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MOBILE & WIRELESS HEALTH

Using Electronic Health Records Data to Evaluate the Impact of Information Technology on Improving Health Equity: Evidence from China

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Abstract
This study evaluates the impact of health information technology in accessing medical resources and identifies its role in improving health equity. We used 262, 771 records from the electronic medical records and outpatient appointment systems of three clinics for logistic regression to analyze the impact of information technology on patients' access to medical care. We interviewed a few health professionals to gauge their reactions and to validate and understand our quantitative results. The proportion of inpatients affected by information technology is low, accounting for only 16.7% (N = 43, 870). The difference between rural and urban groups is statistically significant, and rural households are more susceptible to information technology. In addition, distance has a significant positive effect. We demonstrate an inverted U-shaped relationship between severity of disease and the impact of information technology. Moreover, our interview results are consistent with our quantitative results. Quantitative and interview results suggest that health information technology plays a positive role in accessing medical care for patients with rural household and those in remote areas. Meanwhile, this effect is complex for patients with different severities of illnesses. Governments and managers should vigorously promote health information technology for healthcare delivery in the future and focus their attention on patients with serious diseases.

Keywords Health equity · Health disparity · Information technology · Electronic medical records

Introduction

The extent of health inequities has grown over the past decade despite continuous investments in healthcare and the improvement of people's health [1, 2]. Patients with different geographical locations, household types, and severity of disease have unequal access to available medical services. Health inequities are crucial challenges to underserved groups such as rural households, populations living in remote areas and patients with severe diseases because of their implications. Health inequity is the unfair difference in health, such as the unequal access to quality medical resources [3, 4], which can be mitigated by reasonable strategies and activities [5]. Health information technology has the potential to assist governments and medical institutions in addressing this issue [6, 7].

Given the rapid development of information and communication technologies, such as mobile health and telemedicine, numerous countries are vigorously promoting health information technology for the delivery of high-quality medical care. Patients can access medical resources through the Internet and mobile devices, such as scheduling appointments with doctors through mobile health channels or obtaining health advice through telemedicine. China's State Council set 'Internet + medical' action plans in 2018 to encourage healthcare providers to deliver medical services over the Internet. These action plans aim for 'everyone to enjoy the same health' and to promote a healthy China [8–11]. Despite its tremendous potential for improving the accessibility and equity of medical care, the outcomes of health information technology have yet

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to be fully realized. In contrast, several studies have suggested that health information technology creates new problems, namely, the digital divide, which may further aggravate health disparities [12–14]. Governments, medical institutions, and managers are shifting their focus from user adoption to the outcomes and social impact of health information technology. In addition, it is necessary to understand the potential of information technology to improve health equity and its impact on underserved groups.

Given the uneven distribution in China, high-quality medical resources are concentrated mainly in large cities [15, 16], and people in rural areas, small cities, and remote areas have unequal access to high-quality medical services [17, 18]. Fortunately, health information technology is a convenient channel for such people to obtain medical services in large cities through the Internet. However, health information technology affects groups differently [12, 19, 20]. The impacts of information technology on different patient groups (different geographical locations, household types, and severity of disease) and whether these vulnerable groups are at a disadvantage in this resource competition should be determined. Therefore, it is necessary to understand which groups are susceptible to information technology and would ultimately have access to required medical services, and this will help us determine the role of health information technology in improving health equity.

In this study, we evaluated the impact of health information technology in accessing medical resources and identified its role in improving health equity. We combined data from electronic medical records (EMR) and outpatient appointment systems to observe inpatients' use of information technology during their outpatient visits. In addition, we determined which patient groups benefit more from information technology.

Methods

Study context and available data

We identified medical institutions for the research environment according to the following criteria: firstly, it should have high-quality medical resources, a large coverage, and multiple independent clinics, and secondly, it should have made efforts to improve the delivery of healthcare by using health information technology. We selected the Wuhan Tongji Medical Group in central China, which is a tertiary referral hospital that covers more than 60 million people and serves patients from all over the country.

