Predicting Cost Recovery Rate of Ischemic Stroke Patients: A Potential Application of Big Data Analysis in Hospital

1*Heru Fahlevi, 2Teuku Roli Ilhamsyah Putra and 3Rina Suryani Oktari

1Accounting Department, Faculty of Economics and Business, Universitas Syiah Kuala – Indonesia
2Management Department, Faculty of Economics and Business, Universitas Syiah Kuala – Indonesia
3Faculty of Medicine, Universitas Syiah Kuala - Indonesia
*Corresponding author: hfahlevi@unsyiah.ac.id

Abstract. Cost controlling strategy have become a vital issue in the hospital sector, particularly after the application of a prospective payment system in many countries. This study aims to examine the determinants of the hospital patient actual cost, differences, and Cost Recovery Rate (CRR) in a referral Indonesia hospital. Besides, it also explores the potential use of the analysis result for cost management in the hospital. The population of this study was 2018 Ischemic Stroke inpatient cases (677 observations). The data was obtained from the hospital medical record department and insurance claim department. The multiple regression method is used to analyze the actual patient costs and reimbursement fees data, which is followed by semi-structured interviews with principal officers of the hospital. The interviews were conducted to assess and evaluate the potential and challenges of the big data analysis application. The result of this study indicates that the patient cost, differences, and CRR are determined by severity level and length of stay (LOS), while patient gender and age have no significant influence on the tested dependent variables. The interviews also reveal that the hospital has not used the big patient data in managing cost optimally. Based on the result of this study, the hospital can used the tested statistical model to control patient cost, evaluate the treatment and improve cost-effectiveness of patient treatment.

Keywords: Cost recovery, patient, big data, stroke, hospital, Indonesia

1. Introduction

Health care sector and hospitals around the globe have been experienced simultaneous and significant reforms for the last few decades. One of the recent international trends in improving hospital sector efficiency and cost containment is Diagnostic Related Groups (DRGs) based hospital payment system. The DRGs is a prospective payment system where reimbursement rate for patient costs is predetermined and fixed for each DRG case/patient [1], [2]. Consequently, hospitals are required to understand their costs [3] particularly their patient costs, and classified each patient/case accurately; otherwise, the patient costs are not adequately compensated.

Indonesia has developed Indonesia-Diagnoses Related Group (INA-DRG) in 2006 and adopted firstly in 15 public hospitals since 2008. In 2010, the INA-DRGs had been renamed to INA-CBGs (Indonesia Case Base Group) and has been used to pay all Indonesian hospitals which treat patients who hold social health insurance or BPJS Kesehatan/ Badan Penyelenggaran Jaminan Sosial Kesehatan) for more than
five years [4]. The BPJS, an organization that manages Indonesian social health insurance, pays hospital claims based on tariffs that computed by using the DRGs system. The Indonesian DRGs tariff is set by the INA-CBGs tariff team under the Indonesian Ministry of Health.

According to Handayani & Pratiwi [5], INA-CBGs rate has been calculated and determined based on patient cost data of selected Indonesian hospital samples. The basis of INA-CBCCs rate calculation is hospital costs data collected from selected Indonesian hospitals, and the update is carried out every two years. Unlike other DRGs rates in other countries, the INA-CBGs rate is not similar across the hospitals. The rate is classified into five regional rates, hospital class, and hospital ownership. Many commentators and Indonesian hospital managers have complained that the rate is too low and underestimated for several cases, although the rate is calculated from the cost information of the Indonesian hospital samples.

There has been a growing literature on evaluation of DRGs rates and the determinants of hospital patient costs. Kaye, Adrados, Karia, Protopsaltis, & Bosco [6] studied the impact of severity of illness on the cost of 69,831 spine surgery cases among New York state hospitals from 2009 and 2011. They found a significant difference in patient cost between a patient with extreme severity condition and minor severity condition, although they were classified with the same DRG case. Meanwhile, Mardiah & Rivany [7] unveil the difference between Cost of Recovery Rate (CRR) of hospital cost and CRR of INA-CBGs rate of Coronary Artery Disease cases in a referral hospital in Palembang, Indonesia. Their study confirms that the hospital cost CRR analysis of severity I case is higher than CRR analysis of INA-CBGs, whereas in the severity II, the hospital cost CRR is smaller than the CRR INA-CBGs.

