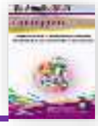
Contagion : Scientific Periodical of Public Health and Coastal Health 7(3)(2025)
e-ISSN : 2685-0389



The Impact of Electronic Medical Records on Hospital Revenue from INA-CBGs Claims

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Track Record Article

Revised: 13 July 2025
Accepted: 03 December 2025
Published: 08 December 2025

How to cite:
Maryati, W., & Susanto, A. (2025). The Impact of Electronic Medical Records on Hospital Revenue from INA-CBGs Claims. *Contagion: Scientific Periodical Journal of Public Health and Coastal Health*, *7*(3), 1–12.

Abstract

Incorrect diagnosis and procedure coding are the major factors which lead to substantial reductions of claims in the INA-CBGs system. Studies have indicated reported losses of up to 23% due to this alone. This paper discusses whether Electronic Medical Records, hereafter referred to as EMRs, will mitigate such financial risks through improved documentation and coding quality. The study is a cross-sectional analysis based on 100 INA-CBGs inpatient claim documents, 50 with the use of EMRs and another 50 with the use of manual records, selected by simple random sampling technique. Five key variables have been related using the Chi-square test, multiple logistic regression analysis, and Structural Equation Modeling (SEM). Of all claims analyzed in this study, only 55% had complete medical information; diagnosis codes were accurate in 66% of them while accurate procedure codes accounted for just about 48%. Hospitals where EMRs are used had less revenue reduction at IDR 119,444,050 or -23.47%, compared to hospitals without EMRs which used manual records with a revenue reduction rate standing at IDR 272,422,069 or -47.92%. Of the claims analyzed, 55% had complete medical information, 66% had accurate diagnosis codes, and 48% had accurate procedure codes. Hospitals using EMRs experienced a smaller revenue reduction (IDR 119,444,050 or -23.47%) compared to those using manual records (IDR 272,422,069 or -47.92%). Diagnosis codes at accuracy (b = 3.595; p = 0.001), procedure codes at accuracy (b = 4.461; p < 0.001), documentation at completeness (b = 2.331; p < 0.001) and EMR use (b = 0.425; p < 0.001) were all significant factors with results of claims. EMRs significantly improve coding accuracy and reduce claim deductions, mitigating financial risk. Accelerating EMR adoption is recommended to strengthen hospital claim performance in the national health insurance system.

Keyword: Electronic medical record; Diagnosis; Procedure; Hospital revenue; INA-CBGs

INTRODUCTION

Indonesia has adoptedthe Indonesian Case Based Groups (INA-CBGs) system as a part of its National Health Insurance (NHI) program, which is managed by the Health Insurance Administration Agency (Athiyah et al., 2019). This system groups tariffs based on diagnosis codes from the International Classification of Diseases and Related Health Problems 10th Revision (ICD-10) and action codes from the International Classification of Diseases 9th Revision Clinical Modification (ICD-9-CM) (Maryati et al., 2020). These codes are crucial because they determine the cost of health care. When diagnosis or action codes are inaccurate, hospitals can suffer financial losses.[3] Beyond cost calculation, the codes also support patient care planning, provide detailed breakdowns of treatment expenses, and help reduce management risks (Hatta, 2013; Cummings et al., 2011; Sunjaya et al., 2022). One major risk is that hospitals may receive lower claim reimbursements under the INA-CBGs system.

A study in Victoria, Australia found that 16% of 752 diagnosis codes were inaccurate, leading to hospital losses of about 575,300 Australian dollars(Cheng et al., 2019). In Indonesia, similar issues have been reported, with 23% of claims showing a negative difference compared to the hospital's actual service rates. For instance, a case of diabetes mellitus with a skin ulcer was coded as E14.9 and L98.4, resulting in a claim of Rp 6,617,568. However, if the diagnosis had been coded as E14.5 in combination, the claim would have been Rp 7,575,541. In that single case, the hospital lost Rp 957,973. Such inaccuracies often occur because medical information is incomplete.

Completeness of medical information is a key factor in ensuring accurate diagnosis and action codes (Maryati et al., 2019; Rohman et al., 2011; Farzandipour et al., 2020). Studies show that information technology helps reduce the problem of incomplete medical records (Derecho et al., 2024; Dicuonzo et al., 2023). One important tool is the Electronic Medical Record (EMR), which makes it quicker and simpler for doctors to prepare claim documents and send them to insurance providers(Janssen et al., 2021). EMRs also improve accuracy and make health care costs more efficient. Research has even shown (Liu & Walsh, 2018) that EMRs can significantly boost the quality of documentation and increase hospital income under Diagnostic Related Groups (DRGs), by as much as USD 14,020 per patient per month ($p < 0.001$).