In addition, the Wuhan Tongji Medical Group encompasses three unique clinics with different geographical locations, sizes and doctor compositions. This medical institution has provided healthcare services by using information technology such as online outpatient appointments since 2013. In this study, we selected inpatients hospitalized for the first time and observed their outpatient visits prior to their first hospitalization. Numerous confounding factors accompany patients admitted multiple times; thus, they are not conducive to assess the impact of information technology. Generally, inpatients have more severe diseases than outpatients; thus, we can better understand the impact of health information technology on health disparities and health equity by analyzing their characteristics and behaviors.

We extracted data from outpatient appointment records and discharge summaries in EMR systems from 2015 to 2018. After a week of data extraction, we obtained 6, 450, 687 outpatient visit records and 264, 348 inpatient discharge summaries for the first admission. The outpatient appointment dataset contained information on the use of information technology for outpatient visits, such as appointment channels and time, and the discharge summary dataset contained the demographic characteristics of inpatients and disease-related information. These two datasets can be merged using the patient ID, which identifies a specific patient. In addition, we interviewed a few clinicians and medical management specialists to gauge their reactions and to validate our results.

Outcome definition

Our primary dependent variable was whether patients' access to medical resources was affected by health information technology, that is, whether inpatients used health information technology to access medical resources prior to their first admission. Generally, patients visit clinics once or twice and are diagnosed by doctors before being admitted. Patients can make doctor appointments through online and offline channels. Online channel appointments can be identified as the use of health information technology to access medical resources. We determined that patients were affected by technology if they used health information technology to make appointments before their first admissions. In this context, we can consider that health information technology played a significant role in the acquisition of medical resources, resulting in a subsequent impact. If patients have never used information technology in numerous appointment records prior to their admissions, they were considered to be unaffected by information technology.

Independent variables

We need to understand patient relevant variables to assess which groups are affected by information technology when accessing medical resources. Numerous patient-level variables were collected in the EMR systems. We screened patient characteristic variables and variables related to health equity and health disparities, and our empirical variables are presented in Table 1.

Extant studies have indicated that gender and age have significant impacts on patients' adoption of health information technology [21–23]. Hence, gender and age were added to our model as control variables. Given their nonlinear effects, the ages of the patients were grouped into three cohorts, which were in line with existing studies [24, 25]. The main effects of our empirical model included severity of disease, household types and the distance between the patients and the medical resources. In this study, severity of disease represented the urgency of treatment and the extent of the patient's consumption of medical resources. Numerous indicators reflected severity of disease, including total cost, length of stay and whether surgery was performed [26, 27]. We used total cost as a measure of disease severity to reduce the complexity of the model and ensure its robustness.

The type of household was the registered permanent residence in China, which consisted of two categories, namely, urban and rural. The type of insurance in the discharge summaries judged the patients' types of households. The new rural cooperative medical system was classified as the rural household, and the urban residents' and workers' insurance were classified as the urban household. Generally, differences in income levels and health statuses exist between these two groups. The distance between the patient and the medical resources was based on the patient's current address, that is, whether the address was within the city or outside. This variable measured the accessibility of medical resources. There was no correlation between the type of household and distance, as the patient may belong to an urban household in other cities. We also added the discharge time and the clinic as control variables to ensure the universality of our model and the reliability of our results.

Development of empirical models

In this research, we constructed a reduced form model to examine the impact of health information technology on health equity. Given the characteristics of the available data, we estimated the research model by using logistic regression analysis [28]. We estimated our model in three steps. First, only the control variables were used in the base model, and then the main effects and squared term were added to the base model. Our full empirical model can be expressed as:

$$\begin{aligned}&\mathrm{logit}(Y_i)\\&=\beta_0+\beta_1 Gender_i+\beta_2 Age_i+\beta_3 DischargeYear_i+\beta_4 Clinic_i\\&+\beta_5 HouseholdType_i+\beta_6 SeverityofDisease_i+\beta_7 Distance_i\\&+\beta_8 SeverityofDisease_i^2+\varepsilon_i\end{aligned}$$

where Y_i is a binary variable and Y_i equals 1 if patient i used health information technology to access medical resources prior to the first admission; 0 otherwise. $Gender_i$ and Age_i are the indicator variables representing the demographic characteristics of patient i. Age consists of three cohorts, namely, under 45 years old, between 46 to 55 years old and above 56 years old. $DischargeYear_i$ and $Clinic_i$ represent when and where patient i was discharged. The model consisted of two types of patient households, namely, urban and rural, which are proxies for patient i's living environment and income level. $SeverityofDisease_i$ is measured by the total cost of hospitalisation of patient i. $Distance_i$ represents the relative distance from patient i's current address to medical resources, which was divided into two categories, namely, within and outside the city where the hospital is located. Severity of disease was a continuous variable in this study. Given the nonlinear relationship between severity of disease and the impact of information technology, we

