Exploratory Analysis of Out-of-Hospital Days Based on Cancer Patients in China

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Abstract

Cancer (re)admission time interval, or Out-of-Hospital Days (OHD) between two consecutive hospital (re)admissions, is commonly considered as an indicator of health service quality. Despite its importance, the risk factors of OHD are largely unknown because of limited access to cancer patients' data and the lack of relevant characteristics (e.g., geographic factors) in the data. To explore the association between patients' conditions and readmission events, we analyze a sample of 22,231 admissions (OHD>30), consisting of demographic, medical, and financial factors, extracted from Electronic Health Records (EHR) of 635,261 cancer patients from 190 hospitals in China. Geographic factors are also included by applying text mining to the free-form address fields of patients' homes and hospitals. Using hierarchical linear regression, we find that various factors significantly influence OHD: age, marital status, number of admissions, and whether the treating hospital is in the same province as the patient's home address.

Keywords: Cancer, OHD, EHR, China, text mining, cost, geographic

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Introduction

Cancer is one of the major diseases threatening human lives and can impose a huge financial burden on patients and their families (Warner et al. 2015). In recent years, China has experienced a dramatic increase in cancer patients. In 2015, more than four million Chinese were diagnosed with cancer and nearly three million died from the disease (Chen et al. 2016). Cancer treatment can be a long-term process, during which cancer patients may be readmitted to the hospital multiple times (Chen 2016; McConnell et al. 2016). Frequent readmission is shown to be associated with poor long-term survival rates and a high financial burden (Orcutt et al. 2016; Slankamenac et al. 2017; Warner 2015; Zhuang et al. 2015). As a result, a patient's readmission rate is an important research topic in the public health field (Ji et al. 2012; Merkow et al. 2015). If factors or trends can be identified, many lives can be positively impacted.

Cancer (re)admission time interval, or *Out-of-Hospital Days (OHD)*, is defined as the time interval between when a patient has been discharged from hospital and when they are (re)admitted again. OHD has been widely adopted as an important measure of healthcare service quality (Bakshi et al. 2017; Cholley et al. 2017). For example, an OHD fewer than 30 days is used as a measure in predictive analytics for congestive heart failure patients (Bardhan et al. 2015).

Multiple time intervals for OHD have been proposed, i.e., 30 days, 90 days, or 180 days between two consecutive hospital (re)admissions. The majority of existing studies choose to examine OHD fewer than 30 days because the expectation is that poor medical service is provided if a patient returns within that time window (Curtis et al. 2018; Lucas et al. 2014; Zhuang 2015).

Very little literature has focused on OHD greater than 30 days. In this study, we aim to analyze OHD over 30 days for cancer patients for the following reasons. In cancer treatment plans, OHD greater than 30 days is typical. Rather than an indicator of poor medical service quality, OHD for cancer patients is usually related to decisions made by the patient and her doctor(s) in order to maximize treatment outcome with minimal costs (Bayati et al. 2014). We are interested in examining OHD greater than 30 days by investigating possible factors that are not related to the quality of medical services. Specifically, for cancer patients, the treatment cost and the patient's demographic, medical, and geographic factors may play important roles in OHD. In this study, we aim to analyze the relationship between OHD over 30 days and the above-mentioned variables. We utilized a dataset collected in China to perform our analysis due to its accessibility and the increasing attention on cancer treatments in China.

Even though some studies have analyzed the risk factors when OHD is within a certain threshold (e.g., 30, 90 or 180 days), an exploratory model for exact OHD can provide more detailed information about healthcare quality and cost (Dorney et al. 2017; Orcutt 2016; Zuckerman et al. 2016). A longer OHD provides dual benefits: it can improve the patient's quality of life, and reduce medical expenses for all stakeholders. Therefore, it is important to understand the factors associated with OHD and predict OHD based on these factors.

There is a paucity of exploratory models that focus on exact OHD and its associated risk factors. Due to the fact that data specific to cancer readmissions are limited, many previous studies largely focus on one cancer type (making it impossible to generalize) and neglect critical factors that might be important in OHD prediction, such as geographic factors (Liu et al. 2016).

