in our dataset, we identified 78 hospitals in the Chicago MSA. Regional characteristics that are the key contingencies in our research model, computing resources and health insurance coverage, come from the U.S. Census Bureau.

Data on hospital characteristics (digital services and readmissions) are extracted from AHA, CMS, and HIMSS datasets. We measured digital services offered by each hospital based on the HIT supplement of the AHA survey. The response rate to this survey was more than 75% in 2013 (AHA, 2014). We matched the hospitals in the initial sample with data records in HIMSS and CMS to extract additional hospital characteristics. Finally, we matched hospitals to a specific MSA based on the hospital address.

The level of analysis is the hospital, and all hospitals are nested within MSAs or external environments. The final matched sample contains 941 hospitals (across 157 MSAs) (see Table 2). We assessed response bias by conducting ANOVA tests to compare hospitals that were retained in the sample to the ones dropped due to missing observations. There were no statistically significant differences based on several variables such as the number of beds and hospital age. The minimum number of hospitals per MSA is one, and the maximum number is 83. The hospitals are located in MSAs that, on average, have 28.5% of citizens living on their own. Within the MSAs, on average, 84.5% of the population has access to computing resources and 86.8% access to health insurance coverage. The representation of females in the sample is approximately 51%. Over ten percent (11.16%) of the population covered by our data has a bachelor's degree. The average age of hospitals is 37.86 years, and, on average, the included hospitals had electronic health records (EHR) systems implemented for 6.65 years. According to the AHA classification of control/ownership of hospitals, investor-owned or for-profit hospitals represent 13% of the sample.

Measures

Outcome variables

Our research model includes two critical hospital outcomes: readmissions (Menon & Kohli, 2013) and patient satisfaction (Gardner et al., 2015; Pye et al., 2014). Using the

[6] To test robustness and examine the causal structure, we also used the outcomes variables–readmission and patient satisfaction–from year 2015. Our results are available upon request.

Table 2 Sample characteristics

MSA Level–N = 157 MSAs				
Demographics			Number of MSAs	Percentage
Number of hospitals	1–10		134	85.3503%
	11–50		21	13.3758%
	50–100		2	1.2739%
Percentage of householders living alone	0–20%		4	2.5478%
	20–30%		104	66.2420%
	30–40%		49	31.2102%
Percentage of households with computing resources	65–75%		6	3.8217%
	75–85%		94	59.8726%
	> 85%		57	36.3057%
Percentage of civilian noninstitutionalized population with public and private health insurance coverage	65–75%		3	1.9108%
	75–85%		44	28.0255%
	> 85%		110	70.0637%
Percentage of citizens with bachelor's degrees	0–10%		94	59.8726%
	10–20%		62	39.4904%
	20–30%		1	0.6369%
Percentage of females in the population	< 50%		24	15.2866%
	> 50%		133	84.7134%
Average age of the MSA population	20–30		1	0.6369%
	30–40		130	82.8025%
	40–50		26	16.5605%
Hospital Level–N = 941 Hospitals				
Demographics		Number of Hospitals		Percentage
Years since the hospital has been established	0–10	74		7.8640%
	10–50	574		60.9989%
	50—100	167		17.7471%
	> 100	126		13.3900%
Years since the hospital started using EHR	0–10	695		73.8576%
	10–20	222		23.5919%
	20–30	24		2.5505%
Type of hospitals	Non-profit	823		87.4601%
	For-profit	118		12.5399%
Location of hospital	Rural	223		23.6982%
	Urban	718		76.3018%

definition and data from CMS, we operationalize *readmissions* as the hospital-wide readmission rate (a risk-adjusted readmission measure that is produced from Medicare claims and enrollment data). The hospital-wide readmission rate represents a broader assessment of the quality of care. It is risk-standardized for all-cause, unplanned readmissions of patients within 30 days of the discharge date (Horwitz et al., 2011).

Consistent with prior research (Gardner et al., 2015), we measured *patient satisfaction* as the average of the patients' willingness to recommend the hospital to family or friends and their overall rating of the hospital, as reported in the national standardized survey by CMS. The measure is based on the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey, which is administrated to patients after they are discharged from the hospital. The measure has been used to represent the patient experience of the quality of care (Gardner et al., 2015; Pye et al., 2014). The original survey captures the percentage of patients who rated the hospital 6 or lower, 7 or 8, and 9 or 10 on a scale from 0 (lowest) to 10 (highest). We created a weighted average of these items.

Independent variables

We used the AHA survey across hospitals to measure *digital services for engaging patients*. We operationalize *digital services for engaging patients* as the sum of various digital services that the hospital offers to patients.[7] The AHA survey captures eight (8) digital services for engaging patients[8]: viewing information, downloading information, transmitting care/referral summaries, requesting updates to health records, requesting prescription refills, scheduling appointments, paying bills, and submitting patient-generated data. Hospitals provide a binary "yes/no" response for the implementation of each service. We operationalized *digital services* for engaging patients as the total number of services/features that are implemented at the hospital level. We collapsed the eight services/features, as they are closely interconnected and form a collective work system to serve patients. This operationalization is consistent with Brodie's view of consumer engagement (Brodie et al., 2011, 2013) as our conceptualization taps into interactive experiences (i.e., all those features involve some interactive experience with patients). On average, hospitals in our sample score 3.16 on digital services, with a minimum of 0 and a maximum of 8.

To examine how regional characteristics influence the effects of digital services on service outcomes, we assessed the characteristics of MSAs where each hospital is located. Consistent with environmental munificence studies that examine macro environments, we used objective measures from official secondary sources (c.f., Castrogiovanni, 1991), the 2013 U.S. Census Bureau, to measure computing access and service access. The variables are operationalized as the percentage of citizens in the MSAs with access to computing resources and health insurance coverage, respectively.

Control variables

We control for several hospital characteristics and other categories of technology to eliminate variance caused by factors that are not included in our research model. Following prior research (Menon & Kohli, 2013; Setia et al., 2011) hospital characteristics include *size*, *hospital age*, *hospital type*, *severity of illness*, *total number of nurses*, *location, and Medicare days at the hospital*.[9] We use the number of beds to control for the hospital size. Differences in quality of care might be attributed to the severity of admitted patients' illnesses or the complexity of their cases (Setia et al., 2011). In general, hospitals that manage diverse, highly complex, and severe cases require resource-intensive treatments, potentially leading to lower patient satisfaction and higher readmissions. Hence, we use the *case mix index* (CMI) to control for resource-intensive treatments.