Table 1 Variable definition and measurement

Variable		Definition and Measurement	Symbols
Dependent variable	Impact	A binary variable was used to measure whether the patients have used information technology to access medical resources before hospitalization for the first time	
Independent variables	Severity of disease	The logarithm of the patients' total cost of hospitalization	SeverityofDisease
	Household type	The patients' types of registered permanent residences based on the type of medical insurance; 0 represents rural, and 1 represents urban	HouseholdType
	Distance	Distance was used to measure the accessibility of medical resources for patients. Value 1 represents patients who live in the city where the hospital is located. Value 0 represents patients who live outside the city where the hospital is located	Distance
	Discharge year	Year of the patients' discharge	DischargeYear
	Clinic	The clinics where the patients were discharged. A dummy variable was used to identify a total of three clinics	Clinic
	Age	Patient age groups: under 45 years old, between 46 to 55 years old and above 56 years old	Age
	Gender	Value 0 represents a male patient,and value 1 represents a female patient	Gender

added the squared term of severity of disease to the model. ε_i represents the error term, which includes the total random effects of the explanatory variables not included in the model and several other random factors on the interpreted variables.

Data analysis

Our data analysis consisted of two steps. Firstly, data were merged, cleaned and transferred. The two datasets included patient ID and the number of visits. The number of outpatient visits indicated the number of visits to the outpatient department. Meanwhile, the number of hospital visits indicated the number of inpatient visits. The patient ID and the number of visits could identify a unique outpatient appointment or hospitalization event. Patients use the same patient ID during outpatient and inpatient visits. Therefore, we could correlate outpatient appointments and discharge summaries. After the data combination, we obtained data on patients' first hospitalization and use of information technology in outpatient visits prior to their first admission. Our data-cleaning strategies included removing patients with no ages and no household types and patients with total costs less than zero. A total sample size of 262, 771 valid patients' records across three clinics remained after the aforementioned operations.

Secondly, we fitted the three models separately using the existing data. The estimated β coefficients and the significance of each variable are shown in Table 3. Our logistic models were implemented in R by using the glmnet package [29].

Results

Descriptive statistics

Our sample consists of 262, 771 patient records from the three clinics from 2015 to 2018. Table 2 reports the descriptive statistics, and we observe that only 43, 870 of the 262, 771 patients used health information technology before their first admissions. These patients account for only 16.7% of the total sample.

The proportion of male and female patients is equal. The average age of all patients is 40.94 (SD 21.86). The three age groups account for 51.8%, 19.4%, and 28.8%, respectively. A total of 172, 202 patients (65.5%) live outside the city and nearly twice as many, that is, 90, 569 patients (34.5%), live in the city where the hospital is located. The proportion of urban households is 80.8%, compared with rural households. The average total cost of hospitalization is ¥ 27, 337.2. Clinic C1 is the largest clinic, with 73.8% of discharged patients.

Empirical results

The regression results are shown in Table 3. Model 1 includes only the control variables. From the logistic regression results of Model 1, we observe that all the control variables are significantly related to the impact of health information technology. Compared with male patients, female inpatients are more susceptible to health information technology, with a β coefficient of 0.209. Age has a significant impact on the use of technology, shifting from positive to negative. As shown in model 1, the β coefficients are 0.132 and − 0.040, respectively. Model 2 includes the main effects, in addition to control variables. Distance has a significant positive impact, that is, if a patient lives far from medical resources, they are more likely to use information technology. The coefficient of household types is negative ($\beta = -0.031$, $p < 0.10$), which means that patients in rural areas are more inclined to access medical services by using information technology. In model 2, severity of disease is measured by the total cost of inpatients, which is a continuous variable. The result shows that the coefficient is negative, indicating that severity of disease does not increase the dependence of patients on technology.