The DRGs data and its reimbursement mechanism have provided comprehensive data of patients that include patient profile, hospital costs, patient costs, DRGs cases, DRG tariff, and treatments that have been undertaken. The generated patient data can be categorized as big data due to its high volume, a variety which potently can be accumulated and analyzed to obtain pattern, trend and other statistical analysis output [8].

Most of the previous studies analyzing the difference between hospital patient costs and DRGs rates to assess the CRR of each DRG case (see for example [5], [9]). Unlike previous studies, this study focuses on patient cost prediction and the potential use of patient cost data. To do so, this study analyses the patient cost, the difference between hospital tariff, and INA-CBGs rate and CRR. Besides, this study also assess the potential use of the cost data analysis for cost management in the hospital.

2. Research Method
This study applies a mixed method to address the research questions and objectives. Firstly, it assessed the CRR of the hospital case and examined potential determinants of the CRR. CRR is a formula to assess the profitability of patient service/ DRGs case based on the comparison between hospital cost and reimbursement fee from the insurance. If CRR is bigger than 100, the DRG case is profitable, vice versa. Besides, it also examined factors that affect patient service cost (hospital cost), differences between hospital cost and tariff. These formula are useful for cost management in the hospital. Secondly, this study explored the potential benefit of such big data application as well as challenges faced by the studied hospital.

This study is carried out in a public referral hospital called ‘Diamond hospital’ (not the real name). The hospital is the biggest referral hospital in one of the Indonesian provinces. It has 514 beds and categorized as ‘A’ level-education-hospital. The number of specialist and doctors working in the hospital is more than 200, which is supported by hundreds of internships, co-assistants, and medical students [10]. In 2018, the hospital admitted 356,836 outpatient and 42,043 inpatient cases.

Data is collected from the hospital patient and claim database, hospital profile, and interviews. The obtained secondary data in this study is the 2018 hospital inpatient cases. The highest inpatient cases,
Ischemic Stroke (A61), is selected as the sample. The stroke case is selected as it is considered as the stroke treatment is expensive and need long-term rehabilitation [11]. The total observations in this study were 664 cases/patients. Data were analyzed by using multiple regression method.

The final objective of the data analysis is to build a mathematical model that can used to estimate patient cost as follow:

\[
\text{HospitalCost} = a + b_1(\text{Gender}) + b_2(\text{Age}) + b_3(\text{LOS}) \quad (1)
\]
\[
\text{Differences} = a + b_1(\text{Gender}) + b_2(\text{Age}) + b_3(\text{LOS}) \quad (2)
\]
\[
\text{CRR} = a + b_1(\text{Gender}) + b_2(\text{Age}) + b_3(\text{LOS}) \quad (3)
\]

HospitalCost = Total hospital cost of each patient  
Difference = Difference between hospital cost/claim and its reimbursement rate  
Gender = Patient Gender (male or female, dummy variable)  
Age = Age of patient  
LOS = Length of stay  
CRR = Cost of Recovery Rate = \( \frac{\text{Hospital cost}}{\text{Reimbursement rate}} \) \times 100

Later on, the interview was conducted with head of insurance claim and head of financial department to explore the potential use of the big data analysis for cost management in the hospital. The interview was conducted in May 2019.

3. Results
Determinant of Patient Cost, Difference and CRR
The descriptive analysis results showed that 50% of cases were classified into severity level II (339 cases). It also unveiled that more male patients than female patients who suffer Ischemic Stroke (A61). In 2018. In average, the patients spend around 60 days in the hospital before they discharged. The reason could be that the average age of the patients is relatively high, namely 59.6 years.

| Variables          | N  | Descriptive analysis   |
|--------------------|----|------------------------|
| Severity level     | 644| Severity I = 219       |
|                    |    | Severity II = 339      |
|                    |    | Severity III = 86      |
| Gender             | 644| Male = 373             |
|                    |    | Female = 271           |
| Maximum            |    | 23.512                 |
| Minimum            |    | 494                    |
| Age (Years)        | 644| 4                      |
| Differences (IDR)  | 644| -112,537,485           |
| Patient_Cost (IDR)| 644| 1,686,660              |
| CRR (%)            | 644| 19.45                  |
| CRR Analysis       | 644| > 100 = 413            |
|                    |    | < 100 = 231            |

Moreover, the difference between patient cost and its reimbursement fee was positive (IDR 120,886). This finding could be associated with the CRR of the case where the number of CRR bigger than 100% is almost double than the number of CRR smaller than 100%. Thus, the total difference is favorable/surplus, or the case is generally profitable as the total of patient costs is lower than reimbursement/payment fees received by the hospital (IDR77,850,737). This finding is not consistent with [11] study. They examine the average rate of stroke treatment actual cost at Jogya Hospital and documented higher actual cost than the INA-CBGs rate.

