

# Improving the Quality of Health Services through Development and Application of Fraud Detection Models

**Nugroho M Wibowo<sup>a</sup>, Yuyun Widiastuti<sup>b</sup>, Puti A Rahma<sup>c</sup>, Nanang F Rozi<sup>d</sup>, Indra P P Salmon<sup>e</sup>,** <sup>a,b</sup>Department of Management, Universitas Wijaya Putra, Surabaya, Indonesia, <sup>c</sup>Center for Health Policy and Management, Universitas Gadjah Mada, Yogyakarta, Indonesia, <sup>d</sup>Department of Informatics, Institut Teknologi Adhi Tama Surabaya, Surabaya, Indonesia, <sup>e</sup>Public Administration Department, Universitas Bhayangkara, Surabaya, Indonesia, Email: <sup>a</sup>[nugrohomardi@uwp.ac.id](mailto:nugrohomardi@uwp.ac.id), <sup>b</sup>[yuyunwidiastuti@uwp.ac.id](mailto:yuyunwidiastuti@uwp.ac.id), <sup>c</sup>[putiauliarahma@gmail.com](mailto:putiauliarahma@gmail.com), <sup>d</sup>[nfrozy@gmail.com](mailto:nfrozy@gmail.com), <sup>e</sup>[indrapratamaps29@gmail.com](mailto:indrapratamaps29@gmail.com)

The purpose of this study is to develop a healthcare fraud detection model and apply the model to detect potential healthcare fraud in hospitals in East Java Province, Indonesia. This study was conducted at the Regional General Hospital (RSUD) in East Java Province by employing purposive sampling technique. The data collection of this study was carried out using the method of documentation and interviews. By using interactive analysis, content and peer review, an analysis model for potential fraud detection can be formulated. This analysis of fraud detection model was based on four groups of potential fraud data, namely referral, costs, room utilisation, and encoding errors. In each group of potential fraud data, the types of claim data needed to analyse potential fraud, analysis techniques for detecting potential fraud, and decision algorithms for the presence or absence of potential fraud have been identified. The decision algorithm is based on the claim data trend and compared to the average value of the claim data for a certain period. The action research method was carried out by applying a potential fraud detection model of healthcare in hospitals through the creation of a Healthcare Fraud Prevention Information System for the National Health Insurance (JKN) Program in Hospitals (SIPADAKES). The analysis results of the potential fraud detection model using SIPADAKES at RSUD in East Java Province show that in the encoding error data group, all types of claim data were detected for potential fraud. This reflects that billing for diagnosis and

treatment was more expensive than what the hospital did. The other findings identified as potential fraud were in the reference data group on the type of inpatient claim data with the 1-day length of stay (LOS) referred. In the cost data group, what was identified as potential fraud was an outpatient case with special procedures, inpatient cases with special drugs, outpatient cases with special drugs, and inpatient cases with special prostheses.

**Keywords:** *Healthcare, Fraud, Detection model, Encoding error.*

## Introduction

The term fraud in Indonesia is not yet widely known and understood by common people; it is still limitedly known by academicians and observers. Even though fraud has plagued, ingrained, and damaged the current state and culture of the Indonesian nation (Dewi YR, 2017). Fraud spread not only to the economic sector but also to the health sector. Fraudulent behaviour in the health sector looks like an iceberg, getting bigger and bigger. The Corruption Eradication Commission (KPK) noted that based on the reports retrieved from the Health Social Security Organising Agency (BPJS Kesehatan), as of June 2015, with minimum supervision, 175,774 Advanced Referral Health Facility (FKRTL) with a value of IDR 440 billion were suspected of fraud. With the increasing number of participants enrolled in the health insurance program, this will result in a huge increase in the volume of money in the health care industry and will lead to an increased risk of fraud (Bauder, Khoshgoftaar, & Seliya, 2017). In the United States, the Federal Bureau of Investigation (FBI) estimates that fraud in health services reaches 3–10% of all bills (Morris, 2009). The Corruption Eradication Commission (KPK) noted that based on the reports retrieved from the Health Social Security Organising Agency (BPJS Kesehatan), as of June 2015, with minimum supervision, 175,774 Advanced Referral Health Facility (FKRTL) with a value of IDR 440 billion were suspected of fraud (Komisi Pemberantasan Korupsi, 2016).