Given the nonlinear impact of severity of disease, we added the squared term of severity of disease to model 3. Model 3 includes the squared term, in addition to the main effects and control variables. The results show that the linear term of severity of disease is positive and significant ($\beta = 0.086$, $p < 0.10$), and the squared term is negative and statistically significant ($\beta = -0.008$, $p < 0.01$). The results demonstrate an inverted U-shaped relationship between severity of disease and the impact of information technology [30].

Robustness test

Based on the results of model 3, we observed an inverted U-shaped relationship between severity of disease and the use of health information technology. Severity differs depending on the types of specialties. Therefore, it is necessary to consider the impact of specialties on the results. In the robustness test, we added 54 specialties across the three clinics as control variables to model 3. The estimation results are shown in Table 4, in which the specialty variables estimated results are not reported in detail. The results illustrate that the coefficients of severity of disease and its squared term are still statistically significant after the addition of specialty variables. These results are consistent with the results in Model 3.

Interview results

We conducted interviews with a few health professionals in April 2019, including three clinicians, four medical managers and one director from the information technology department. After interviews on several topics, we obtained the responses

Table 2 Descriptive statistics for inpatients

	Mean	Std. Dev.
The proportion of inpatients affected by technology before admission	16.7% (43, 870)	0.37
The proportion of inpatients not affected by technology before admission	83.3% (218, 901)	
Gender		
Male	50.0% (131, 255)	
Female	50.0% (131, 516)	
Age	40.94	21.86
45 years old and under	51.8% (136, 097)	
between 46 to 55 years old	19.4% (50, 937)	
56 years old and above	28.8% (75, 737)	
Distance		
Inside the city where the hospital is located	34.5% (90, 569)	
Outside the city where the hospital is located	65.5% (172, 202)	
Household type		
rural	19.2% (50, 548)	
urban	80.8% (212, 223)	
The total cost of hospitalization	27, 337.2 ¥	40, 371.92
Discharge year		
2015	24.0% (63, 106)	
2016	30.9% (81, 100)	
2017	35.9% (94, 256)	
2018	9.2% (24, 309)	
The clinic where the patient was discharged		
C1	73.8% (193, 980)	
C2	15.8% (41, 377)	
C3	10.4% (27, 414)	

Note: $N = 262, 771$

of health professionals on our quantitative results. Table 5 provides quotes from interviews with health professionals. The results show that most of the professionals believe that health information technology positively promotes health equity and allows vulnerable groups (patients in remote areas, patients in rural households and those with serious diseases) access to needed medical services.

Discussion

This study demonstrates how health information technology improves health equity through empirical methods and interviews. The role of health informatics interventions in improving health equity is still unclear, and several studies have suggested that these interventions may create a digital divide that exacerbates health disparities [31]. However, we show that health information technology has a positive effect on the health of patients in rural groups, patients in remote areas and those with severe diseases (excluding patients with serious diseases resulting from inverted U-shaped relationships) and positively impacts the improvement of health equity.

To illustrate the role of health information technology in improving health equity, we observed inpatients' use of information technology during outpatient visits to analyze its impact on patients' access to medical care. We obtained 262, 771 records from the EMR systems and outpatient appointment systems of three clinics and found that the overall proportion of inpatients affected by information technology is low, accounting for only 16.7% ($N = 43, 870$). This result indicates that patients' acceptance of information technology is generally low and the role of information technology needs further exploration. Therefore, we constructed three logistic regression models at the patient level, with the main effects including household type, distance, and severity of disease.

