Predictive model for high cost and complications in Nephrolithiasis patients

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Abstract
The average cost of treatment for patients with nephrolithiasis complications was twice that for those without (47,792.08 vs. 22,995.33 Thai Baht, THB). In-patient data for October 2014 to December 2018 were used to create predictive models in R. The C5.0 algorithm was used to create a decision tree to predict patients with high costs (>24,000 THB). The patient care team used the predictive model to revise their standard treatment procedures, and the model was evaluated after 8 months (May 2019–December 2019). In this period, 395 nephrolithiasis patients were treated using new treatment protocols. The average cost for patients with no complications did not change, but the average cost for patients with one or two complications decreased significantly ($p < 0.05$). Quality of care and patient safety were not affected, complication rates did not increase, but average length of stay increased from 3.72 days to 4.25 days.

Keywords: Predictive Analysis, Predictive Model in Clinical Use, Nephrolithiasis, Highcost Healtcare, International Classification of Diseases, Complications in Healthcare, Quality Healthcare, Length or Stay

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INTRODUCTION

Urolithiasis, or urinary stones disease, is common in northern and northeastern Thailand. The International Statistical Classification of Diseases and Related Health Problems, 10th Revision (ICD-10) divided urolithiasis into four major classes: nephrolithiasis (kidney stones), ureteric stones, urinary bladder stones, and urethra stones (World Health Organization [WHO], 2016). Nephrolithiasis has one of the top-10 highest costs of treatment, especially in the Nan province in the northern part of Thailand.

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During 2014 to 2018, there were 4,600 nephrolithiasis cases admitted to Nan Hospital. The cost of treatment for these cases was over 100 million THB (Thai Baht; around 3.4 million USD), which was the highest cost for all groups of inpatient cases in Nan Hospital. The average cost for each patient was 24,270.48 THB. For patients with any complications, the average cost of treatment was 47,792.08 THB, or twice the average cost for those without complications (22,995.33 THB). These high costs of treatment generate a huge burden for Nan Hospital, which operates under the universal health care schema in Thailand.

If we can predict which nephrolithiasis patients will yield a high cost of treatment, we will be able to identify the factors that affect high-cost risk. Then, root causes analysis should be conducted, and preventive actions could be taken to reduce the risks for the patient, as well as reducing the burden for the hospital.

BACKGROUND

Nan Hospital Information System

Nan Hospital is a 502-bed public hospital in the Nan province in northern Thailand. All inpatient admission diagnoses and operations must be summarized by medical doctors within 7 days after the patient was discharged from the hospital. The medical doctors have to classify all patient diseases into four categories based on Thailand's standard discharge summarization handbook for doctors (Bureau of Policy and Strategy [BPS], 2009):

1. **Principal Diagnosis:** a disease that was the reason for admission;
2. **Comorbid Conditions:** all underlying diseases of the patient;
3. **Complications:** all major illnesses that happened after admission; or
4. **Other Diagnosis:** other trivial diseases.

All types of diagnoses must be coded by a clinical coder into ICD-10 codes within 14 days after discharge. All ICD-10 codes must be entered into the hospital information system within 30 days after discharge.

The Nan Hospital information system was custom built by a team of programmers in 2000. In 2015, the system was upgraded to comply with the standard 43 datasets, as announced by the Ministry of Public Health, Thailand (BPS, 2015), to be used by all public hospitals. The important table includes admission data (identification key, sex, date of birth, dates of admission and discharge, cost of treatment for each episode) and ICD-10 codes (identification key; ICD-10 codes for principle diagnosis, comorbid conditions, complications, other diagnoses).

Nan inpatient data warehouse is another database system which imported selected tables with diagnoses, procedures, drugs, treatment costs and charges information for each inpatient from main hospital database into the warehouse. The data scientists use this warehouse for analysis and report the result to hospital management board every month. The data in the warehouse were updated monthly.