Given our core research objective of estimating the effects of implementing digital services, we control for a number of variables that may cause potential confounds arising from the hospital's expertise in leveraging technology. These include *EHR age*, *Clinical Decision Support Systems,* and *HIT intensity*. To the degree that hospitals that are more experienced with EHR are likely to be better at utilizing technology to offer superior services to patients and reduce readmissions, we control for *EHR age*. We control for *Clinical Decision Support Systems* as they may influence hospital outcomes (see for example Agha, 2014). To measure clinical decision support, we used six items from the AHA survey, which assess the use of clinical guidelines, clinical reminders, drug allergy alerts, drug interaction alerts, drug-lab interaction alerts, and drug dosing support. Similar to the measurement of digital services, clinical decision support represents the total number of clinical decision support functions implemented by a hospital. We include a control for overall *HIT intensity,* operationalized as the extent to which a hospital implements diverse technologies that are related to documentation, viewing, and order entry in clinical settings.

Finally, we use controls at the regional level to exclude variance arising from an MSA's *education*, *age*, *loneliness,* and *gender representation*, i.e., the percentage of females. MSA variables are measured as a percentage of the overall population. For example, the U.S. Census Bureau reports the percentage of citizens that belong to different age groups (Under 5 years and five-year interval groups, until 85 years and above). We used the categories to calculate a weighted average of age. Table 3 summarizes the operationalization of variables and lists their data sources.

[7] Our study calculates the sum of digital services assuming all services have equal weights (i.e., the effects of the services on healthcare outcomes have similar magnitudes). Future research may adopt a different weighting scheme wherein the effects of the services on healthcare outcomes have different magnitudes.

[8] We re-estimated our models with the eight digital services individually. Most of the services were significant. Hence, we decided to use the sum of the services. Complete results are reported in Web Appendix D.

[9] Other relevant research that focuses on non-technology interventions or policies use additional control variables, such as total patient days, market share, net patient revenue, teaching status, number of outpatient visits, number of emergency visits, and total operating expenses (e.g., Govind et al., 2008; Mehta et al., 2017). We re-estimated the models using these additional control variables and found the results to be consistent. Our results are reported in the endogeneity section.

Table 3 Description of variables

Variable Name	Explanation/Calculation	Source
Dependent variables		
Readmissions	30-day hospital-wide readmission rate	CMS
Patient satisfaction	The average of Patient_Rate and REC. Patient_Rate is the weighted average of the percent of patients who gave low, medium, and high ratings	CMS
Independent variable		
Digital services	Aggregate score on digital services for engaging patients	AHA
Moderators		
Computing access (external environment of a hospital)	Percentage of the MSA's households owning a desktop computer, a handheld computer, or some other type of computer with a broadband Internet subscription	U.S. Census
Service access (external environment of a hospital)	Percentage of the MSA's civilian noninstitutionalized population with public and private health insurance coverage	U.S. Census
Control variables		
HIT intensity	Various information technologies that are related to documentation, viewing, and order entry	AHA
Nurses	Total number of nurses	HIMSS
Location	Whether a hospital is located in a rural or urban area	HIMSS
Type of care	Whether the hospital is government, non-profit (e.g., church), or for-profit	AHA
Clinical decision support systems	Aggregate score on fully implemented clinical decision support functions	AHA
Electronic health records age	Years since the facility started using EHR	AHA
Case mix index	Case Mix Index providers paid under their hospital-specific payment rate based on diversity, complexity, and severity of illnesses	CMS
Medicare days	Percentage of Medicare days relative to total inpatient days	CMS
Hospital age	Years since the facility has been established	HIMSS
No of beds	Total number of beds	AHA
Female	Percentage of females in the population	U.S. Census
Education	Percentage of citizens with bachelor's college degrees	U.S. Census
Loneliness	Percentage of householders living alone	U.S. Census
Age	Mean age of the MSA population calculated as the weighted average of the different age categories	U.S. Census

Analyses and results

Bivariate correlations and descriptive statistics for the study variables are shown in Table 4. To establish the causality implied in the research model, we use the dependent variable (readmissions and patient satisfaction) for the year 2014 and the independent variables for the year 2013. Based on the correlation matrix, the independent and dependent variables are associated and in the expected directions, i.e., digital services are positively associated with patient satisfaction and negatively associated with readmissions. The association is one of the conditions for causal analysis, and the other two conditions include temporal precedence and refuting the alternative hypotheses (Cook & Campbell, 1979). For the former, we separate the independent variables (IV) and the dependent variable (DV) by a year and test a new model using data for readmissions and patient satisfaction from the year 2014. We used various control variables and ran other tests to refute alternative explanations for the proposed effects. In this section, we explain these tests, describing our approach to (a) hypothesis testing and (b) endogeneity and robustness testing.

Hypothesis tests

To test the impact of digital services, we estimated three models for each dependent variable—readmissions and patient satisfaction. Equation 1 reflects direct effects only. Equation 2 includes the two-way interaction effect between digital services and MSA's computing access. Finally, Equation 3 adds a three-way interaction effect among digital services, MSA's computing access, and service access munificence. The DV in Eqs. 1–3 is readmissions or patient satisfaction.