The regression results show that the difference between rural and urban groups is statistically significant and that rural households are more susceptible to information technology. The β coefficients in model 2 and model 3 are both −0.031. According to the result, we find that health information technology has a significant effect in addressing health disparities between urban and rural groups. Significant differences exist between patients who live far from medical resources (outside the city where the hospital is located) and those who live in the

Table 3 Logistic regression results

Variable	Model1	Model2	Model3
Constant	−1.629*** [0.020]	−1.234*** [0.052]	−1.902*** [0.201]
Gender	0.209*** [0.011]	0.209*** [0.011]	0.208*** [0.011]
Age			
between 46 to 55 years old	0.132*** [0.014]	0.118*** [0.014]	0.121*** [0.014]
56 years old and above	−0.040** [0.013]	−0.034* [0.013]	−0.032* [0.013]
Discharge year			
2016	0.048*** [0.014]	0.057*** [0.014]	0.057*** [0.014]
2017	0.065*** [0.013]	0.087*** [0.013]	0.087*** [0.013]
2018	0.792*** [0.066]	0.810*** [0.066]	0.810*** [0.066]
Clinic			
C2	−3.010*** [0.048]	−3.001*** [0.048]	−3.000*** [0.048]
C3	−4.077*** [0.082]	−4.029*** [0.082]	−4.031*** [0.082]
Distance		0.273*** [0.013]	0.275*** [0.013]
Household type		−0.031* [0.013]	−0.031* [0.113]
Severity of disease		−0.060*** [0.005]	0.086* [0.043]
Severity of disease^2			−0.008*** 0.002
CoxSnell	0.083	0.085	0.085
McFaddenAdj	0.096	0.098	0.098

Notes: The data size for this logistic regression is N = 262, 771. Significant codes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

city where the hospital is located, and patients who live far from medical resources are more susceptible to information technology. One possible explanation for this result is that patients in remote areas tend to use information technology to access medical resources. Information technology increases the possibility of access to quality medical resources for these groups. Therefore, information technology has a significant effect on the health of patients in remote areas. The results of Model 3 indicate that an inverted U-type relationship exists between severity of disease and the impact of information technology. The impact of information technology will gradually increase as severity of disease increases. However, the impact becomes negative when severity of disease reaches a certain level and becomes detrimental to the use of information technology.

Table 4 Robustness test results

Variable	Model4
Constant	−1.834*** [0.214]
Gender	0.159*** [0.012]
Age	
between 46 to 55 years old	0.072*** [0.016]
56 years old and above	−0.070*** [0.015]
Discharge year	
2016	0.184*** [0.014]
2017	0.307*** [0.015]
2018	1.018*** [0.067]
Clinic	
C2	−2.537*** [0.051]
C3	−3.786*** [0.085]
Specialty	Partial significant
Distance	0.083*** [0.013]
Household type	0.019 [0.014]
Severity of disease	0.112* [0.045]
Severity of disease^2	−0.010*** [0.002]
CoxSnell	0.115
McFaddenAdj	0.134

Notes: The data size for this robustness test is N = 262, 771. Significant codes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

The results demonstrate that information technology has a negative effect on patients with serious diseases. The promotion and use of information technology may aggravate the health disparities between patients with general diseases and those with serious diseases. Given the heterogeneity of diseases in different specialties, specialties were added to the model in the robustness test. The results show that an inverted U-shaped relationship between severity of disease and the impact of information technology still exists, which demonstrates that our conclusions are reliable. In addition, our results also show significant differences between different age groups and gender groups. Women are more susceptible than men to use information technology. Patients between 46 to 55 years old are more susceptible to information