Fraud in health services aims to obtain unauthorised benefits through deliberate fraud (Busch, 2012). Unlike mistakes and harassment, fraudulent behaviour is usually defined as a crime in law. However, there is no global consensus on the definition of fraud and abuse in health care services or health insurance arrangements (Joudaki et al., 2015).

Fraud in health services can be grouped into 3 (three), namely fraud by health service providers (provider fraud), patients (consumer fraud), and insurance (insurer fraud). In this case, the party mostly committing fraud in health services is the health service provider. Based on a literature study on fraud-themed papers in health services, it was found that there were 69% of papers which concluded that the health service provider was the party that did a

great deal of fraud, while 31% of the paper stated that insurance customers committed fraud (Li, Huang, Jin, & Shi, 2008).

To anticipate the spread of fraud in the health sector, the Government of Indonesia through the Ministry of Health issued the Regulation No. 36/2015 on Prevention of Fraud in the Implementation of the Health Insurance Program in the National Social Security System. The development of service-oriented quality control and cost control is done through the use of evidence-based information technology and the establishment of a National Health Insurance (JKN) fraud prevention team at the Advanced Referral Health Facility (FKRTL). The Fraud Prevention Team is responsible for detecting potential fraud through analysis of claim data. However, Djasri, Rahma, and Hasri (2016) state that the detection of potential fraud is currently done manually by comparing an alleged fraud with the regulations of the Ministry of Health and the BPJS Kesehatan.

Payment for health services in Indonesia in the JKN program uses the INA-CBGs (Indonesia Case Base Groups) system, which is the average cost spent by a diagnosis group. Most hospitals consider that INA-CBGs rates are still far below normal hospital rates. The hospital considers that the INA-CBGs payment system is burdensome to the hospital. The payment system for the INA-CBGs model has not satisfied some hospitals in Indonesia. This condition has the potential to decrease the quality of healthcare for JKN program patients because the INA-CBGs rates are not enough to cover the costs of healthcare. In addition to the low INA-CBGs tariffs that have an impact on low service quality, another arising problem is cost control (Tribunnews.com, 2018).

### *Previous Related Literature*

Thornton et al. (2015) found that there were 18 potential frauds in the health service, and they also found in Indonesia.

**Table 1:** The potential frauds found in Indonesia

No	Potential Fraud	Example
1	Kickback	A doctor writes a prescription for a particular drug brand
2	Self-referral	Doctors will get a commission by referring patients to clinics, hospitals, laboratories (diagnostic services)
3	Doctor shopping	Patients pretend to be sick to get certain drugs
4	Identity fraud	A patient uses someone else's insurance card to get health services
5	Fraud by pharmaceutical companies	Selling the drugs that do not pass the drug and food control agency

No	Potential Fraud	Example
6	Device and service price manipulation	Providing prices to certain users, beyond the normal price
7	Improper encoding and upcoding	Billing for more expensive procedures or services
8	Unbundling	Making separate claims on services that are supposed to be a package
9	Submitting double bills	Sending the same bill more than once
10	Billing for services not provided	Making a claim even though the service does not exist
11	Providing unnecessary & maximising care	Conducting checks or health services that are not as indicated
12	False negotiation cases	Health service providers make fake negotiations so that the government enters a health service program
13	Using the wrong diagnosis	Using a wrong diagnosis to get a certain drug
14	Billing for services rendered by unqualified personnel	Health service providers hire health workers who do not have a license/credentials;
15	Lying about eligibility	Patients lie to doctors or health care providers about the information on insurance benefits they get
16	Reverse false claim cases	A state where health service providers do not return money that has been submitted on a false claim
17	Managed care fraud	Transferring risk from the main payer to an intermediary insurance company, payments using capitalisation rates for the population they insure
18	Waiving co-payments	Removing incentives and violating participant agreements with insurance companies

**Source:** Hasri (2019); Thornton et al. (2015).

Kalb (1999) defines fraud as a deliberate and intentional action to commit or try to take action to deceive health insurance or obtain benefits by faking or cheating or promising money or any property owned by the health insurance program. Abuse is commonly defined as actions that are inconsistent with business practices or unhealthy business. Unlike fraud, abuse is an unintentional practice that directly or indirectly results in overpayments to health care providers. Fraud in the form of upcoding or encoding errors is common in a large number of patients. Based on the Regulation of the Minister of Health of the Republic of Indonesia No. 36/2015, fraud in health services in the JKN program is an action taken by

participants, BPJS Kesehatan officials, health service providers, health service providers, as well as providers of drugs and medical devices to benefit financially from the health insurance program in the National Social Security System through fraudulent acts that are not in accordance with the provisions. The purpose of this study is to develop a healthcare fraud detection model and apply the model to detect potential health service frauds in hospitals in East Java Province, Indonesia.