Our Electronic Health Records (EHR) dataset, collected from a national public health reporting system in China, has several advantages for studying OHD. We have access to cancer patient data from 190 hospitals located in 127 cities in China from 2010 to 2014. In total, we obtained 635,261 inpatients' (re)admissions EHR. Our dataset contains 18 various types of cancer (e.g., skin cancer, stomach cancer, and larynx cancer). The large numbers and wide coverage of cancer type, time series, and patients' information allow us to conduct a comprehensive analysis. Results of analysis from a national-level, multiple-cancer-type dataset may be more generalizable compared to studies conducted with small samples targeting one or two cancer types.

In this article, we examine the factors that can influence the number of OHD between consecutive cancer treatments. Specifically, we have four types of independent variables: patient demographic (e.g., gender, age), medical (e.g., a patient's number of diagnosed cancers), financial (e.g., accumulated cost of previous treatments), and geographic factors (e.g., whether patient's home and hospital are in the same province).

Our central research question is:

What factors (e.g., demographic, medical, financial, geographic) interact with Out-of-Hospital Days?

In the next sections, we present the theoretical background, the methodology of studying OHD, results, discussion, and conclusions.

Theoretical Background

In many research domains, empirical studies grounded in Self-Determination Theory (SDT)

(Ryan and Deci 2000) have typically examined relations between SDT-based constructs and outcome variables. Intrinsic motivation emphasizes inherent sources of self-feeling, not consequences of actions, while extrinsic motivation focuses on a desired outcome (Ryan and Deci 2000). When one internalizes the extrinsic reasons for an act, the boundaries between intrinsic and extrinsic motivations can vary, and both motivations can become self-determined. A deep understanding of these motivating factors is needed. Ryan et al. (2008) found that motivations such as autonomy, competence, and relatedness are central to patients' health.

Based on SDT theory, we assume that a wide variety of factors can motivate patients to alter OHD length. Readmission (OHD<30) has been widely adopted as an important measure of healthcare service quality, where patients' decision-making is mostly overshadowed by urgent medical needs; while in the cases of OHD>30, patients' decision-making is likely the outcome of consideration of various factors, such as financial, geographic ones. Therefore, we focus on a thorough examination of the potential associated factors for OHD>30.

Methodology

Figure 1. Research Framework

Using Hevner et al.'s (2004) design science framework, we position our work as an exploratory analysis of factors associated with the readmission of cancer patients based on an EHR dataset. We have adopted the framework proposed by Peffers et al. (2007) as a schematic (see Figure 1) of the steps followed in building the explanatory models in this study.

Problem Identification and Motivation

We are highly motivated to study OHD of cancer patients because hospital readmissions are increasingly recognized as drivers of healthcare spending (Hu et al. 2014). A better understanding of OHD can be leveraged by public health researchers, practitioners, and policymakers to allocate medical resources more efficiently. Moreover, cancer patients and health insurance agencies can optimize payment and disease treatment plans according to OHD, which then reduces medical expenses and improves quality of life.

Patient demographic information (e.g., age, sex, and marital status) could be one factor that influences OHD (Doumouras et al. 2016; Luryi et al. 2016).

Medical variables, including the number of cancers, admissions, and visited hospitals preceding/prior to the next readmission have been demonstrated to correlate with OHD (Greenblatt et al. 2010). Financial variables (e.g., admission costs), which also can influence patients' OHD decisions (Luryi 2016), have not been well studied. Our EHR dataset contains detailed financial information about each patient and visit, including time spent in the hospital and cost of each treatment, which allows us to examine costs in different forms (e.g., overall cost, daily costs).

