Can Telehealth Mitigate Health Disparities Caused by Language Barrier and Travel Distance? Evidence from a Four-Year Panel in the United States

Introduction

According to the Centers for Medicare and Medicaid Services (CMS), national health expenditure in the United States (US) in 2020 accounted for 19.7% of Gross Domestic Product averaging about $12,530 per person. One of the major drivers for this rising healthcare cost is hospital *readmission* (Bardhan et al. 2015; Ben-Assuli and Padman 2020). Preventable patient readmissions after hospital discharge cost about $25 billion every year. Aside from the hospital readmission, *length-of-stay* (LOS) also attributes to the skyrocketing health care expenditure (Bardhan et al., 2015), attracting scholars to apply LOS as an operation efficiency measurement to remedy the issue (DesRoches et al. 2010; Oh et al. 2018). To prevent unnecessary readmissions and reduce excessive LOS, especially during the novel coronavirus disease 2019 (COVID-19), telehealth is being increasingly adopted for in-hospital and home-cased care in recent years.

As part of technology-enabled smart healthcare infrastructure, telehealth, defined as “the use of electronic information and telecommunication technologies to support long-distance clinical health care, patient and professional health-related education, health administration, and public health” (Health Resouces & Services Administration 2021), has been adopted to (1) extend regular in-person hospital services for more efficient hospital operations and patient convenience, and (2) reach out and accommodate vulnerable patient populations with access barriers to the healthcare services, such as minorities, people living in rural areas and typically with financial disadvantages and language barriers that lead to health disparities especially in the US (Hilty et al. 2020; Hwang et al. 2022; O’Connor et al. 2016; Payvandi et al. 2022; Sun et al. 2020; Tsou et al. 2021; Wosik et al. 2020). The access barriers result in significant health disparities, defined as health differences that are related to economic, social, and/or environmental disadvantages (U.S. Department of Health and Human Services 2020), and hospital telehealth implementation is critical to reducing such health disparities in the US healthcare system (Hilty et al. 2020; Hwang et al. 2022; Payvandi et al. 2022; Tsou et al. 2021).

Prior studies showed that compared to patients without language barrier, patients with language barrier experience more healthcare disparity in care, including longer LOS (John-Baptiste et al. 2004), increased number of hospitalizations, emergency department (ED) visits, 30-day readmissions (Rawal et al. 2019; Rodriguez et al. 2021), and decreased access to services (Anderson et al. 2020). Previous studies also found that travel distance to the hospital can also cause health disparity. In general, travel distance from healthcare facilities has a negative correlation and effect with health outcomes. Often, the association is known as distance decay, meaning compared to patients who live closer, those patients who live further away from healthcare facilities have worse health outcomes (Kelly et al. 2016; Målqvist et al. 2010). As such, *limited English proficiency* (LEP) and *travel distance* are identified as two main causes of health disparities, we focus on these two access barriers in this study.

While documenting the existence of health disparities that are associated with LEP and travel distance to hospital, scholars suggested that future studies should focus on examining how LEP and distance barrier (i.e., long travel distance to hospital) can cause negative patient outcomes as evidence to further propose feasible interventions that could mitigate these health disparities (Schwei et al. 2016; Turrentine et al. 2017). Telehealth is seen as a possible solution because it may mitigate health disparities (1) caused by language barrier with the aid of interpreters via telehealth (Hilty et al. 2020; Payvandi et al. 2022) and (2) generated by distance barrier with virtual care, enabling patients to self-manage their diseases and to communicate with healthcare providers virtually (O'Connor et al. 2016). However, the current literature indicates that how telehealth impacts health outcomes associated with language barriers and travel distances is under explored and lacks solid evidence-based studies to uncover its underlying mechanisms, and thus requiring further investigation to inform associated intervention programs and public health policies.

Thus, in this study, we aim to comprehensively examine how health disparity caused by LEP and long travel distance to hospital could be mitigated via telehealth implementation by analyzing a large inpatient longitudinal dataset in the US. Our overarching research question is: *How can telehealth implemented by hospitals leverage the effects of limited English proficiency and travel distance to hospital,* *mitigate health disparities, and thereafter positively influence patients' health outcomes in terms of reduced readmission risk and LOS?*