Table 4 Descriptive statistics and correlations

Variables	Mean	SD	Min	Max	1	2	3	4	5	6	7
1. Readmissions	15.3870	1.0179	11.6000	18.7000	1.0000						
2. Patient satisfaction	4.5223	0.1328	3.5700	4.8000	-0.3979*	1.0000					
3. HIT intensity	12.9426	5.1037	0.0000	18.0000	-0.0135	0.0637	1.0000				
4. Nurses	5.6352	1.1101	0.0000	8.5826	0.1725*	-0.0353	-0.0284	1.0000			
5. Location	1.7630	0.4255	1.0000	2.0000	0.0062	-0.1169*	-0.2948*	0.1106*	1.0000		
6. Type of care[1]	0.1254	0.3313	0.0000	1.0000	0.0282	-0.1692*	0.0212	-0.1784*	0.0375	1.0000	
7. Clinical decision support systems	4.8523	1.8348	0.0000	6.0000	0.0418	0.1333*	0.0155	0.1758*	-0.0176	-0.2057*	1.0000
8. Digital services	3.1647	2.5145	0.0000	8.0000	-0.0931*	0.2369*	-0.0108	0.1788*	0.0425	-0.2610*	0.3502*
9. Electronic health records age	1.6839	0.9258	0.0000	3.5264	-0.0311	0.1037*	0.0140	0.0811*	0.0154	-0.1767*	0.1060*
10. Case mix index	1.5608	0.2698	0.8330	3.4948	-0.0555	0.2085*	0.0114	0.5042*	0.0787*	0.0652*	0.1663*
11. Hospital age	3.3658	0.9238	0.0000	5.2781	-0.0049	0.0455	-0.0068	0.2038*	0.0500	-0.3258*	0.0017
12. Beds[2]	2.3635	0.3573	1.0792	3.3520	0.2289*	-0.1216*	-0.0550	0.7990*	0.0879*	-0.1747*	0.1713*
13. Female	0.5108	0.0066	0.4721	0.5269	0.2459*	-0.1319*	-0.0180	0.1522*	-0.0590	-0.0886*	-0.0123
14. Education	11.1552	3.5475	1.9000	20.6000	0.1692*	-0.1207*	0.0785*	0.1038*	-0.0602	-0.2008*	-0.0032
15. Medicare days	0.3775	0.1401	0.0000	1.8809	-0.0799*	-0.0173	-0.1145*	-0.2202*	-0.0781*	-0.0309	-0.0784*
16. Loneliness	28.5007	2.5371	12.8000	33.7000	0.0826*	0.0178	-0.0456	0.0341	-0.0528	-0.1728*	0.0228
17. Age	37.8637	1.9983	28.6215	46.9420	0.1539*	-0.0842*	-0.0783*	0.0412	0.0187	-0.1805*	0.0072
18. Computing access	84.5097	3.6554	66.1000	93.9000	-0.0511	0.0178	-0.0934*	-0.0292	-0.0481	-0.1094*	0.0235
19. Service access	86.7829	4.9255	63.6000	96.4000	0.0091	0.1047*	0.2745*	-0.0168	-0.3094*	-0.2979*	-0.0292
20. Digital services*Service access	-0.0323	0.9765	-4.6098	4.1660	-0.0086	0.0047	0.1706*	-0.0241	-0.0855*	0.0748*	0.0119
21. Digital services*Computing access	-0.0284	0.9235	-6.0985	3.6150	-0.0756*	0.0937*	0.0082	-0.0597	0.0465	0.0236	-0.0193
22. Digital services*Computing access*Service access	-0.0400	0.9511	-6.9153	10.1273	0.0482	-0.0198	-0.0058	0.0126	-0.1118*	0.0869*	0.0415
23. Computing access*Service access	-0.0061	1.3808	-3.1984	13.7268	-0.0122	-0.0228	0.1168*	-0.0115	-0.2197*	0.0726*	-0.0396
Variables	8	9	10	11	12	13	14	15	16	17	18
8. Digital services	1.0000										
9. Electronic health records age	0.0901*	1.0000									
10. Case mix index	0.1818*	0.0499	1.0000								
11. Hospital age	-0.0171	0.0622	0.0407	1.0000							
12.Beds[2]	0.1728*	0.0806*	0.4983*	0.1904*	1.0000						
13. Female	-0.0372	0.0296	-0.0374	0.0224	0.1678*	1.0000					
14. Education	-0.0094	0.0855*	-0.0528	0.0846*	0.1425*	0.2385*	1.0000				
15. Medicare days	-0.0858*	-0.0276	-0.1434*	-0.0055	-0.2213*	0.0922*	0.0364	1.0000			
16. Loneliness	0.0761*	0.0414	-0.0385	0.0559	0.0455	0.2858*	0.1238*	0.1129*	1.0000		
17. Age	0.0268	0.0391	-0.1065*	0.0908*	0.0749*	0.4373*	0.0068	0.1405*	0.6783*	1.0000	
18. Computing access	0.1001*	0.0538	0.0121	0.0079	-0.0148	-0.2261*	0.4917*	-0.0222	-0.2374*	-0.3124*	1.0000
19. Service access	0.0551	0.1047*	-0.1027*	0.1305*	-0.0061	0.1497*	0.4835*	0.1072*	0.4607*	0.3569*	0.1268*
20. Digital services*Service access	0.0713*	0.0446	0.0557	-0.0097	0.0149	-0.0015	0.0605	0.0062	0.1086*	0.0509	-0.1075*

Table 4 (continued)

21. Digital services*Computing access	-0.0804*	-0.0036	0.0367	-0.0236	-0.0406	-0.1337*	0.0166	-0.0430	-0.2195*	-0.2338*	0.1938*
22. Digital services*Computing access*Service access	-0.0676*	-0.0645*	0.0378	-0.0242	0.0693*	0.0447	0.0591	-0.0156	0.0107	-0.0037	-0.0347
23. Computing access*Service access	-0.0550	-0.0551	-0.0167	-0.0725*	0.0377	0.0145	0.2085*	-0.0053	-0.3058*	-0.2506*	0.0111
Variables	19	20	21	22							
19. Service access	1.0000										
20. Digital services*Service access	0.2356*	1.0000									
21. Digital services*Computing access	-0.1092*	-0.0537	1.0000								
22. Digital services*Computing access*Service access	-0.0083	0.0566	0.1421*	1.0000							
23. Computing access*Service access	-0.0029	0.2367*	0.2013*	0.2676*							

*$p < .05$

[1]Categorical variable

[2]Log transformed

$$
\begin{aligned}
DV_{i,t+1} = \beta_0 &+ \beta_1 HIT\_Intensity_{i,t} + \beta_2 Nurses_{i,t} \\
&+ \beta_3 Location_{i,t} + \beta_4 T\_Care_{i,t} + \beta_5 DSS_{i,t} \\
&+ \beta_6 EHR\_Age_{i,t} + \beta_7 CMI_{i,t} + \beta_8 H\_Age_{i,t} \\
&+ \beta_9 BTOT_{i,t} + \beta_{10} Female_{i,t} + \beta_{11} Education_{i,t} \\
&+ \beta_{12} M\_Days_{i,t} + \beta_{13} Alone_{i,t} + \beta_{14} Age\_Mean_{i,t} \\
&+ \beta_{15} DigServ_{i,t} + \beta_{16} CompAcc_{i,t} + \beta_{17} ServAcc_{i,t} + \varepsilon_{i,t}
\end{aligned} \tag{1}
$$

$$
\begin{aligned}
DV_{i,t+1} = \beta_0 &+ \beta_1 HIT\_Intensity_{i,t} + \beta_2 Nurses_{i,t} + \beta_3 Location_{i,t} \\
&+ \beta_4 T\_Care_{i,t} + \beta_5 DSS_{i,t} + \beta_6 EHR\_Age_{i,t} + \beta_7 CMI_{i,t} \\
&+ \beta_8 H\_Age_{i,t} + \beta_9 BTOT_{i,t} + \beta_{10} Female_{i,t} + \beta_{11} Education_{i,t} \\
&+ \beta_{12} M\_Days_{i,t} + \beta_{13} Alone_{i,t} + \beta_{14} Age\_Mean_{i,t} + \beta_{15} DigServ_{i,t} \\
&+ \beta_{16} CompAcc_{i,t} + \beta_{17} ServAcc_{i,t} + \beta_{18} DigServ_{i,t} * CompAcc_{i,t} + \varepsilon_{i,t}
\end{aligned} \tag{2}
$$