Table 5 Illustrations of interviews

Interviewees	Topic	Representative quotes
Clinician	Health equity	At present, the distribution of medical resources in China is uneven, and high-quality medical resources are concentrated in cities, which make it difficult for rural groups and patients in remote areas to obtain needed medical services […] and health information technology is expected to mitigate this issue.
Clinician	Use of health information technology	It is true that more and more patients are using information technology to access medical resources, and health information technology enables patients to access needed medical resources.
Manager	Health equity	We have adopted a variety of technologies to enable more patients, especially from rural groups and patients in remote areas and with serious diseases, to access high-quality medical resources […] but for patients with severe diseases, information technology plays a minimal role in obtaining resources because they are admitted directly to hospitals through emergency green channels or from lower-level hospitals.
Manager	Health equity and health information technology	With the use of health information systems and information technologies, more and more patients (from remote areas, rural groups and with serious diseases) have access to required medical services. I believe that with the development of information technology, more and more patients may enjoy the advantages of health information technology, which may play a positive role in promoting health equity.
Clinician	Health equity and health information technology	By communicating with my patients, they (patients) acknowledge health information technologies, which give them more opportunities to access high-quality medical resources, especially for rural groups, patients in remote areas and those with serious illnesses.
Manager	Information technology and access to medical resources	Yes, from our observations health information technologies have greatly facilitated the delivery of medical resources, and more patients, especially those in remote areas and those with serious diseases, use information technologies to access medical resources, which may reduce their medical costs and improve the accessibility of medical resources.
Director of the technology department	The role of information technology in improving health equity	…I agree with the conclusion that information technologies promote health equity. With the popularisation of information technology, medical resources can be obtained through Internet channels. For rural groups, patients with serious diseases and those in remote areas, information technology provides a new channel for accessing medical resources, which reduces the cost of access to medical resources…these patients have more significant opportunities to obtain the medical resources necessary. Information technologies have played a significant role in improving health equity.
Manager	Use of health information technology	…as the national medical management departments and medical institutions continue to promote the construction of health information and with the popularity of smartphones, more and more patients can use information technology to obtain needed medical resources…information technology enables vulnerable groups of patients to have equal access to the necessary medical resources, which has played a positive role in improving health equity.

Notes: Results are sorted by the interview date

technology than those under 45 years old, while the opposite is observed in patients who are 55 years old and above.

The results of the interviews show that most health experts affirmed the positive role of information technology in promoting health equity, and unanimously recognized that health information technology has significantly improved the access of medical services for patients in rural groups, patients in remote areas and those with serious diseases. The interviews are consistent with our quantitative results, which further suggest that our conclusions are reliable. In addition, the results of the interviews enrich the professional interpretation of our quantitative results. One manager believes that information technology has a limited effect on patients with serious diseases because they may have access to medical services through other means, such as emergency green channels. This view may partly explain the inverted U-type relationship between severity of disease and the impact of information technology. However, economic or other factors may also affect the use of technology of seriously ill patients.

Our findings confirm the role of information technology in improving health equity. Information technology has a significant positive impact on patients with rural households and those in remote areas. However, the effect is complex and significant for patients with differing severity of disease, even if the heterogeneity of specialty is controlled. This study has considerable practical implications for governments, medical institutions, and insurers.

Our findings show that whilst information technology improves health equity; its low utilization rates severely limit its function. Future efforts should be made to promote health information technology and its delivery of medical services to increase the allocation of medical resources through network channels and to actively guide patients in using information technology. Governments and medical institutions should focus increasing attention on patients with serious diseases. In view of the insignificant impact of information technology on such groups, safeguard measures should be taken in the future, such as establishing additional green channels to ensure that patients with severe diseases have equal access to medical services and to reduce their health disparities.

There are a few limitations to our research. Firstly, our sample is obtained from a single medical group. Despite our large sample, the scarcity of quality medical resources leads patients to compete for medical resources through information technology, thereby amplifying its role. Although we compare patients discharged from different clinics, the sizes and compositions of these clinics differ; thus, the selection bias cannot be completely ruled out. Furthermore, we only assess technological impacts during outpatient visits and did not investigate the use of information technology during the hospitalization of inpatients. Other countries have developed patient portals wherein patients can obtain disease-related information and researchers can learn about the patients' use of information technology during hospitalization [32–34]. At present, the development of patient portal in China is still in its infancy; thus, future research can consider the use of information technology during hospitalization.

Conclusions

Overall, our results indicate that health information technology plays a positive role in the access of medical care for patients in rural groups and those far from medical resources. Our results highlight that health informatic interventions are expected to achieve health equity and to improve the health of people in remote areas. In addition, this study observes an inverted U-shaped relationship between severity of disease and information technology, providing a theoretical basis for the future development of information technology interventions, particularly for patients with severe illnesses.

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Compliance with Ethical Standards

Conflict of Interest All authors declare that there is no conflict of interest.

Ethical Approval This article does not contain any studies with human participants or animals performed by any of the authors.

Abbreviations EMR, Electronic medical records

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