## Methodology

The population of this study was all District or City General Hospitals (RSUD) in East Java Province. RSUD sampling was determined based on purposive sampling technique by considering four cultural regions in East Java Province, namely Mataraman Culture, Arek Culture, Pandalungan Culture, and Madura Culture (Wibowo, 2013). Therefore, the sample hospitals in this study were RSUD Ibnu Sina, Gresik Regency (representing Arek cultural area), RSUD Dr Slamet Martodirdjo, Pamekasan Regency (representing Madura cultural area), RSUD Ngudi Waluyo Wlingi, Blitar Regency (representing Mataraman Cultural area), and Dr Koesnadi Regional Hospital Bondowoso Regency (representing Pandalungan Cultural area).

Data collection techniques in this study used documentation and interviews. To detect the potential for fraud in hospitals, researchers used documentation techniques in the form of BPJS Kesehatan claim data each month in 2018. BPJS Kesehatan claim data used show the number of monthly inpatients, the number of monthly outpatients, the number of monthly inpatient bills, the number of monthly inpatient bills, the number of inpatients per class, percentage of inpatient cases per class (class III, II, and I), the number of inpatient cases with 1-day length of stay (LOS), average LOS/month, average cases with 1-day LOS referred, number of ways to go home (recovered, referred, forced to go home, died, unknown), comparison between hospital rates and claims of INA CBGs every month, percentage of cases compared with and without referrals, the number of percentage of cases of severity level I , level II, and level III every month, the number of monthly cases with special procedures, the number of monthly cases with special drugs, the number of monthly cases with special investigation, the number of monthly cases with a special prosthesis, the number of 10 most inpatient primary diagnoses based on the International Classification of Diseases (ICD)-10 code every month, the number of 10 most outpatient primary diagnoses based on ICD-10 code every month, the number of 10 most inpatient primary diagnoses with 1-day LOS referred based on the ICD-10 code every month, the number of 10 inpatient Primary diagnoses with the highest bill based on the ICD-10 code every month, the number of 10 outpatient primary diagnoses with the highest bill based on the ICD-10 code every month, the number of 10 most inpatient secondary diagnoses based on the ICD-10 code every month, the number of 10 most outpatient secondary diagnoses based on the ICD-10 code every month,

the number of 10 most inpatient actions based on ICD-9 every month, the number of 10 most outpatient actions based on ICD-9 each month, the number of 10 inpatient primary measures with the highest bill based on ICD-9 every month, and the number of 10 outpatient primary actions with the highest bill based on ICD-9 every month. Taking into account the principle of hospital confidentiality, not all hospitals provided the data needed for the study. Only 1 (one) Regional Hospital provided 2018 claim data needed by researchers. By mutual agreement between the RSUD and the researcher, the researcher must maintain the confidentiality of the data and not include the name of the RSUD in the research publication. An interview technique was conducted with the informants from RSUD officials who were in charge of medical services and guarantees, information technology department, and anti-fraud team. It aimed to explore information related to policies and procedures for health services in the national health insurance program and the problems faced in conducting fraud detection in hospitals. The results of the interviews were used to develop a model for detecting potential fraud.

The analysis technique used to determine the potential fraud detection model was interactive, content, and peer review analysis. A peer review was conducted to review the decision algorithm for potential fraud. Peer review analysis was carried out by health management experts at the Center for Health Policy and Management at Universitas Gadjah Mada. The application of the potential fraud detection model was carried out using the action research method through the design of the Information System for the Prevention of Fraud Health Services National Health Insurance Program (JKN) in Hospitals (SIPADAKES). With this information system, the researchers could detect potential fraud by using claim data.