$$
\begin{aligned}
DV_{i,t+1} = \beta_0 &+ \beta_1 HIT\_Intensity_{i,t} + \beta_2 Nurses_{i,t} + \beta_3 Location_{i,t} \\
&+ \beta_4 T\_Care_{i,t} + \beta_5 DSS_{i,t} + \beta_6 EHR\_Age_{i,t} + \beta_7 CMI_{i,t} \\
&+ \beta_8 H\_Age_{i,t} + \beta_9 BTOT_{i,t} + \beta_{10} Female_{i,t} + \beta_{11} Education_{i,t} \\
&+ \beta_{12} M\_Days_{i,t} + \beta_{13} Alone_{i,t} + \beta_{14} Age\_Mean_{i,t} + \beta_{15} DigServ_{i,t} \\
&+ \beta_{16} CompAcc_{i,t} + \beta_{17} ServAcc_{i,t} + \beta_{18} DigServ_{i,t} * CompAcc_{i,t} \\
&+ \beta_{19} DigServ_{i,t} * ServAcc_{i,t} + \beta_{20} CompMun_{i,t} * ServAcc_{i,t} \\
&+ \beta_{21} DigServ_{i,t} * CompAcc_{i,t} * ServAcc_{i,t} + \varepsilon_{i,t}
\end{aligned} \tag{3}
$$

In our sample, hospitals are nested within MSAs and it is likely that variance is not homogenous across MSAs. To verify this, we tested the residuals for both dependent variables for equality of variances across MSAs, using Breusch-Pagan and White's test to assess the presence of MSA heteroscedasticity. The tests refute the hypothesis of equal variance across the MSAs, indicating that results from an OLS estimation will be biased. To further confirm this assertion, we used another test of heteroskedasticity by Levene (1960), which is robust against the violation of the normality assumption of the residuals. The test also refutes the assumption of homoscedasticity. Therefore, following previous marketing research (Kumar et al., 2016), we used a Feasible Generalized Least Squares (FGLS) estimator that accommodates the MSA differences in variance. Such an FGLS estimator creates a GLS estimate, whereby the original equations are transformed by incorporating an analytical weight. We calculate the fitted values of the residuals following Wooldridge's approach (Wooldridge, 2015, page 260). In our analysis, we use an estimate of the variance of the fitted values of the residuals for the MSA as the analytical weight. The models were run considering the weights.[10] Table 5 shows the results of the FGLS analysis for readmissions and patient satisfaction.

[10] For robustness checks, we conduct OLS with heteroscedasticity-consistent standard errors. The OLS results are generally consistent with the FGLS results.

Table 5 FGLS analyses

	Readmissions				Patient Satisfaction			
	M1	M2 (H1a)	M3	M4 (H2a)	M5	M6 (H1b)	M7	M8 (H2b)
Controls								
HIT intensity	0.0398**	0.0057	-0.0284**	-0.0141	-0.0048**	-0.0049**	-0.0026*	-0.0023**
	(0.0120)	(0.0143)	(0.0079)	(0.0121)	(0.0009)	(0.0006)	(0.0010)	(0.0009)
Nurses	-1.1255**	-1.0556**	-0.2555**	-0.3247**	-0.0245**	-0.0126*	-0.0148*	-0.0181**
	(0.0589)	(0.0622)	(0.0587)	(0.0807)	(0.0060)	(0.0055)	(0.0068)	(0.0058)
Location	-0.3058**	-0.2796**	-0.4660**	0.4045**	-0.0529**	0.0138*	0.0168*	0.0117+
	(0.0673)	(0.0955)	(0.0725)	(0.1086)	(0.0067)	(0.0067)	(0.0077)	(0.0067)
Type of care	-0.2820	-0.4567	0.5156**	1.5433**	-0.0369**	-0.0818**	-0.1258**	-0.1071**
	(0.2533)	(0.2817)	(0.1946)	(0.2755)	(0.0115)	(0.0089)	(0.0137)	(0.0125)
Clinical decision support systems	0.0089	-0.0360	-0.0371+	0.1691**	0.0206**	0.0133**	-0.0220**	-0.0003
	(0.0308)	(0.0310)	(0.0211)	(0.0320)	(0.0020)	(0.0014)	(0.0019)	(0.0019)
Electronic health records age	-0.2949**	-0.2159**	-0.2309**	-0.4580**	-0.0254**	0.0278**	0.0425**	0.0186**
	(0.0422)	(0.0500)	(0.0420)	(0.0595)	(0.0027)	(0.0021)	(0.0032)	(0.0029)
Case mix index	-2.2819**	-1.8119**	0.1136	-1.1891**	0.1052**	0.1016**	0.2236**	0.1813**
	(0.2231)	(0.2331)	(0.2077)	(0.2543)	(0.0191)	(0.0172)	(0.0245)	(0.0206)
Hospital age	-0.0933*	-0.0886+	-0.0471	0.4581**	0.0262**	-0.0073**	-0.0106**	0.0011
	(0.0446)	(0.0507)	(0.0372)	(0.0344)	(0.0031)	(0.0025)	(0.0036)	(0.0031)
Beds	2.8193**	1.8142**	0.9238**	3.2703**	-0.1001**	-0.0797**	-0.1577**	-0.0927**
	(0.2626)	(0.2622)	(0.2376)	(0.2165)	(0.0201)	(0.0175)	(0.0208)	(0.0182)
Female	6.3283	-3.5987	6.2482	57.8734**	-0.3718	0.6838	2.8644**	0.7334
	(7.2849)	(7.0451)	(5.9870)	(8.3285)	(0.5935)	(0.5398)	(0.5744)	(0.5171)
Education	0.0285+	0.1376**	0.1134**	0.0107	-0.0004	-0.0042**	-0.0045**	-0.0036**
	(0.0171)	(0.0155)	(0.0138)	(0.0182)	(0.0014)	(0.0012)	(0.0011)	(0.0011)
Medicare days	-5.5198**	-8.3529**	-5.0194**	-3.0035**	-0.2235**	0.0557*	-0.1090**	0.0293
	(0.2894)	(0.2662)	(0.2730)	(0.3417)	(0.0243)	(0.0219)	(0.0361)	(0.0299)
Loneliness	-0.0595*	-0.0564*	-0.0477*	-0.0667*	0.0014	-0.0035**	-0.0128**	-0.0075**
	(0.0256)	(0.0255)	(0.0196)	(0.0260)	(0.0016)	(0.0010)	(0.0014)	(0.0012)
Age	0.1023**	0.0493	0.1137**	0.0021	0.0019	-0.0001	0.0249**	0.0160**
	(0.0334)	(0.0376)	(0.0297)	(0.0421)	(0.0024)	(0.0021)	(0.0027)	(0.0024)
Independent variable								
Digital services	-0.1303**	-0.0621**	-0.0848**	-0.1465**	0.0097**	0.0029*	0.0118**	0.0079**
	(0.0132)	(0.0166)	(0.0150)	(0.0259)	(0.0012)	(0.0015)	(0.0021)	(0.0017)
Moderators								
Computing access	-0.1477**	-0.1578**	-0.0925**	0.0165	0.0004	0.0014	-0.0012	0.0023*
	(0.0120)	(0.0148)	(0.0158)	(0.0227)	(0.0009)	(0.0010)	(0.0011)	(0.0010)
Service access	0.1059**	0.0832**	0.1015**	0.2186**	0.0010	0.0051**	0.0073**	0.0049**
	(0.0102)	(0.0149)	(0.0124)	(0.0163)	(0.0009)	(0.0007)	(0.0010)	(0.0008)
Interactions								
Digital services*Computing access#		-0.0609*	-0.1217**	-0.2519**		0.0072*	0.0308**	0.0143**
		(0.0276)	(0.0260)	(0.0395)		(0.0030)	(0.0033)	(0.0030)
Digital services* Service access#			0.0311	-0.0679			-0.0056	-0.0019
			(0.0514)	(0.0681)			(0.0048)	(0.0047)
Computing access*Service access#				-0.2415**				0.0042
				(0.0790)				(0.0030)
Digital services* Computing access*Service access#				0.2731**				0.0115*
				(0.0598)				(0.0050)