Urolithiasis in Thailand

Urolithiasis is a major health problem in northern and northeastern Thailand. Previous studies (Yanagawa et al., 1997; Tanthanu, Apiwatgaroon, & Pripatnanont, 2005) revealed a prevalence rate as high as 16%, males more affected than females (1.6:1). The main causes of urolithiasis are genetic factors (inherited biochemical defect, congenital kidney defect) and environmental factors (drinking water, diet pattern, deficiency of trace elements in food and drink). Standard treatments include percutaneous nephrolithotomy (Ziamba & Matlaga, 2015), open nephrolithotomy, and endoscopic shockwave lithotripsy (ESWL) with new equipment, for example, the Holium laser lithotripsy that was introduced in recent years (Turney, Reynard, Noble, & Keoghane, 2011).

Complications after treatments of urolithiasis were frequently found (El-Nahas, Eraky, & Shokier, 2012). Akolarikos and de la Rosette (2008) found that the most common complications include septicemia, renal hemorrhage, and tearing of other organs (lung, colon, etc.), and that most complications are preventable.

RELATED WORK

Biomedical data analysis or healthcare analytics is a new field of research that has gained popularity during the past 10 years (Koch, 2019). Descriptive analytics is a basic form of healthcare analytics, and predictive analytics is a technique that uses healthcare data from the past to predict factors that determine outcomes and create predictive models that can be used in the modern clinical care system.

Stille, Chadler, and Reddy (2016) used data from the United States Centers for Disease Control and Prevention (CDC) to study patients with diabetes mellitus for 14 years (2001–2014). They created a predictive model to predict the risk of diabetes onset in the target group and found that predictive factors include age, income, education, and body mass index (BMI). This model predicted the risk probability using 0.13 to identify people with a high risk of being diagnosed with diabetes mellitus in the near future. The model has not been used in a real situation.

Khichi, Parsons, and Winters-Miners (2015) analyzed data from patients diagnosed with Disseminated Intravascular Coagulation (DIC) in a hospital. They tried to find a model to predict which patients have a high risk of death. They found 10 factors, including underlying heart disease, septic shock, and dehydration. However, there was no report of any real use of this model.

Varanasi (2015) used data from a pathological biopsy of 699 breast cancer patients to create a predictive model using the support vector machine technique. They used some parameters, such as cell size, cell shape, and base nuclei, to predict cancer detection. The accuracy of detecting cancer is 97 percent. However, again, there was no report of a real use of this model.

Tortajada et al. (2019) used data from 1,397 postpartum women from seven Spanish general hospitals to train multilayer perceptrons and create a model to predict postpartum depression during the 32 weeks after delivery. Testing of the model yielded high sensitivity and specificity, but evaluation of real use in a clinical setting has not occurred.

OBJECTIVES

The objectives of this study are 1) to create a model for predicting high-cost nephrolithiasis cases, and 2) to test the usability of the predictive model to reduce the cost of treatment of nephrolithiasis in a hospital.

METHODS

In-patient data from Nan Hospital were analyzed using data from October 2014 to December 2018. Data visualization and a basic analysis were conducted using Qlikview version 12. ICD-10 classification was used for the analysis of comorbid conditions and complications. All nephrolithiasis cases were reviewed to make sure that there was no error in doctor summarization or incorrect ICD-10 coding, then these data were used to create predictive models in the R Programming language (Windows version release 3.34). The C5.0 algorithm was used to predict patients with high costs (> 24,000 THB). Selection of a predictive model was done after discussion among researchers and the nephrolithiasis patient care team. The predictive model was a decision tree that could be used for predicting high-cost patients based on complications. Root causes analysis was conducted by the patient care team. Preventive actions were added to the standard treatment protocol for nephrolithiasis cases admitted after May 2019. Data collection was completed in December 2019, and the study report was summarized.

RESULTS

Between October 2014 and December 2018, 4,666 nephrolithiasis cases were admitted to Nan Hospital (Table 1). There were 3,143 male and 1,523 female patients. The age range of 46–70 years made up 76.36% of the cases (3,563 patients; Figure 1). The top-five most common comorbid conditions based on ICD-10 were I10 hypertension, E87.6 hypokalemia, E78.9 dyslipidemia, E11.9 diabetes mellitus type 2, and M10.09 idiopathic gout (Figure 2).