## **Results and Discussion**

### ***Potential Fraud Detection Analysis Model***

From the interactive and content analysis based on the Regulation of the Minister of Health of the Republic of Indonesia No. 36/2015 on the Prevention of Fraud in the Implementation of the Health Insurance Program in the National Social Security System and peer review, data groupings on potential health service fraud in hospitals were found. There were 4 (four) data groupings on the potential fraud, namely Referral, Cost, Room Utilisation, and Encoding Errors. In each group of potential fraud, the types of claim data with potential fraud, analysis of potential fraud detection, and the decision algorithm for the presence or absence of potential fraud could be identified. The potential fraud decision algorithm for each type of claim data and potential fraud data group were arranged based on data trend and/or compared with the average value. The detailed potential fraud detection analysis model can be explained in Table 2.

**Table 2:** Potential Fraud Detection Analysis Model for Health Service in Hospital

<i>No</i>	<i>Data grouping of Potential Fraud</i>	<i>Type of Claim Data</i>	<i>Technique of Potential Fraud Detection Analysis</i>	<i>Decision Algorithm for Potential Fraud</i>
1	Referral	The number of inpatient cases with 1-day LOS	Time Series Linear Regression	If the trend of data on the number of inpatient cases with 1-day LOS has a tendency to increase and exceed the average value of the data in that period, there is a potential for fraud.
		The number of inpatient cases with 1-day LOS referred	Time Series Linear Regression	If the trend of data on the number of inpatient cases with 1-day LOS referred has a tendency to increase and exceed the average value of the data in that period, there is a potential for fraud.
		The number of patients referred to another hospital	Time Series Linear Regression	If the trend of the data on the number of patients referred tends to increase and exceed the average data, there is a potential for fraud.
2	Cost	Comparison of the number of JKN inpatients with the number of inpatient INA CBGs claims	Time Series Linear Regression	If the trend of the data on the number of JKN inpatients tends to be flat or down, but the number of INA-CBGs claims for inpatients tends to rise, it can be said that there is a potential for fraud.
		Comparison of the number of JKN outpatients with the number of inpatient INA-CBGs claims.	Time Series Linear Regression	If the trend of the data on the number of JKN outpatients tends to be flat or down, but the number of outpatient INA-CBGs claims tends to rise, it can be said that there is a potential for fraud.
		Case Severity Level	Time Series Linear Regression	If the trend of data on level 3 severity tends to increase among others, it can be said that there is a potential for fraud.

<i>No</i>	<i>Data grouping of Potential Fraud</i>	<i>Type of Claim Data</i>	<i>Technique of Potential Fraud Detection Analysis</i>	<i>Decision Algorithm for Potential Fraud</i>
		Inpatient bills billed to BPJS Kesehatan	Time Series Linear Regression	If the trend of the data on the number of inpatient bills billed to BPJS Kesehatan tends to increase more than the average of the available data, it can be said that there is potential for fraud.
		Outpatient bills billed to BPJS Kesehatan	Time Series Linear Regression	If the trend of the data on the number of outpatient bills billed to the BPJS Kesehatan tends to increase more than the average of the available data, it can be said that there is potential for fraud.
		The number of inpatients with special procedures	Time Series Linear Regression	If the trend of the data on the number of inpatient cases with special procedures tends to increase and exceed the average of existing data, there is a potential for fraud.
		The number of outpatients with special procedures	Time Series Linear Regression	If the trend of the data on the number of outpatient cases with special procedures tends to increase and exceed the average of existing data, there is a potential for fraud.
		The number of inpatients with special drugs	Time Series Linear Regression	If the trend of the data on the number of inpatient cases with special drugs tends to increase and exceed the average of existing data, there is a potential for fraud.
		The number of outpatients with special drugs	Time Series Linear Regression	If the trend of the data on the number of outpatient cases with special drugs tends to increase and exceed the average of existing data, there is a potential for fraud.
		The number of inpatients with special prosthesis	Time Series Linear Regression	If the trend of the data on the number of inpatient cases with special prosthesis tends to