Table 5 (Continued)

	Readmissions				Patient Satisfaction			
	M1	M2 (H1a)	M3	M4 (H2a)	M5	M6 (H1b)	M7	M8 (H2b)
Constant	19.3815**	30.6974**	9.9197*	-37.8669**	4.7574**	3.8155**	2.2085**	3.1867**
	(4.2539)	(4.6740)	(4.0088)	(5.1249)	(0.3424)	(0.2958)	(0.2955)	(0.2697)
$R^{2\,\alpha}$	0.918**	0.925**	0.700**	0.999**	0.857**	0.869**	0.869**	0.613**

$^\dagger p < .10$; $*p < .05$; $**p < .01$; $***p < .001$

$^\alpha$The use of analytical weights changes the dependent variable, so the reported R^2 is not comparable to the R^2 in the original model

$^\#$ Residuals used to assess the interactions

We log-transformed age and hospital age to reduce issues related to skewness. The results are similar without log transformation

N = 941

To incorporate the scaling effects, some numbers have been rounded to .0001

For consistency purposes, we use the abundance of resources in the external environment to measure computing access and service access. By doing so, we obtain a positive sign of the three-way interaction for readmissions. Although the sign is positive, the result matches H2a as the logic discusses the scarcity of service access (a reverse scale of the current scale used in the analyses)

Models 1 and 5 in each major column represent the direct effects of digital services on readmissions and patient satisfaction, respectively as illustrated previously in the first equation. A unit increase in digital services results in a 0.85% decrease in readmissions and a 0.21% increase in patient satisfaction. To test the interaction effects in Models 2, 4, 6, and 8 (as illustrated previously in Eqs. 2 and 3 above), it is important to detect and address multicollinearity issues. Hence, in Eqs. 4–6, we regress the interaction terms, i.e., digital services with both MSA's computing access and service access, against their residuals and higher-order terms as suggested by Xue et al. (2011). With this procedure, the residuals are used as interaction terms in the FGLS regression, thereby addressing multicollinearity issues that may result due to the presence of multiple interaction effects.[11] Hence, we used the residuals for the following regressions instead of the interactions, to examine H1a-H2b:

$$DigServ_{i,t} * CompAcc_{i,t} = \beta_0 + \beta_1 DigServ_{i,t} + \beta_2 CompAcc_{i,t} + \varepsilon_{i,t} \tag{4}$$

$$DigServ_{i,t} * ServAcc_{i,t} = \beta_0 + \beta_1 DigServ_{i,t} + \beta_2 ServAcc_{i,t} + \varepsilon_{i,t} \tag{5}$$

$$\begin{aligned} DigServ_{i,t} * CompAcc_{i,t} * ServAcc_{i,t} = \beta_0 + \beta_1 DigServ_{i,t} + \beta_2 CompAcc_{i,t} \\ + \beta_3 ServAcc_{i,t} + \beta_4 DigServ_{i,t} * CompAcc_{i,t} \\ + \beta_5 DigServ_{i,t} * ServAcc_{i,t} + \beta_6 CompAcc_{i,t} \\ * ServAcc_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{6}$$

[11] For robustness, we also test the effects of the interaction terms by using the multiplication between the mean-centered values of the single terms. Our results are available upon request.

H1a and H1b posit that the effects of digital services on readmissions and patient satisfaction are contingent on MSA's computing access. As seen in Model 2 in Table 5, H1a was supported as the effect of the interaction term on readmissions was significant and in the hypothesized direction (β = -0.06; p < 0.05). Similarly, Model 6 in Table 5 shows that the effect of the interaction term between digital services and MSA's computing access on patient satisfaction was significant, supporting H1b (β = 0.007; p < 0.05). As argued theoretically, MSA's computing access complements the beneficial effects of digital services on both readmissions and patient satisfaction. Web Appendix E depicts the examined interactions in H1a and H1b. We provide a numerical description, identifying as cross-tabulations of variables examined in the 2-way interactions.

H2a and H2b posit that the combined effects of digital services and MSA's computing access on readmissions and patient satisfaction are contingent on the MSA's service access. As seen in Model 4 in Table 5, H2a is supported as the combined effect of service access, computing access, and digital services was significant (β = 0.27; p < 0.01). However, the results of Model 8 (in Table 5) show that H2b is not supported as the combined effect of MSA's service access, MSA's computing access, and digital services was not negative (β = 0.01; p < 0.05). In regions with limited health insurance coverage, a hospital's digital services together with regional computing resources lower readmissions, but they do not increase patient satisfaction. In such MSAs with low service access, i.e., a standard deviation below the mean, a unit increase in digital services results in a 39.16% increase and 36.72% decrease in readmissions when computing access is one standard deviation below the mean and one standard deviation above the mean, respectively. But, in such MSAs with high service access, i.e., a standard deviation above the mean, a unit increase in digital services results in a 5.77% decrease and a 5.7% increase in patient satisfaction when computing access is limited and abundant, respectively. Web Appendix E depicts the interactions proposed in H2a and H2b. We provide a numerical description, identifying as cross-tabulations of variables examined in the 3-way interactions. Figure 2 presents interaction plots that depict 2-way and 3-way interactions.