Data and Measurement

To solve this research question, we collected data from four sources. *First*, we used data from the Healthcare Cost and Utilization Project's state inpatient datasets (HCUP-SID) to obtain patient characteristics, admission, and clinical information. *Second*, we applied data from the American Hospital Association (AHA)'s annual surveys to obtain hospital characteristic data. *Third*, we used AHA's information technology (IT) supplement files for 2011–2014 to obtain Health IT (HIT) implementation data. Considering the lagged effects of HIT adoption, we followed the method that has been widely adopted to map the datasets with HIT variables lagged by one year (Lin et al. 2019). *Fourth*, we collected additional census-based data such as English proficiency level at the census tract level using data.census.gov. We then matched the reference data between the census tracts and the USPS's zip codes[1] to allocate each census tract data proportionally. We merged HCUP, AHA survey, and AHA IT with unique hospital identifications before integrating census data using patients' zip codes from HCUP-SID into these datasets. Our final valid merged sample consists of 1,686,755 admissions originating from 553,892 patients within 63 hospitals in New York (NY) and Florida (FL) states[2] from 2012 to 2015.

We focused on two patient outcomes – *30-day all-cause readmission* and *in-hospital LOS* – to investigate telehealth's impact on clinical outcome and hospital operations efficiency (Bardhan et al. 2015; DesRoches et al. 2010; Oh et al. 2018). We used *30-day all-cause readmission*, defined as patient's admission to a hospital within a 30-day range after being discharged from the same or another hospital for any diagnosis condition, to measure the clinical outcome. We applied *in-hospital LOS*, measured as the number of days of hospital stay from admission to discharge, as a proxy for hospital operations efficiency measure.

[1] Travel distance: https://www.huduser.gov/portal/datasets/usps_crosswalk.html

[2] We chose datasets from NY and FL because these two states have linkage variables to connect patients with their hospital admissions so that we can examine telehealth impact on patients with recurrent admissions.

Telehealth implementation in hospital is measured as a dummy variable, where 1 indicates telehealth is fully implemented across all units, and 0 otherwise (AHA 2022).[3] *Travel distance* is measured by driving time in minutes from the centroid (the midpoint) of the zip code for each patient to the address of the hospital. The language barrier in terms of *LEP level* is measured by the percent of the population in each zip code that speaks English less than well.

We also included hospital-level, patient-level, and admission-level variables as control variables to account for other factors that may influence 30-day all-cause readmission and in-hospital LOS. Specifically, we applied the following hospital characteristics and other HIT variables at the hospital level: hospital bed size, teaching status, profit status, in the health system or not, market share,[4] advanced HIT, and support HIT.[5] At the patient level, we included age at the discharge, gender, and race. At the admission level, we used insurance types including Medicare, Medicaid, and private insurance, the total number of comorbidities, chronic diagnoses, diagnoses, procedures, total charge at the current admission, the number of times the patient visited the hospitals since the first hospital visit, and the number of days between the current visit and the previous visit. We employed 17 different types of body systems[6] and a dummy variable that records whether the patient's primary diagnosis is in the same body system at the current admission compared to the last admission. We also included 29 different types of comorbidities[7] and the diagnosis-related group (DRG) codes that were shared by at least 0.4% of the admissions as control variables.

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[3] According to the AHA IT survey (AHA 2022), full implementation means a hospital has completely digitalized telehealth function. Telehealth implementation level is coded in a six-point scale in AHA IT survey: 1 = Fully implemented across all units, 2 = Fully implemented in at least one unit, 3 = Beginning to implement in at least one unit, 4 = Have resources to implement in the next year, 5 = Do not have resources but considering implementing, 6 = Not in place and not considering implementing. In the future research, we may consider coding telehealth implementation as an ordinal variable to examine its impact at different implementation stages.

[4] Market share is measured by Herfindahl-Hirschman Index (HHI).

[5] Advanced HIT is the HIT that facilitates the primary clinical functions of physicians, including diagnosing patients' symptoms, recommending, and delivering treatment plans; and the support HITs are those that facilitate the process of documenting patients' medical history and physicians and nurses' clinical notes and viewing results of patients' previous tests and treatments (Mishra et al. 2022).

[6] 17 different types of body systems are used in the study, including infectious and parasitic disease, neoplasms, endocrine, nutritional, and metabolic diseases and immunity disorders, diseases of blood and blood-forming organs, mental disorders, diseases of the nervous system and sense organs, diseases of the circulatory system, diseases of the respiratory system, diseases of the digestive system, diseases of the genitourinary system, diseases of the skin and subcutaneous tissue, diseases of the musculoskeletal system, congenital anomalies, certain conditions originating in the perinatal period, symptoms, signs, and ill-defined conditions, injury and poisoning, factors influencing health conditions and contact with health services.