<i>No</i>	<i>Data grouping of Potential Fraud</i>	<i>Type of Claim Data</i>	<i>Technique of Potential Fraud Detection Analysis</i>	<i>Decision Algorithm for Potential Fraud</i>
				increase and exceed the average of existing data, there is a potential for fraud.
3	Room Utilisation	Percentage of inpatient class	Time Series Linear Regression	If the trend of the use of class 1 rooms increases and is higher than class 2 and 3, there is a potential for fraud.
		Average LOS	Time Series Linear Regression	If the trend of the data on average LOS tends to decrease and below the average LOS in hospital, there is a potential for fraud.
4	Encoding Errors	Ten most inpatient primary diagnoses based on ICD-10 code	Time Series Linear Regression	If the trend of the data of 10 most inpatient primary diagnoses tends to increase, there is a potential for fraud.
		Ten inpatient primary diagnoses with the highest bills based on ICD-10 code	Time Series Linear Regression	If the trend of the data on 10 inpatient primary diagnoses with the highest bills tend to increase, there is a potential for fraud.
		Ten most inpatient secondary diagnoses based on ICD-10 code	Time Series Linear Regression	If the trend of the data on 10 most inpatient secondary diagnoses tends to increase, there is a potential for fraud.
		Ten most outpatient primary diagnoses based on ICD-10 code	Time Series Linear Regression	If the trend of the data on 10 most outpatient primary diagnoses tends to increase, there is a potential for fraud.
		Ten outpatient primary diagnoses with the highest bills based on ICD-10 code	Time Series Linear Regression	If the trend of the data on 10 outpatient primary diagnoses with the highest bills tends to increase, there is a potential for fraud.
		Ten most outpatient secondary diagnoses based on ICD-10 code	Time Series Linear Regression	If the trend of the data on 10 most outpatient secondary diagnoses tends to increase, there is a potential for fraud.

<i>No</i>	<i>Data grouping of Potential Fraud</i>	<i>Type of Claim Data</i>	<i>Technique of Potential Fraud Detection Analysis</i>	<i>Decision Algorithm for Potential Fraud</i>
		Ten most inpatient primary diagnoses based on ICD-10 code with 1-day LOS referred	Time Series Linear Regression	If the trend of the data on 10 most inpatient primary diagnoses with 1-day LOS referred tends to increase, there is a potential for fraud.
		Ten most inpatient treatments based on ICD-9	Time Series Linear Regression	If the trend of the data on 10 most inpatient treatments tends to increase, there is a potential for fraud.
		Ten inpatient treatments with the highest bills based on ICD-9	Time Series Linear Regression	If the trend of the data on 10 inpatient treatments with the highest bills tends to increase, there is a potential for fraud.
		Ten most outpatient treatments based on ICD-9	Time Series Linear Regression	If the trend of the data on 10 most outpatient treatments tends to increase, there is a potential for fraud.
		Ten outpatient treatments with the highest bills based on ICD-9	Time Series Linear Regression	If the trend of the data on 10 outpatient treatments with the highest bills tends to increase, there is a potential for fraud.

**Source:** Analysis (2018).

### ***Implementation of the Fraud Detection Analysis Model***

The fraud detection model was implemented by designing the National Health Insurance Program (JKN) Fraud Prevention Information System in hospitals (SIPADAKES). With this information system, the researchers could detect potential fraud by using hospital claim data retrieved from January to December 2018.

### ***Potential Fraud Analysis of Referral Data Groups***

The potential fraud analysis in the referral data group with SIPADAKES retrieved from January to December 2018 obtained that the type of inpatient case claim data with 1-day LOS referred had a potential for fraud. These results indicate that it was possible for the hospital to try to take advantage of providing temporary services that were not based on medical indications at the hospital. After undergoing hospitalisation for one day and not getting

complete treatment, it was then referred to another hospital. Meanwhile, the data of inpatient cases with 1-day LOS and inpatient who went home did not indicate the potential for fraud.

### ***Potential Fraud Analysis of Cost Data Group***

Based on the potential fraud analysis of the cost data group, there were four types of data that indicated potential fraud out of ten types of data in the cost data group. The types of data indicating a fraud were the outpatient case with special procedures, inpatient cases with special drugs, outpatient cases with special drugs, and cases with special prostheses. This condition shows that the hospital is suspected of trying to get profit in an unnatural way. While the other types of data including the comparison of the number of JKN inpatients with the number of inpatient INA CBGs claims, the comparison of the number of JKN outpatients with the number of inpatient INA-CBGs claims, Severity of Cases, Inpatient Bills billed to BPJS Kesehatan, outpatient Bills billed to BPJS Kesehatan, and the number of inpatient cases with special procedures did not prove to have any potential for fraud.