Endogeneity and robustness tests

The context of our study is sensitive to multiple sources of endogeneity. In our hypothesis testing, we controlled for a wide variety of hospital characteristics, including hospital size and the use of other types of technologies. Additionally, we ensure that our results are robust to alternative measures. Instead of MSA-level computing resources, we use MSA-level internet access to measure MSA's computing access and obtain results consistent with our main findings (see Web Appendix F). Further, our analyses are robust to the simultaneity problem. We controlled for reverse causality in the main analysis by examining the effects of digital services on readmissions and patient satisfaction a year later, in 2014, allowing for the time needed for hospitals to realize value from interventions in healthcare contexts (Dobrzykowski et al., 2016). Extending the lag to two years, we additionally tested the effect of digital services on readmissions and patient satisfaction in 2015. Results remain qualitatively the same for all but one relationship. The complementary effect between digital services and MSA's computing access for patient satisfaction is not significant. While more research is required to evaluate the rationale, it is plausible that over time more advanced digital services are required to engage patients.

We further assess the robustness of our results by examining if digital services might be an endogenous variable and if selection bias could be a confounding factor, as the sample may not be representative of hospitals across the United States. For instance, there might be a significant oversampling of hospitals per MSA. These tests are described below.

Endogeneity tests

We conducted 2SLS and 3SLS procedures with multiple instruments. We ran the first stage of the 2SLS procedure with four instruments including the location of the hospital, the gender composition of citizens at the MSA level, the education of citizens at the MSA level, and the average age of the citizens at the MSA level. One of these instruments is at the hospital level while the others are at the MSA level. This empirical approach is consistent with previous studies that have used industry-level and county-level variables as instruments to address the endogeneity of firm-level and hospital-level variables respectively (Menon & Kohli, 2013). These instruments were chosen because they do not have a direct effect on patient satisfaction and readmissions. Moreover, they are exogenous (especially, the age and gender of the population) meaning that other variables used in the study do not predict them. Finally, these instruments are relevant as they are correlated with the endogenous variable–digital services.

The location of the hospital influences the implementation of digital services because hospitals in urban areas have greater access to resources (e.g., human and infrastructural) to implement digital services than hospitals in rural areas (see Hikmet et al., 2008). The age, education, and gender of citizens in an MSA may influence the implementation of digital services because demographic variables such as the population age, education, and gender have been found to influence the adoption of digital services (see Venkatesh et al., 2000). For example, previous studies found that older individuals use more electronic health record portals than younger individuals (Tavares & Oliveira, 2016). We conducted tests to ensure that the instruments are valid. The Anderson-Rubin Wald test and the Stock-Wright LM statistic suggest that the instruments are not weak. Moreover, the Cragg-Donald Wald F statistic rejects the null hypothesis that there is a weak identification. Furthermore, the Anderson Canon. Corr. LM statistic supports the hypothesis that there is no under-identification. Finally, the Sargan statistic suggests that there is overidentification. Web Appendices G and H report the results of the 2SLS and 3SLS procedures. The results remain consistent with the original estimates.[12] To mitigate concerns about omitted variables, we re-estimated the models with additional control variables, such as total patient days, market share, net patient revenue, teaching status, number of outpatient visits, number of emergency visits, and total operating expenses (e.g., Govind et al., 2008; Mehta et al., 2017). Web Appendix I shows these results, confirming that the main findings remain consistent.

Robustness tests

We also tested the robustness of our results to selection bias that may be caused by the oversampling of hospitals within some MSAs and the potential unequal representation of MSAs in the sample. Specifically, we replicated the analyses using a sample of hospitals located in MSAs with two (2) to twenty-four (24) hospitals per MSA, instead of all

[12] Consistent with Um et al. (2022), we also conducted an instrumental variables estimation using heteroskedasticity-based instruments (IVHI regressions) to mitigate endogeneity concerns. Our results are available upon request.