[7] 29 comorbidity indicators are used in the study, including acquired immune deficiency syndrome, alcohol abuse, deficiency anemias, rheumatoid arthritis/collagen vascular diseases, chronic blood loss anemia, congestive heart failure, chronic pulmonary

Our summary statistics shows, on average, the percentage of patients admitted to a hospital with telehealth was 22.3% and 30-day all-cause readmissions was 22.1% for each admission. The average LOS was 6.071 days and the average travel distance was about 20 minutes. On average, patients live in areas with 0.4% of the population with LEP. We also found 44,700 patients with 96,982 hospital admissions live in areas with more than 1% of the population with LEP.

Data Analysis and Results

In this study, logistic regression was applied to assess the impact of telehealth on readmission risks, and Ordinary Least Squares (OLS) regression was applied to examine the impact of telehealth on in-hospital LOS. For both models, robust standard errors were applied to account for potential heteroskedasticity, and the errors were further clustered at the patient level to account for the possible within-patient correlations. We controlled for other hospital-level, patient-level, and admission-level factors as described above that may influence patient 30-day all-cause readmission risk and in-hospital LOS.

We first examined the *main effect* of the language barrier (i.e., LEP) and travel distance on 30-day all-cause readmission risk and in-hospital LOS.[8] Since language barrier was measured in percentage (percentage of residents not proficient in English), this variable was standardized to have a mean of zero and a standard deviation of one before adding to the model to obtain a better result explanation. We found that for patients from a zip code with one unit increase of standard deviation of the language barrier, the risk of 30-day readmission increased by 2.56% ($p<0.001$), and the LOS increased by 0.0504 ($p<0.001$) days. We also found that one minute increase in drive time is associated with a 1.2% increase of 30-day readmission risk ($p<0.001$) and 0.0531 days decreased LOS ($p<0.001$). To further explore whether telehealth leverages the effects of the language barrier and travel distance on 30-day all-cause readmission risk and in-hospital LOS, we estimated the interaction effect between telehealth and language barrier and

disease, coagulopathy, depression, uncomplicated diabetes, diabetes with chronic complications, drug abuse, hypertension, hypothyroidism, liver disease, lymphoma, fluid and electrolyte disorders, metastatic cancer, other neurological disorders, obesity, paralysis, peripheral vascular disorders, psychoses, pulmonary circulation disorders, renal failure, solid tumor without metastasis, peptic ulcer disease excluding bleeding, valvular disease, weight loss.

[8] Due to the space limitation, we omitted the result table for the main effect analysis here.

between telehealth and travel distance. We did not find a significant interaction effect between telehealth and language barrier for 30-day readmission risk but found the interaction effect is negatively associated with LOS at $p < 0.001$ level. We further explored whether the moderating role of telehealth on the distance decay effects relates to the distance to hospitals by splitting the sample using 30-minute drive distance.[9] We found that for patients who live within 30 minutes' drive, the joint effect of telehealth and travel distance was negatively associated with readmission risk ($p<0.01$) but has no impact on LOS and that for patients who live more than 30 minutes' drive time, the interaction effect had no impact on the 30-day readmission risk but slightly decreased LOS ($p<0.05$).[10]

Conclusion

With a large longitudinal dataset from multiple sources across 63 hospitals in the US from 2012 to 2015, this study provides strong empirical evidence that telehealth may mitigate health disparities generated by language and distance barriers, but this effect may differ in different healthcare contexts. Overall, we found that for patients who live in an area with a high level of language barriers, telehealth alleviates health disparities in terms of LOS. We also found that telehealth has different impacts on patients who live within or more than 30 minutes of travel time to the hospital. Our study contributes to the health disparity literature by identifying the important role of telehealth in mitigating health disparities generated by language and distance barriers for patients with recurrent admissions. This study also offers critical evidence-based implications for policymakers, indicating that telehealth can mitigate certain health disparities caused by language and distance barriers for patients with recurrent admissions, but can vary in different contexts. In the future, we also plan to explore the role of telehealth to mitigate other critical health disparities, such as rurality (Goh et al. 2016) and racial disparities (Ganju et al. 2020; Samorani et al. 2021).

[9] We split the sample using 30-minute drive distance because, in our dataset, the majority (85.98%) of patients live within 30-minute drive distance.
[10] Due to the space limitation, we omitted the result table and interaction plots for this post hoc analysis here.

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