Preliminary studies show clear differences in the accuracy of diagnosis codes between hospitals that use Electronic Medical Records (EMR) and those that do not. Hospitals with EMR report an average inaccuracy rate that is 10% lower than hospitals without EMR, which stand at 35%. Even so, the overall percentage of inaccurate codes in Indonesia remains high, above the domestic average of 31.5% (Maryati et al., 2018; Sarwastutik, 2013). It is still far higher (Sudra & Pujihastuti, 2016; Hailegebreal et al., 2023) compared to hospitals abroad, where the average inaccuracy rate is only 12.71%.

Earlier studies have focused on several factors that influence INA-CBGs claims, such as the quality of medical records, the accuracy of diagnosis and action codes(Bhima et al., 2023; Ng'ang'a, 2024), hospital characteristics, and grouper codes (Bhima et al., 2023). However, none of these studies examined how the use of electronic medical records (EMR) might affect hospital income from INA-CBGs claims. Researchers have begun to analyze the impact of EMR implementation on increasing hospital income through INA-CBGs claims.

At the study site, initial assessments revealed that hospitals relying on manual medical records often faced claim deductions due to incomplete documentation and inaccurate diagnosis or procedure codes. Before the introduction of Electronic Medical Records (EMR), hospital income from INA-CBGs claims was significantly reduced, with average losses reaching IDR 272,422,069 (47.92%) per claim cycle (Sunjaya et al., 2022; O'Donnell et al., 2018; Janssen et al., 2021). After EMR was implemented, notable improvements were recorded: completeness of medical information increased by 55%, accurate diagnosis coding rose to 66%, and procedure coding improved by 48%. As a result, claim deductions decreased substantially, with average income loss dropping to IDR 119,444,050 (23.47%) (Putri et al., 2023; Umstead et al., 2021). These findings suggest that EMR enhances coding accuracy and the quality of clinical documentation, thereby reducing claim mismatches and strengthening hospital income. Building on this evidence, the present study evaluates how EMR implementation improves medical information completeness, coding accuracy, and financial outcomes in INA-CBGs claims.

METHODS

This study employed a cross-sectional, quantitative design in two private Type D medical centres located within the same geographical area and sharing similar characteristics. The population consisted of all inpatient INA-CBGs claim records filed in 2024 from both hospitals. From this, 100 claim records were selected, divided equally into two groups: 50 from hospitals using manual medical records and 50 from hospitals using EMR. The sample size met the recommended standard for multivariate analysis, 15 to 20 subjects per variable (Ratnawati & Kholis, 2019; Murti, 2015), and was considered appropriate for the five variables examined. Sampling was conducted using a simple random technique, with each claim file assigned a number before selection. The two hospitals were matched based on key features, including their classification as Type D facilities, patient admission numbers, private ownership, and location within the same regional health service zone (Okello, 2022), ensuring comparability in operational scale and service provision.

The data collected were secondary, obtained through document review of submitted claim files. Five key factors were examined: EMR use, completeness of medical data, accuracy of diagnostic codes, specificity of procedure codes, and increased revenue from INA-CBGs claims (Maryati et al., 2021; Vos et al., 2020). Completeness of medical records was assessed using a checklist that covered patient history, long and short case notes, diagnoses and related examination reports, detailed progress notes, procedures performed during hospitalization, and prescribed treatments. Each item was reviewed by the researchers and validated by disease experts. For coding accuracy, ICD-10 was applied to diagnosis codes and ICD-9-CM to procedure codes. As part of the analysis, researchers re-coded the diagnoses and procedures, and the results were subsequently verified by coding auditors in the participating hospitals.

After completing observation and documentation at the hospital, the researcher proceeded with data processing, which involved compiling, categorizing, verifying, evaluating, and analysing the data before drawing conclusions. The analysis began with univariate methods to reveal the frequency distribution of each variable, followed by bivariate analysis using the Chi-Square test and multivariate analysis through Multiple Logistic Regression. Path analysis was then conducted to identify the best model explaining the general relationships among the variables (Krawiec, 2019). Because simpler models could not capture the multi-path dependencies, Structural Equation Modelling (SEM) was employed to examine complex relationships and secondary effects. The analysis was carried out using STATA version 13, which included model specification with exogenous and endogenous variables, identification through degrees of freedom, assessment of model fit, estimation of regression coefficients, and iterative re-specifications until an optimal fit was achieved (Mvududu & Shannon, 2023). Ethical approval has been obtained from the Health Research Ethics Committee of the Faculty of Medicine, Sebelas Maret University (Approval Number: 153/UN27.06.11/KEP/EC/2024).