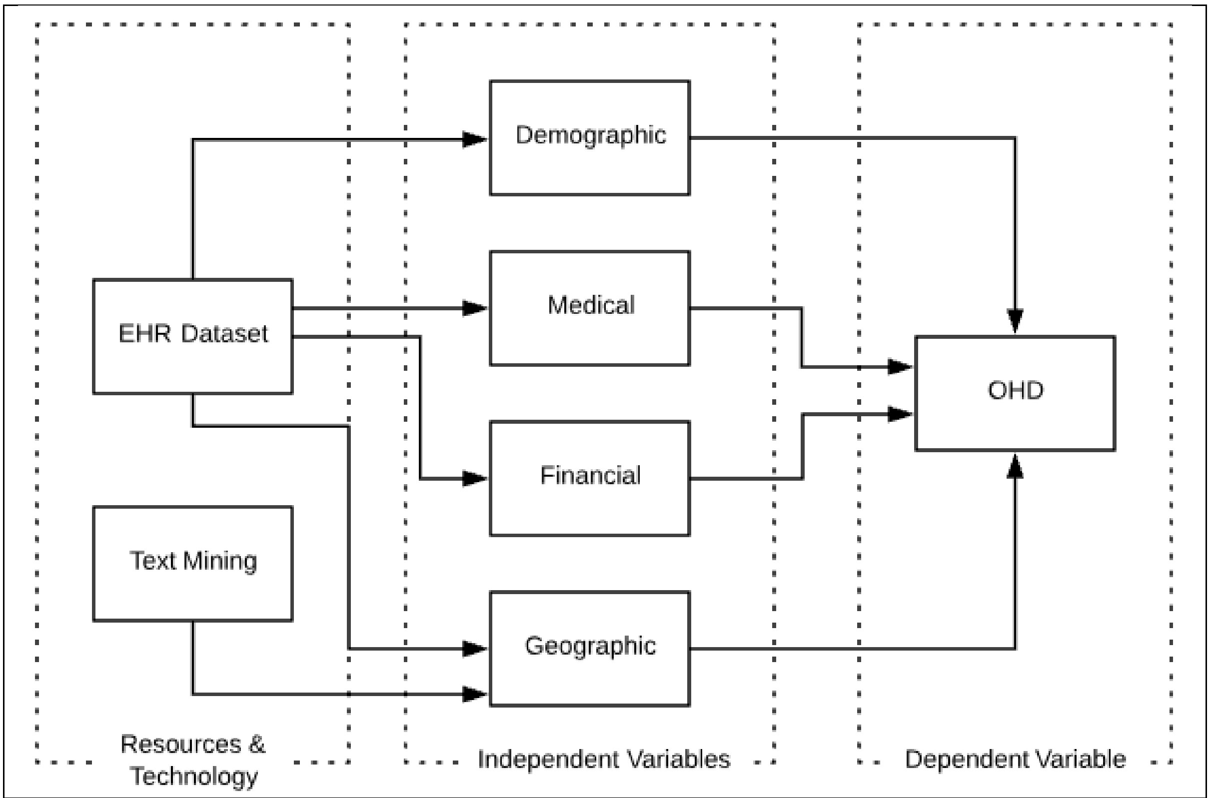

Figure 2. Research Objective and Plan

Geographic location might be an important consideration for patients when deciding whether to go back to the hospital. Many studies have shown that quality of treatment and OHD are highly correlated (Puri et al. 2015). In China, treatment quality is strongly determined by geographic location. Larger cities tend to have better doctors and equipment than smaller cities, especially for treating severe diseases like cancer. Rural areas in China have the lowest quality of medical care, sometimes lacking healthcare facilities entirely.

The cost of traveling from one location (e.g., patient's home) to another (e.g., hospital) can be a concern. For example, rural patients may have to travel long distances to large cities (both time-consuming and expensive) for medical treatment, thereby choosing to delay treatment. However, previous studies appear to have neglected the impact of geographic location (Chaudhary et al. 2017; Donzé et al. 2017) on cost and therefore OHD. To this end, our EHR dataset contains detailed information for each admission including hospital address and home address, allowing an examination of geographic factors.

We explore the factors that influence the number of OHD between consecutive cancer treatments. Specifically, we analyze the relationship between OHD and demographic, geographic, medical, and financial characteristics.

Objectives and Variables

In this study, OHD is our main target and thus is the dependent variable. We analyze four types of independent variables: patient demographic (e.g., gender, age), medical (e.g., number of cancers), financial (e.g., accumulated cost of previous treatments), and geographic (e.g., whether patient's home and hospital are in the same province) factors, as illustrated in Figure 2. While other factors were readily available in the dataset, geographic variables were not. We extracted geographic variables using text mining techniques based on the address filed, written in free text, with the help of extensive published lists of cities and provinces.