The regression analysis method unveils that severity and length of stay (LOS) are the determinants of patient cost, differences, and CRR as the significant level of the variables are less than 0.5. The other
two tested variables (patient gender and age) do not significantly affect patient cost, differences and CRR. Following are the first result of regression model:

\[
\text{Patient Cost} = -2,653,134 + 3,072,746(\text{Sev}) - 1,134,617(\text{Gen}) + 1,354,813(\text{LOS}) + 29,807(\text{Age})
\]

\[
\text{Differences} = 7,052,522 + 2.095.564(\text{Sev}) + 162,174 (\text{Gen}) - 1,205,328 (\text{LOS}) - 9,625(\text{Age})
\]

\[
\text{CRR} = 165.05 + 19.93(\text{Sev}) + 0.56(\text{Gen}) - 9.55(\text{LOS}) + 0.16(\text{Age})
\]

In the today cost-containment era, hospitals are encouraged to accurately assess the patient severity so that the CRR can be fully compensated [6]. The second regression step was conducted to examine the influence of severity and LOS toward patient cost, differences and CRR. The result of the second regression as follows:

| Formulas                        | Coefficient determination (R²) |
|---------------------------------|--------------------------------|
| \text{Patient Cost} = -5,926,972 + 2,996,825(\text{Sev}) + 1,357,151(\text{LOS}) | 0.65                           |
| \text{Differences} = 6,599,321 + 2,075,424 (\text{Sev}) - 1,204,258(\text{LOS}) | 0.64                           |
| \text{CRR} = 174.8 + 20.2(\text{Sev}) - 9.6(\text{LOS}) | 0.68                           |

The above three formulas can be used to predict the patient costs, differences and CRR at the beginning of patient admission. The doctor/specialist and hospital accountant can estimate patient cost and respond to any negative difference once it is discovered. If the results indicate that the patient cost is higher than the predicted DRGs fees received, the doctor/specialist who treat the patient can manage the treatment producers more carefully in term of costs without losing the medical ethics. At the end of the year, doctors, together with the accountant may convene together to evaluate each case/patient with lower CRR and to explore strategies to reduce the treatment costs. Thus, financial deficit at the end of the year can be reduced or even avoided, and more sustainable financial management can be attained.

This study supports previous studies conducted by Rahayuningrum, Tamtomo, & Suryono [12]. They investigated the determinants of hospital tariff with sample 100 inpatient cases from 4 hospitals in Central Java, Indonesia. The study uncovered that ICU utilization and LOS have an influence on hospital patient actual costs. A similar result is also found by Satibi et al., 2019 [13] who undertook a study in a referral hospital in Bali, Indonesia. They found that factors associated with actual patient costs are procedure number, type of patient room, and LOS.

The Potential and Challenges of Big Data Analysis

The second aim of this study is to explore the potential and challenges faced by the Diamond Hospital in using the model as the basis for cost management strategies. Data was collected through interviews with two key officers in the hospital who are responsible for maintaining and controlling patient costs. The results unveil some potential and challenges.

Firstly, the hospital collects and maintain the patient costs, profile, and payment from the insurance regularly. This data is in excel file, and the hospital has all the patient data. Thus, the analysis of the data can be performed for each DRG case. However, the hospital has only the raw material (in excel), and it does not have supporting facilities to run and analyze the data yet. Besides, the raw data is not shared with other departments and doctors, and it only used for claiming purpose only.