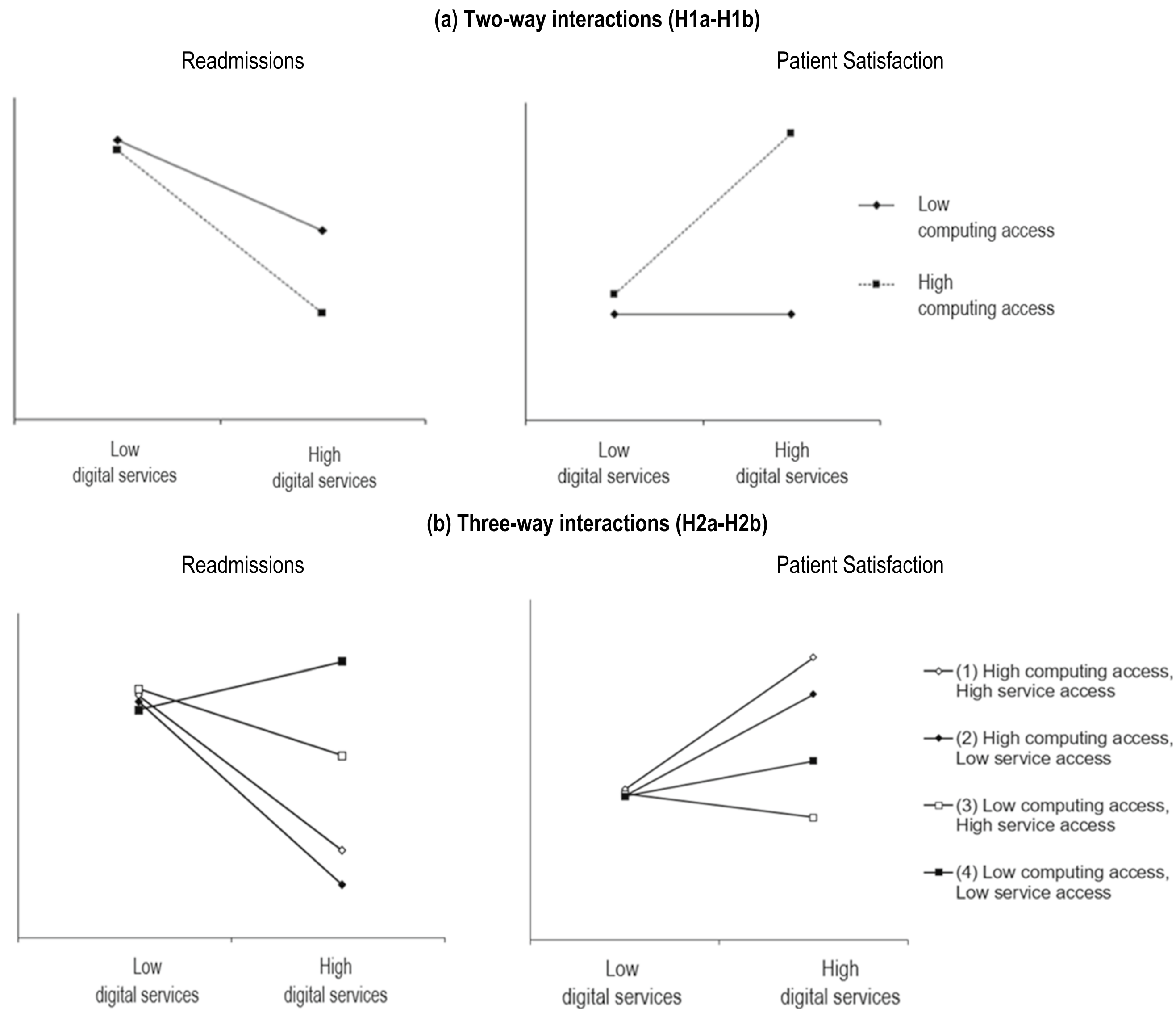

Fig. 2 Interaction plots. Because the constant term in an FGLS is not interpretable, the scale for the plots may not be indicative of actual effects. Although the sign of the three-way interaction for readmissions is positive, the negative slope of line (2) is consistent with the result since line (2) focuses on the scarcity of service access.

hospitals, spread across MSAs with one (1) to eighty-three (83) hospitals per MSA as in the original analyses.

The number of hospitals per MSA is less variable in the reduced sample (mean = 8.96; standard deviation = 6.77) than in the original sample (mean = 22.38; standard deviation = 24.31). Moreover, the reduced sample represents observations that have a total number of hospitals per MSA below the 75th percentile. Web appendix J shows the results of FGLS analyses for readmissions and patient satisfaction. Our original hypotheses were corroborated, reducing the threats due to selection bias. Furthermore, we randomly selected a few numbers of hospitals per MSA and reran the analyses. We conducted analyses with 1 to 7, and 1 to 17 randomly selected hospitals per MSA. We chose the numbers to reduce the oversampling while retaining a sufficient sample size to have adequate statistical power. The results support our main findings. We conducted analyses controlling for the number of hospitals per MSA. The results are similar to the main findings and indicate that the effect of digital services on readmissions and patient satisfaction depends on the number of hospitals per MSA. This could be an indication of network effects, and future research could examine the differential effect of digital services on readmissions and patient satisfaction among different MSA sizes.

Furthermore, we estimated how the predictors in 2018 affect the outcomes in 2019. We excluded the years 2020 and 2021 because Covid19 has profoundly affected the operations of hospitals and healthcare outcomes. The results in Web Appendix K corroborate our main findings. Finally, we re-estimated the models with alternative classifications of digital services, as each classification may represent different facets of engagement. For instance, viewing information from medical records online and downloading information from medical records can be classified under *accessing medical information* and electronic transmission of care/referral summaries to a third party, and submitting patient-generated data (e.g., blood, glucose, weight) can be classified under *contributing medical information*. We report the complete results in Web Appendix L.

Discussion

The advent of patient-engaging digital services is potentially transformative for hospitals; however, heterogeneity in the regional environment can introduce variability in their impacts. Drawing upon resource dependency and environmental munificence perspectives and highlighting the local nature of healthcare consumption, we conceptually argued that abundance/scarcity in environmental resources within a hospital's region would moderate the relationship between digital services and a hospital's service outcomes: readmissions (clinical) and patient satisfaction (relational). We identified two regional resources that have a moderating influence on the impacts of patient-engaging digital services: computing and health insurance coverage.

Using a national sample of hospitals and regions, our empirical results provide robust evidence for a majority of the hypothesized interactions. We find that implementing digital services for engaging patients significantly reduces readmissions and increases patient satisfaction overall, but these effects are experienced heterogeneously across hospitals based on the abundance/scarcity of computing access in the hospital's external environment. Computing access has a synergistic effect with digital services, amplifying their influence on reducing readmissions and enhancing patient satisfaction. We argued that this effect is a result of the digital efficacy and learning collectively by a population of patients and providers that aid participation in care creation.

For the second regional resource, service access (operationalized as health insurance coverage), we find mixed effects across readmissions and patient satisfaction. Our results support one of the proposed relationships: lower levels of health insurance coverage enhance the combined effect of digital services and the region's computing resources on lowering readmissions, likely because patients are more motivated to utilize digital services as a means of cost efficiency. Unexpectedly, lower levels of health insurance coverage reduce patient satisfaction with digital services when co-present with relatively abundant computing access. That is, the effects of lower levels of health insurance coverage in a region are different on the clinical care quality and relational outcomes of a hospital using patient-engaging digital services.

Theoretical contributions

Emerging models of care creation and delivery are evolving to embrace greater engagement of patients through the use of digital services. We contribute to the growing discourse on the performance effects of digital services for engaging consumers in general and patients in particular (Essén et al., 2016; Immonen & Koivuniemi, 2018; Rust & Chung, 2006). We emphasize the need to understand the value of digital services for engaging patients in terms of relational and clinical outcomes. While clinical outcomes have traditionally been the main focus in healthcare research, outside healthcare, digital services have been found to engage consumers to influence individual-level outcomes including consumer satisfaction (Zolfagharian et al., 2018), consumer retention (Scherer et al., 2015), and consumer loyalty (Selnes & Hansen, 2001). With patients becoming participants in care, relational or affective outcomes become more important for the assessment of digital services. There has been some focus on relational outcomes (e.g., Gardner et al., 2015), but few studies examine those in relation to digital services for engaging patients (see Web Appendix A). In that regard, our study shows that traditional approaches that focus on clinical outcomes may not give an accurate and complete assessment of performance impacts, as environmental heterogeneity can drive relational outcomes differently. Specifically, we find that the two environmental contingencies influence clinical and relational outcomes differentially. Thereby, we underscore the need for more studies examining the two outcomes in combination.

A more extensive understanding of the impacts of environmental contingencies also brings into focus the complexity associated with the performance of a patient-centric care model and the relationship between digital services and hospital outcomes. In identifying these contingencies, we contribute to the discourse on the relationship between the hospital and its macro environment or the broader population (see Web Appendix A). Interactive dynamics that cross multiple levels are challenging yet critically important for a deeper understanding of complex systems (Castrogiovanni, 1991). Our environmental level analysis provides a theoretical lens that may reconcile conflicting findings on the relationship between digital services and consumer outcomes (Haumann et al., 2015; Scherer et al., 2015; Zolfagharian et al., 2018). Without accounting for resources within the external environment, two comparable hospitals may have distinct outcomes, i.e., unexpected patterns in their performance. Our findings demonstrate how population-level insurance coverage could create a scarcity mindset that encourages patients to leverage digital services, ultimately influencing hospital outcomes. We note that focusing on environmental heterogeneity appears to be one promising direction to more effectively and accurately assess the impacts of digital transformations across industries. Organizational environments captured in the characteristics of the local populace may also be relevant to studies of other customer-side digital services such as for developing new products (Pavlou & El Sawy, 2006). The inclusion of macro considerations has been broadly identified as imperative to examine the efficacy of service ecosystems (Vargo & Lusch, 2016) or digital business capabilities (see for example Wielgos et al., 2021). In healthcare contexts, our population-level view of the macro environment will enrich our understanding of digital transformations for building more effective ecosystems.