Design and Development

Table 1. Variables	
Variable	**Description**
OHD	"Out-of-Hospital Days"; number of days between this admission date and previous discharge date
AGE	Age
S	Sex. Binary, Male = 0, Female = 1
MAR	Marital status. Binary, Married = 0, Non-married (Single/Widowed/Divorced) = 1
CAN	Number of cancers diagnosed prior to this admission
ADM	Number of admissions prior to this admission
LOGCIN	Log of cost per day of all previous admissions
IP	Whether home and hospital are in same province (No = 0, Yes = 1)
IC	Whether home and hospital are in same city (No = 0, Yes = 1)

After we clearly define the dependent variable and independent variables, we design and develop the relevant variables with the help of external resources and text mining techniques.

Our dataset contains rich information about demographics, diseases, and cost (see Tables 1 and 2). The average cost (over all years) for each treatment was 24,839 Chinese Yuan (about US $3,604), and the maximum cost for one treatment was 99,997 Chinese Yuan (about US $14,509). To put this in perspective, in 2010, the average annual income in China was $10,220 [1] . Clearly, these costs can represent a huge economic burden on patients and their families.

We leveraged the text mining process to extract the variable values from the dataset. This process is complex and time-consuming since some fields (i.e., patient's home address) are written in free text (using Chinese characters). Thus, we combined an automatic information retrieval process and a human check-up step to extract variable values. We therefore designed and built a Java-based software application to handle the information retrieval and error reporting and handling. Human effort was heavily relied on to identify possible errors and exceptions and verify the quality of retrieved values.

[1] https://www.forbes.com/sites/moneybuilder/2010/06/24/one-big-difference-between-chinese-and-american-households-debt/#43f9935a22b4 (last accessed November 6, 2018)

Table 2. Descriptive Statistics for Continuous Variables

Variable	Mean	Standard Deviation
OHD	126.50	129.35
AGE	55.38	15.58
CAN	1.11	0.33
ADM	3.09	1.86
LOGCIN	7.52	1.17

Note: Means and standard deviations are based on data at visit level with 22,231 records excluding ADM = 1 and OHD < 30.

For example, in order to compute IP and IC values, we first had to extract each patient's and hospital's city and province information. Unfortunately, patient addresses were included in one field of the database table instead of in several more atomic fields. We had to identify the city and province from a long text string containing the entire address. Our bespoke Java-based software program automatically identified each patient's city and province based on a dictionary containing all province-city pairs in China. Moreover, since patient addresses were written in free-style text, the address could contain typographic errors or missing information (e.g., missing province or city text). We also used the zipcode information based on a dictionary containing all the zipcode-(province, city) pairs in China. If zipcode was missing or no province/city was found, the program would report an error alert to prompt someone to manually handle the error or exception. The entire text mining process is illustrated in Figure 3.

During the text mining process, we extracted city and province. Then we coded these to identify whether a patient was living in a rural or urban area and whether they lived in the same province as the hospital they attended.

Since we focused on readmission time intervals from decision-making perspective, we filtered out the patients with only one admission record and the OHD records that were fewer than 30 days.