RESULTS

Descriptive analysis

The study analyzed pending claim documents that had been returned by the Health Insurance Administration Agency due to non-compliance with submission requirements. In total, 100 inpatient claim documents were reviewed. Of these, 55% contained complete medical information. Accurate diagnosis codes were found in 66% of the documents, while only 48% had accurate procedure codes. Furthermore, 54% of the claims generated hospital revenue above the standardized tariff, whereas the remainder fell below. These results are summarized in Table 1.

Table 1. Descriptive Analysis

Variables	Accurate/Complete		Inaccurate/Incomplete	
	n	Percentage	n	Percentage
Medical Information	55	55 %	45	45 %
Diagnosis Code	66	66 %	34	34 %
Procedure Code	48	48 %	52	52 %
Hospital Revenue	54	54 %	46	46 %

Bivariat Analysis

Bivariate analysis (Table 2) showed that EMR had a significant relationship with the completeness of medical information. EMR could improve the completeness of medical information by 3.5 times better than manual medical records (b = 3.500; 95%CI = 1.529 to 8.012; p = 0.003).

Table 2. Relationship between EMR and Completeness of Medical Information

Medical Record	Medical Information		OR	CI (95%)		*p*
	Complete (%)	Incomplete (%)		Lower	Upper	
EMR (%)	30 (60)	20 (40)	3.500	1.529	8.012	0.003
Manual (%)	15 (30)	35 (70)				

In addition, bivariate analysis on Table 3 also showed that the completeness of medical information has a significant relationship with the accuracy of the diagnosis code. Completeness of medical information can increase the accuracy of the diagnosis code by 10.286 times better than incomplete media information (b = 10.286; 95%CI = 3.813 to 27.743; p <0.001).

Table 3. Relationship between Completeness of Medical Information and Accuracy of Diagnosis Code

Medical Information	Diagnosis Code		OR	CI (95%)		*p*
	Accurate (%)	Inaccurate (%)		Lower	Upper	
Complete (%)	27 (60%)	18 (40%)	10.286	3.813	27.743	<0.001
Incomplete (%)	7 (12.7%)	48 (87.3%)				

Completeness of medical information was also shown to have a significant relationship with the accuracy of the procedure code (Table 4). Completeness of medical information can increase the accuracy of the action code by 9.750 times better than incomplete medical information (b = 9.750; 95%CI = 3.832 to 24.807; p <0.001).

Table 4. Relationship between Completeness of Medical Information and Accuracy of Procedure Code

Medical Information	Procedure Code		OR	CI (95%)		*p*
	Accurate (%)	Inaccurate (%)		Lower	Upper	
Complete (%)	36 (80)	9 (20)	9.750	3.832	24.807	<0,001
Incomplete (%)	16 (29.1)	39 (70.9)				

The results of the analysis also prove that diagnosis codes and procedure codes have a significant relationship with hospital income from INA-CBGs claims that can be seen on Table 5. Accurate diagnosis codes can increase hospital income from INA-CBGs claims by 7,475 times better than inaccurate diagnosis codes (b = 7.475; 95%CI = 2.889 to 19.338; p <0.001). Meanwhile, accurate action codes can increase hospital income from INA-CBGs claims by

23.333 times better than inaccurate action codes (b = 23.333; 95%CI = 7.992 to 68.120; p <0.001).

Table 5. Relationship between Accuracy of Diagnosis Codes and Hospital Income from INA-CBGs Claims

Code Accuracy	Hospital Revenue on INA-CBGs Claim		OR	CI (95%)		*p*
	Positive (%)	Negative (%)		Lower	Upper	
Diagnosis Code						
Accurate (%) Inaccurate (%)	26 (76.5) 20 (30.3)	8 (23.5) 46 (69.7)	7.475	2.889	19.338	<0.001
Procedure Code						
Accurate (%) Inaccurate (%)	40 (76.9) 6 (12.5)	12 (23.1) 42 (87.5)	23.333	7.992	68.120	<0.001

Electronic medical records greatly assist hospitals in controlling the quality of medical records and service costs. In 100 pending claim documents studied, the results of the BPJS audit showed that there was a difference in the amount of decrease in income obtained from INA-CBGs claim results between hospitals that had implemented EMR and those still using manual EMR. Hospitals that had implemented EMR experienced a lower decrease in income of IDR 119,444,050 (-23.47%), while hospitals that still used manual EMR experienced a higher decrease in income of IDR 272,422,069 (47.92%) (Table 6).