Moreover, our multi-level analysis that focuses on the population's characteristics from a technology perspective (i.e., computing access) builds on studies that emphasize the importance of consumers' skills or abilities for co-creation at the individual level. Specifically, we go beyond the individual-level variables addressed in prior work such as perceived ability (Dong et al., 2008, 2015) and self-efficacy (Yim et al. 2012) in highlighting the role of the external environment of a hospital and the availability of computing resources therein. Finally, we provide a granular assessment of the effects of two-way (digital services and MSA's computing access) and three-way (digital services, MSA's computing access, and MSA's service access) interactions on healthcare outcomes by separating clinical and administrative features. The disaggregation of digital services features allows us to strengthen our conceptualization of such services as an integrated system of intrinsically interconnected capabilities. We find significant effects for digital services as a collective system, but inconsistent effects when we unbundle the capabilities (see Web Appendix L).

Managerial implications

This study offers new insights into ways to shape emerging care models in healthcare systems. As the digital transformation of healthcare operations unfolds, hospitals are digitizing patient engagement to support new care models, such as for shared and informed decision-making that aim to improve efficiency and effectiveness. Digital services are central to the design of such models. For example, in 2018 Apple released a health app to bring health records to the iPhone, changing patients' access to and use of healthcare services. Our findings offer three key insights for hospital administrators who are contemplating using or have already invested in digital services for engaging patients.

First, the findings illuminate the question of how hospitals should acquire and maintain digital services to better serve patients. We identify important contextual contingencies that hospital executives need to consider for improving the management and prediction of health outcomes. For instance, hospitals operating in regions with limited health insurance coverage in the population may more proactively invest in, and promote the use of, digital services to reduce readmissions. Second, although patient engagement strategies are recognized as important and promising strategic interventions (Nease et al., 2013), the cost of implementing and disseminating digital services for engaging patients remains high (Volpp & Mohta, 2017). Our findings indicate that healthcare executives can pursue targeted investments in particular digital services, based on regional characteristics, to avoid inefficiencies (e.g., greater costs) in digital services implementation. For example, healthcare executives may invest in digital services if computing resources are abundant in their region. When computing resources are scarce, it may be necessary for executives to avail local and federal government programs for improving population-level digital literacy.

Third, healthcare executives operate in an environment that is under considerable pressure to reduce costs, while maintaining high quality (Coulter, 2011; Davis et al., 2014). These two goals may conflict with each other: digital services offer the potential to overcome this tradeoff. While we have argued for the enhanced implementation of digital services, policymakers monitoring and assessing hospital performance should consider MSA's regional profile— notably its population's access to computing resources and their health insurance coverage— as they develop national programs for designing and implementing interventions, such as initiatives related to the use of digital services (e.g., meaningful use, CMS 2017). Further, hospital administrators may partner with the government and other organizations in the hi-tech industry to bridge the digital divide in MSAs and enhance broader access to computing resources, as these are crucial for harnessing the potential of digital services for creating a healthy population.

Limitations and future research

We acknowledge the limitations of our work and identify promising opportunities for future research. Our measurement of digital services for patient engagement relied on the implementation of the service by the hospital. More research is required to measure the actual use of these services by patients. Although we addressed issues related to self-selection and unobserved heterogeneity at the hospital level, future research that has access to patient-level data can further study these issues at the patient level. Conceptually, future research may extend our study by identifying additional patient-engaging digital services (e.g., proxy access – a family has access to a patient's information) and non-digital services, differentiating between inpatients and outpatients, discussing the use of artificial intelligence (e.g., chatbots) for patient engagement, and expanding to other digital services (e.g., digital services for monitoring treatment progress and adherence).

Our use of cross-sectional data to operationalize digital services represents another methodological limitation due to sustained effects over time and temporal variation of the adoption of digital services. It is important to assess the sustained effects of digital services over time, and future research could use longitudinal designs to assess these dynamics. To some extent, our research captures these effects through the use of lagged dependent variables. However, our measures of independent variables are limited over time. Our model does not account for temporal variation in the adoption of digital services across hospitals. Future research may examine adoption and assimilation timelines to get a more accurate assessment of the digital service impacts.

Our estimated regional effects are based on the population's access to crucial resources at the MSA level, as patients in this population are more likely to visit hospitals located in the same MSA. An MSA is a geographical region with close economic ties throughout the region. However, there may be other determinants of a hospital's environment. Thus, future research should build on our models to consider other geographical delineations such as at the zip code level or a hospital service area (HSA). Even within the MSA, scholars may explore new measures of munificence (e.g., number of physicians per 1000 habitants instead of healthcare insurance) and investigate the impact of digital services at various levels (e.g., small medical practices instead of hospitals). Future research may also model and examine spillover effects across MSAs, whereby resources of one MSA enhance the performance impacts of digital services in hospitals within neighboring regions. Finally, while MSA characteristics enable the assessment of moderating contingencies, more research is required to unravel the mediating mechanisms that drive the impact of digital services on service outcomes.

In conclusion, healthcare represents a critical societal sector that has traditionally been challenged by the high cost and low quality of healthcare services. A digital transformation of healthcare that engages patients in service creation is demonstrating the potential to alleviate some of these challenges. Our research addresses an urgent need for scholars and policymakers to understand new approaches to leveraging digital services for engaging patients to improve service outcomes. As the global pandemic of 2020 has vividly underscored, an effective healthcare ecosystem is foundational for the growth of communities, individuals, and nations. The findings and implications of this study have the potential to inspire more research, managerial, and policy interventions to create, assess, and manage digital healthcare services.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11747-023-00972-0.

Data availability The Census data are publicly available from the Census website, https://www.census.gov/. The Center of Medicare and Medicaid data are publicly available from the CMS website, https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/HospitalQualityInits/HospitalHCAHPS. The Healthcare Information and Management Systems Society (HIMSS) analytics data are available from the HIMSS website, https://www.himss.org/enterprise-taxonomy-topic/data-and-information. The healthcare IT data sources are proprietary. They can be obtained for a fee from the American Hospital Association website, https://www.ahadata.com/aha-healthcare-it-database.

Declarations

Conflict of interest The authors have no conflict of interest to declare that are relevant to this article.

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