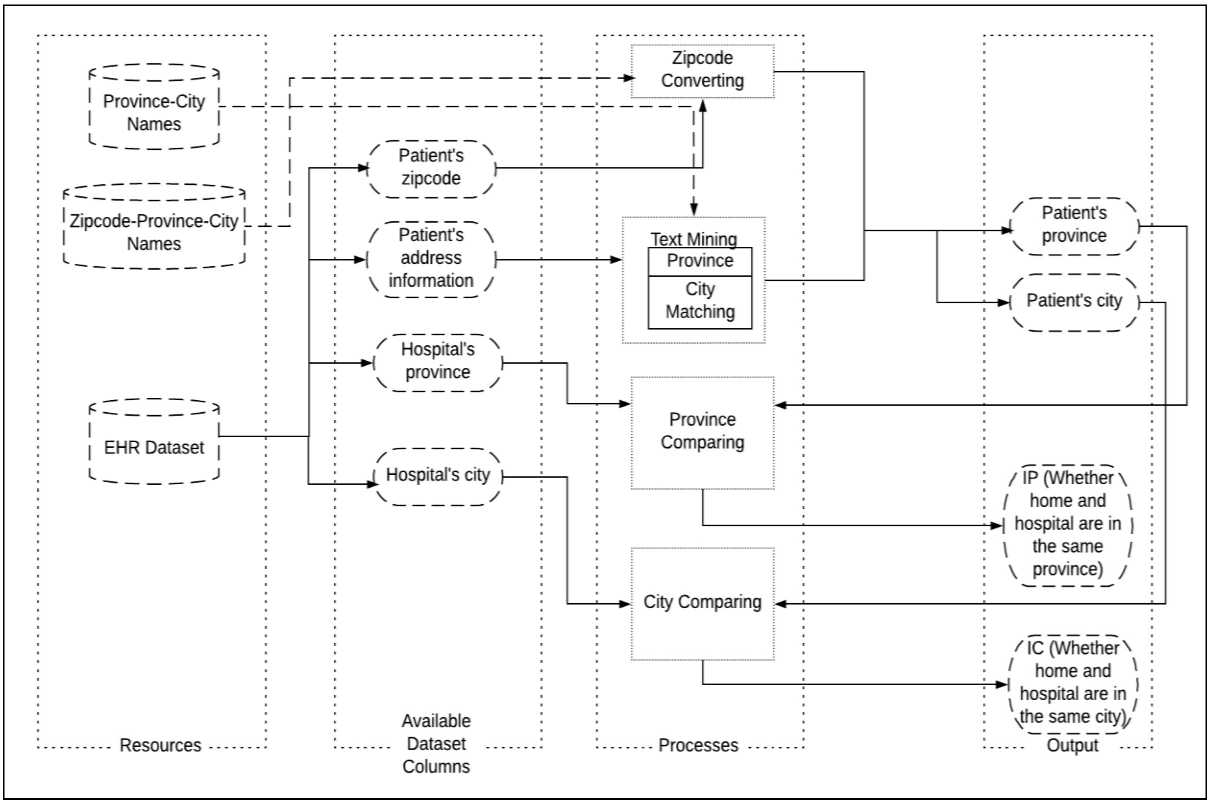

Figure 3. Text Mining Procedure

Individual patients had multiple hospital visits; thus, we have nested data. We used hierarchical linear modeling (HLM) (Raudenbush et al. 2004) to analyze our data because this approach is particularly well suited for nested data. We ran a null model for the dependent variable with no predictor to determine whether there was sufficient variance among individuals. The ICC1 value for OHD was 0.33, indicating that the variability among individuals was large and using HLM was appropriate (Raudenbush 2004).

Demonstration and Evaluation

After building our model on the dataset, we could see that several of our proposed four types of independent variables influenced OHD significantly (see Tables 3 and 4): age, marital status, number of cancers, number of admissions, and whether hospital is in a different province from where they live. Gender, treatment cost, and whether the hospital is in the same city were not significant influences.

Communication

One interesting finding is that geographic factors can significantly influence OHD. Patients whose homes and hospitals are not in the same province have higher OHD than patients whose homes and hospitals are in the same province. Perhaps this is not surprising, because there is usually a longer distance between homes and hospitals not in the same province (than in the same province). It is possible that crossing provincial boundaries may keep patients from getting treatment again due to a psychological reason or higher traveling expense.

Table 3. Type III Tests of Fixed Effects

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	22219	57.503	.000
AGE	1	22219	4.025	**.045 ***
S	1	22219	.931	.335
MAR	1	22219	12.525	**.000 *****
CAN	1	22219	7.905	**.005 *****
ADM	1	22219	526.801	**.000 *****
LOGCIN	1	22219	.396	.529
IP	1	22219	4.728	**.030 ***
IC	1	22219	.454	.500

Dependent Variable: OHD.
* = p<.05, ** = p<.01, *** = p<.001

Table 4. Estimates of Fixed Effects

					95% Confidence Interval	
Parameter	Estimate	Std. Error	t	Sig.	Lower Bound	Upper Bound
AGE	.135	.067	2.006	s.	.003	.267
[S=0]	-1.706	1.768	-.965	n.s.	-5.173	1.760
[MAR=0]	-16.832	4.756	-3.539	s.	-26.155	-7.510
CAN	-7.571	2.6923	-2.812	s.	-12.850	-2.293
ADM	-11.225	.489	-22.952	s.	-12.183	-10.266
LOGCIN	-.466	.740	-.629	n.s.	-1.917	.985
[IP=0]	-5.837	2.684	-2.174	s.	-11.098	-.575
[IC=0]	-30.414	45.135	-.674	n.s.	-118.882	58.055