### ***Potential Fraud Analysis of Room Utilisation***

The results of potential fraud analysis of the room utilisation show that all types of claim data did not indicate any potential for fraud. The type of claim data in room utilisation group consists of the percentage of inpatient classes and average LOS.

### ***Potential Fraud Analysis of the Encoding Error Data Group***

The results of potential fraud analysis of encoding error data group show that all types of claim data in the encoding error group had a potential for fraud. The types of claim data in encoding error data group include: (i) the number of 10 most inpatient primary diagnoses based on the ICD-10 code every month, (ii) the number of 10 inpatient primary diagnoses with the highest bills based on the ICD-10 code every month, (iii) the number of 10 most inpatient secondary diagnoses based on the ICD-10 code every month, (iv) the number of 10 most outpatient primary diagnoses based on the ICD-10 code every month, (v) the number of 10 outpatient primary diagnoses with the highest bills based on the ICD-10 code every month, (vi) the number of 10 most outpatient secondary diagnoses based on ICD-10 code every month, (vii) the number of 10 most inpatient primary diagnoses with 1-day LOS referred based on ICD-10 code every month, (viii) the number of 10 most inpatient actions based on ICD-9 every month, (ix) the number of 10 inpatient primary treatments with the highest bills based on ICD-9 every month, (x) the number of 10 most outpatient treatments based on ICD-9 every month, and (xi) the number of 10 outpatient primary treatments with the highest bills based on ICD-9 every month. In this case, all were detected for potential frauds.

Among the four potential fraud data groups analysed, the encoding error data group was found to be the most potentially fraudulent. This finding is in line with the results of the study by (Thornton et al., 2015). They concluded that encoding error is one of the health fraud research topics most widely discussed by researchers. (Agrawal, Tarzy, Hunt, Taitsman, & Budetti, 2013) state that encoding errors describe billing for services, diagnoses and actions that are more expensive than those performed or double-billing for the same services, diagnoses and actions. In connection with the results of the analysis of the potential for fraud in the encoding error data group, the hospital's anti-fraud team must conduct an investigation, especially on diagnoses and outpatient and inpatient treatments in which its trend in number and billing has increased.

## **Conclusion**

This research has succeeded in developing a framework for detecting potential health service fraud in the form of a potential fraud detection analysis model. This fraud detection analysis model is based on four groups of potential fraud data, namely referral, costs, room utilisation, and encoding errors. In each group of potential fraud data, the types of claims data needed to analyse potential fraud, analysis techniques for detecting potential fraud, and decision algorithms for the presence or absence of potential fraud have been identified. The decision algorithm is based on the claim data trend and compared to the average value of the claim data for a certain period.

The model of detecting potential health service fraud has been implemented in hospitals through the establishment of a JKN Program for the Prevention of Health Services Fraud in Hospitals. The results of the application of potential fraud detection analysis model by using SIPADAKES in RSUD in East Java Province show that in the encoding error data group, all types of claim data were detected for potential fraud. This reflects that billing for diagnosis and treatment were more expensive than what the hospital did. In connection with these results, the hospital's anti-fraud team must conduct an investigation, especially on diagnoses and outpatient and inpatient treatments, which had an increasing trend in the number and billing. The other findings identified as potential fraud were in the reference data group on the type of inpatient claim data with 1-day LOS referred. In the cost data group, the potential frauds identified were the outpatient case with special procedures, inpatient cases with special drugs, outpatient cases with special drugs, and inpatient cases with special prostheses.

The novelty of this research is the classification of potential frauds, namely referral, cost, room utilisation, and encoding errors as well as algorithms in the potential fraud detection analysis model. In addition, this study designed the Information System for Fraud Prevention of Health Services at the JKN Program in Hospitals (SIPADAKES) that can be used by hospital's anti-fraud teams to easily detect potential frauds that were previously done



manually. It is hoped that with the effective detection of fraud, opportunities and intentions to commit fraud in health services will cease. Thus, if the opportunity to commit fraud is limited, it will indirectly affect the improvement in the quality of health services.