The top-five complications after admission based on ICD-10 were D62 acute blood loss anemia, E87.6 hypokalemia, R57.2 septic shock, T81.0 massive intraoperative bleeding, and T81.2 intraoperative tear of other organs.The number of comorbid conditions in a patient had little effect on the cost of treatment. Cases without complications had some comorbid conditions, but the average cost never reached 26,000 THB (Table 2). However, the number of complications in a patient had a huge effect on the cost of treatment, raising the cost as high as 109,097 THB (Table 3).

The predictive model used five major complications to predict the possibility of a high-cost outcome for any patient (Figure 4). A root causes analysis of the top-five complications found that acute blood loss anemia, massive operative bleeding, and intraoperative tear of other organs lacked modern operative equipment that could avoid a major wound. Post-operative hypokalemia was due to insufficient correction of a potassium deficit. Post-operative septicemia was due to some lack of preoperative prophylaxis for infection and post-operative delay of early infection detection in some cases.

The nephrolithiasis patient care team revised their standard treatment procedures to include protocols to make sure that all patients had sufficient potassium replacement prior to their operation and to get effective preoperative infection prophylaxis and early detection of infection post-operative. Purchasing new equipment (Holium laser lithotripsy) was approved by the hospital board in the first quarter of 2019. All new treatment protocols have been in effect since May 2019.

During May to December 2019, 395 nephrolithiasis patients were treated in Nan Hospital using the new treatment protocols. The average cost for patients with no complications did not change, but the average cost for patients with one or two complications decreased significantly ($p < 0.05$), from 44,081.17 to 27,866.04 THB, and from 59,552.02 to 56,349.88 THB, respectively (Table 4).

Complication rates for anemia, post-operative tear, and bleeding decreased slightly, while complication rates for sepsis and hypokalemia increased slightly. However, these rate changes were not statistically significant based on a Chi-square McNemar test (Table 5).

The average length of stay for nephrolithiasis patients increased slightly (from 3.72 days to 4.25 days, $p = 0.002$).

CONCLUSION

Our study evaluated the predictive model using data from real cases. This differs from previous studies. For example, Lie et al. (2018) used a Bayesian multi-task and feature relationship leaning approach to predict complications among patients with diabetes mellitus type 2 as the underlying disease. They found that age, electrolyte disorders, and insulin treatment were the top-three most common risks for complications, such as retinopathy, nephropathy, and neuropathy. This prediction model was evaluated using testing data, and there was no mention of treatment guidelines adaptation.

Thompson, Whitaker, Kohli, and Jones (2019) used clinical data from patients with chronic diseases with claim data from Vermont and predicted cases with high probabilities of producing high-cost outcomes. Patients with high risks received personalized treatment protocols in a Patient-Center Medical Home (PCMH) program. Initial outcomes revealed some cases with lower costs and that complications could be reduced, as well.

Hilbert, Zasadil, Keyser, and Peele (2017) used 1-year patient discharge data (~80,000 cases) from California inpatient databases to build a decision tree as a model to predict readmission risk for patients with acute myocardial infarction, heart failure, and pneumonia. Despite its medium predictive value, the decision tree had advantages in terms of transparency, interpretability, and adaptability. However, no report on real use of the tool was found.

The predictive model for nephrolithiasis patients could be used successfully to decrease costs of treatment in Nan Hospital with no impact on quality of care. The complication rates did not change. Length of stay might increase slightly, but this had no effect on patient safety or quality of care.

This study indicates that more clinical data in Nan Hospital should be analyzed, and more predictive models should be created, to improve quality of clinical cares for some major diseases. In the near future, a framework that supports clinical data-driven improvements of healthcare quality should be established, as suggested by some studies (AbdelRahman et al., 2020; Talaei-Khoei, Tavana, & Wilson, 2019; Kamble, Gunasekaran, Gaswami, & Manda, 2019).

Ethics Standards

This study has been reviewed in compliance with ethical standards of the responsible committee on human experimentation (institutional and/or national, as pertinent) and with the World Medical Association Declaration of Helsinki on Ethical Principles for Medical Research Involving Human Subjects. Approved by Nan Hospital Research Ethics Committee, COA No 017, Nan Hos. REC no. 017/2562 on 30 April 2019.

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