Dependent Variable: OHD.
n.s. = not supported, s. = supported

Besides the geographic factors mentioned above, demographic and medical factors can also significantly influence OHD. We find that older patients have higher OHD. This might be due to the fact that older citizens are less likely to seek treatment (Hou et al. 2016; Prince et al. 2015). In addition, married people have higher OHD. Studies have shown that family members play important roles in cancer treatment decision-making (Laidsaar-Powell et al. 2016; Öhlén et al. 2006). On the other hand, we find that the number of admissions negatively influences OHD.

Surprisingly, the cost was not a significant factor. We note that our dataset contains the overall treatment cost, which might be covered by patients' insurance. Perhaps if we had access to patients' out-of-pocket payments, we might see a different result.

Discussion and Conclusion

The treatment for cancer, a chronic and often terminal disease, can be extremely lengthy and costly (Soerjomataram et al. 2012). The goal of this investigation was the development and validation of variables and a model to explain OHD (>30 days). We used factors from four different perspectives: demographic, medical, financial, and geographic.

This investigation is an important step towards the development and evaluation of new factors, geographic enabled by text mining and geographic lookup knowledge in particular, which are important for explaining OHD. Even though there are some studies on OHD, to the best of our knowledge, we are the first to combine four different types of factors. This study might help healthcare providers and policymakers identify new ways to enhance cancer management, particularly as it relates to where patients live.

We found that whether the location is rural or urban, traveling between provinces can significantly influence OHD. A patient living in a different province from the hospital she is being treated at will have a longer OHD than a patient who lives in the same province.

Our analysis can help hospital practitioners and administrations better allocate medical resources and improve treatment plans according to a patient's medical, demographic, and geographic factors. In this study, we found that OHD is significantly impacted by the patient's age and previous medical admissions; providers may need to pay extra attention to them. Our analysis also suggests doctors should take patient's location into consideration. Doctors need to be aware that those patients who live in a different province or have to travel further tend to have longer OHD. Special attention and awareness are necessary for these patients since they may not come back for another treatment soon.

Another interesting finding that may provide guidelines for hospital administrations is to consider the patient's marital status. Non-married patients tend to have lower OHD than married patients. This implies that spouses may play a role in patients' OHD, such as influencing patients' physical condition (Laidsaar-Powell 2016; Öhlén 2006).

Future Study

This research has several limitations. First, due to the complex nature of OHD, we do not know exactly how the amount of time between admissions is decided by the patient, her family members, or her doctors. For future study, we intend to conduct a survey with a questionnaire for patients and doctors to reveal a more detailed story on how the (re)admission decision is made. Second, hospitals in this study are anonymous with only geographic information available. We currently know little about their qualities, facilities, or technological capabilities. We are collaborating with hospital administrations to obtain more descriptive dimensions of hospitals. Third, in this study, LOGCIN ("log of cost per day of all previous admissions") is not a significant factor for OHD. However, the medical cost that has been used in this study is the total medical charges posted by the hospital. It is not the actual cost to the patient since the patient's medical insurance status is not available at this stage. We are working to collect the patients' insurance information and the actual cost to the patient. It is possible that the actual out-of-pocket cost to the patient may be a significant factor for OHD.

Our analysis underscores the importance of understanding the factors that are related to OHD. Using this comprehensive dataset reveals that OHD is affected by factors from different perspectives. For example, patient's marital status can influence OHD. As a future extension of our work, we are interested in discovering how marital status may affect the number of days that a patient stays hospitalized. We will investigate how long a married patient stays in the hospital during treatment and how that will influence OHD before the next (re)admission. We will explore a spouse's role in comforting the patient, communicating with doctors, etc., and how those efforts affect the patient's treatment plan and OHD. As a result, these data may offer us an opportunity to shed light on the underlying causes of OHD length and the potential for administrators and policymakers to allocate healthcare resources better and deliver healthcare services more effectively.

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