The limitation of this study is that the scope is limited only to government-owned hospitals. The research area is only in East Java Province so that it has not yet described the level of health service fraud in Indonesia. Therefore, for further studies, other researchers can expand the object of research not only to the Regional Hospital but also to private hospitals and expanded areas, not only East Java Province.

### **Acknowledgment**

The authors would like to thank the Director of Research and Community Service of the Directorate General of Reinforcement of Research and Development, Ministry of Research, Technology, and Higher Education who has funded this research.

## REFERENCES

- Agrawal, S., Tarzy, B., Hunt, L., Taitsman, J., & Budetti, P. (2013). Expanding physician education in health care fraud and program integrity. *Academic Medicine*, 88(8), 1081–1087. <https://doi.org/10.1097/ACM.0b013e318299f5cf>
- Bauder, R., Khoshgoftaar, T. M., & Seliya, N. (2017). A survey on the state of healthcare upcoding fraud analysis and detection. *Health Services and Outcomes Research Methodology*, 17(1), 31–55. <https://doi.org/10.1007/s10742-016-0154-8>
- Dewi YR, R. (2017). *Fraud Penyebab dan Pencegahannya* (1st ed.). Bandung: Alfabeta.
- Djasri, H., Rahma, P. A., & Hasri, E. T. (2016). Korupsi dalam Pelayanan Kesehatan di Era Jaminan Kesehatan Nasional: Kajian Besarnya Potensi dan Sistem Pengendalian Fraud. *Integritas*, 2(1), 113–133.
- Hasri, E. T. (2019). Bisa jadi, potensi-potensi fraud ini juga sedang berkembang di Indonesia. Retrieved 9 September 2019, from <http://mutupelayanankesehatan.net/3112-bisa-jadi-potensi-potensi-fraud-ini-juga-sedang-berkembang-di-indonesia>
- Joudaki, H., Rashidian, A., Minaei-Bidgoli, B., Mahmoodi, M., Geraili, B., Nasiri, M., & Arab, M. (2015). Using data mining to detect health care fraud and abuse: a review of literature. *Global Journal of Health Science*, 7(1), 194–202. <https://doi.org/10.5539/gjhs.v7n1p194>
- Kalb, P. E. (1999). Health care fraud and abuse. *Journal of the American Medical Association*, 282(12), 1163–1168. <https://doi.org/10.1001/jama.282.12.1163>
- Komisi Pemberantasan Korupsi. (2016). Pembangunan alat diagnostik dan petunjuk pelaksanaan pencegahan korupsi di FKRTL. Retrieved from <https://www.kpk.go.id/id/publikasi/kajian-dan-penelitian/kajian-dan-penelitian-2/501-pembangunan-alat-diagnostik-dan-petunjuk-pelaksanaan-pencegahan-korupsi-di-fkrtl>
- Kualitas Pelayanan Kesehatan Dipertanyakan, Tarif INA-CBG Perlu Direvisi. (2018, April 10). Retrieved from <https://www.tribunnews.com/kesehatan/2018/04/10/kualitas-pelayanan-kesehatan-dipertanyakan-tarif-ina-cbg-perlu-direvisi?page=all>
- Li, J., Huang, K. Y., Jin, J., & Shi, J. (2008). A survey on statistical methods for health care fraud detection. *Health Care Management Science*, 11(3), 275–287. <https://doi.org/10.1007/s10729-007-9045-4>
- Morris, L. (2009). Combating fraud in health care: An essential component of any cost containment strategy. *Health Affairs*, 28(5), 1351–1356.



<https://doi.org/10.1377/hlthaff.28.5.1351>

Thornton, D., Brinkhuis, M., Amrit, C., & Aly, R. (2015). Categorising and describing the types of fraud in healthcare. *Procedia Computer Science*, 64, 713–720.  
<https://doi.org/10.1016/j.procs.2015.08.594>

Wibowo, N. M. (2013). Strategi pengembangan pelayanan rawat inap puskesmas berbasis service delivery system. *Ekuitas (Jurnal Ekonomi Dan Keuangan)*, 17(3), 337–356.  
Retrieved from <https://ejournal.stiesia.ac.id/ekuitas/article/view/343/320>