Secondly, the hospital does not have an updated unit cost of each treatment/patient. In fact, the hospital did not calculate the unit cost of each medical service and patient treatment. But, the hospital has hospital tariff that has been legalized by the government of the province. The tariff is not updated as it is calculated in 2010 and did not use a comprehensive costing method. Consequently, the unit or total patient costs used in this analysis could be underestimated.
Lastly, the motivation to control cost in the hospital seems to be weak. The main reason could be that the existence of financial guarantee from the owner in which any public hospital will be paid fully if the management bears financial deficit at the end of the year [1]. As a result, the motivation to understand and manage patient cost rather weak.

4. Conclusions
Cost management in hospitals has become a crucial feature in today era. The advancement of technology has offered big data that can be used for better cost management strategies in hospitals. This study found that patient data and profiles can be analyzed and utilized. It is found that two of four tested variables, namely LOS and severity, are the determinants of the patient cost, differences, and CRR. The statistical formulas produced in this study can be used to estimate patient cost at the beginning of patient admission, as well as evaluation of delivered services. However, the studied hospital has not been used the big data properly, although it has the capacity to produce comprehensive patient data on a regular basis. Currently, the hospital used only for patient claim administrative purposes, rather than cost controlling purposes.

Acknowledgments
Authors would like to thank LPPM Universitas Syiah Kuala which have provided a grant for this research and conference participation. This study is funded by grant Penelitian Hibah Lektor 2019.

References
[1] Fahlevi H 2016 Understanding why the role of accounting is unchanged in Indonesian public hospitals Journal of Accounting and Organizational Change 12 203-222
[2] Longo F, Siciliani L and Street A. 2017 Are cost differences between specialist and general hospitals compensated by the prospective payment system? The European Journal of Health Economics 20
[3] Haas D A and Kaplan R S 2016 Arthroplasty Today Variation in the cost of care for primary total knee arthroplasties Arthroplasty Today 3 33–37
[4] Rawung L C and Sholihin M 2017 Does Extended Autonomy of Public Service Agency Lead to A Better Performance? A Case of Indonesian Community Health Centers Jurnal Dinamika Akuntansi Dan Bisnis 4 231–248
[5] Handayani L and Pratiwi N L 2018 Unit Cost Rumah Sakit dan Tarif INA-CBGs: Sudahkah Pembiayaan Pelayanan Kesehatan Rumah Sakit Dibayar dengan Layak? Buletin Penelitian Sistem Kesehatan 21 219–227
[6] Kaye I D, Adriados M, Karia R J, Protopsaltis T S, and Bosco J A 2017 The Effect of Severity of Illness on Spine Surgery Costs Across New York State Hospitals Business of Medicine 30 407–412
[7] Mardiah M and Rivany R 2018 Cost Recovery Rate Tarif Rumah Sakit dan Tarif INA-CBG’s Berdasarkan Clinical Pathway pada Penyakit Arteri Koroner di RS Pemerintah A di Palembang Tahun 2015 Jurnal Ekonomi Kesehatan Indonesia 1 175–184
[8] Bates D W, Saria S, Ohno-Machado L, Shah A, and Escobar G 2014 Big data in health care: Using analytics to identify and manage high-risk and high-cost patients Health Affairs 33 1123–1131
[9] Wirastuti K, Sulistyaningrum I H, Cahyono E B, Santoso A, and Miftahudin Z 2019 Perbandingan Biaya Riil dengan Tarif INA-CBG’s Penyakit Stroke pada Era Jaminan Kesehatan Nasional di RS Islam Sultan Agung Jurnal Ilmiah Ibnu Sina 4 117–126.
[10] Diamond Hospital Profile 2018 Indonesia
[11] Hadning I Ikawati Z and Andayani T M 2015 Stroke Treatment Cost Analysis for Consideration on Health Cost Determination Using INA- CBGs at Jogja Hospital International Journal of Public Health Science 4 288
[12] Rahayuningrum I O, Tamtomo D, and Suryono A 2017 Comparison Between Hospital Inpatient Cost and INA-CBGs Tariff of Inpatient Care in the National Health Insurance Scheme in Solo, Boyolali and Karanganyar Districts, Central Java Journal of Health Policy and Management 01
102–112

[13] Satibi S, Andayani T M, Endarti D, Suwantara I P T, Wintariani N P, and Agustini N P D 2019 Comparison of real cost versus the Indonesian Case Base Groups (INA-CBGs) tariff rates among patients of high- incidence cancers under the national health insurance scheme Asian Pacific Journal of Cancer Prevention, 20 117–122