Table 6. Differences in Hospital Rates with INA-CBGs Rates in Pending Claim Documents

Medical Record	Hospital Tariff (IDR)	INA-CBGs Tariff (IDR)	Difference Tarif (IDR)	Percentage (%)
EMR	389,332,300	508,776,350	119,444,050	23.47%
Manual	296,108,600	568,530,669	272,422,069	47.92%

Path Analysis

Based on the results of path analysis using STATA, the most fit model to describe the relationship between variables is as follows on Figure 1:

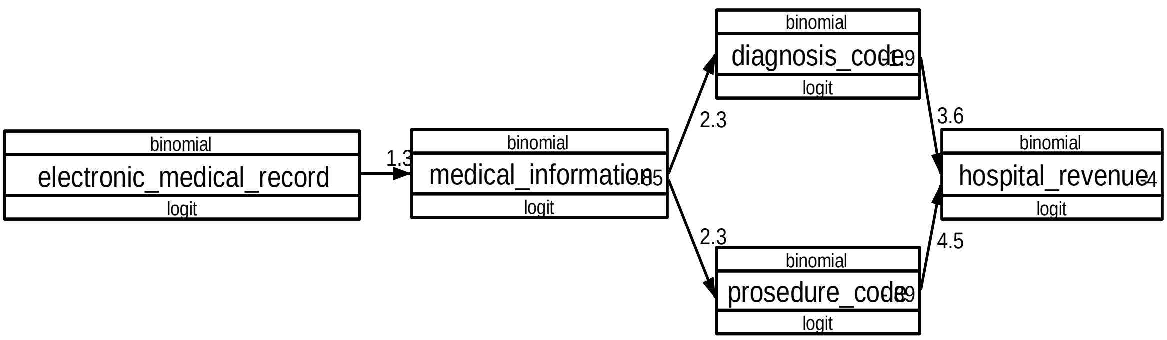

Figure 1. Path Analysis Model

Table 7. Path Analysis Results

Dependent Variables		Independent Variables	Path Coefisien (b)	Error Standrat	CI (95%) Lower	Upper	*p*
Direct Effect							
Hospital Revenue from INA-CBGs Claims	←	Diagnosis Code	3.595	1.080	1.478	5.712	0.001
	←	Procedure Code	4.461	1.056	2.392	6.531	<0.001
Indirect Effect							
Diagnosis Code	←	Medical Information	2.331	0.506	1.339	3.323	<0.001
Procedure Code	←	Medical Information	2.278	0.476	1.343	3.211	<0.001
Medical Information	←	EMR	1.253	0.423	0.425	2.081	0.003
N Observasi		100					
Log likelihood		-205.46746					
Df		9					
AIC		428.9349					
BIC		452.3815					

Table 7 shows the results of path analysis with the selection of Generalized Structural Equation Modeling (GSEM) in STATA 13 with the following details:

1) Direct Relationship

a) Accurate diagnosis codes have log odds of 3.595 better in determining hospital income from INA-CBGs claims than inaccurate diagnosis codes and are statistically significant (b=3.595; CI95%= 1.478 to 5.712; p=0.001)

b) Accurate action codes have log odds of 4.461 better in determining hospital income from INA-CBGs claims than inaccurate action codes (b=4.461; CI95% =2.392 to 6.531; p<0.001).

2) Indirect Relationship

a) Complete medical information has log odds of 2.331 better in determining hospital income from INA-CBGs claims than incomplete medical information and is statistically significant (b=2.331; CI95%= 1.339 to 3.323; p<0.001)

b) Complete medical information has log odds 2.278 better in determining hospital revenue from INA-CBGs claims than incomplete medical information and is statistically significant (b=2.278; CI95%= 1.343 to 3.211; p<0.001)

Electronic medical records have log odds 1.253 better in determining hospital revenue from INA-CBGs claims than manual medical records and is statistically significant (b=0.425; CI95%= 5.712 to 2.081; p<0.001).

DISCUSSION

Accuracy of Coding (Diagnosis and Procedures)

The investigation revealed that only 66% of diagnosis codes and 48% of procedure codes in the assessed claim documents were accurate. This highlights the persistent problem of poor coding, especially in hospitals that still rely on manual records. Errors in both diagnosis and procedure coding can have serious financial consequences, as they affect DRG group classifications and casemix value calculations under the INA-CBGs system. This issue is consistent with global evidence showing that miscoding often leads to DRG downgrading and significant economic losses. For instance, in Denmark, incorrect diagnosis coding was found in 35% of cases, with 12% resulting in lower DRG values, an estimated annual loss of DKK 23 million(Sunjaya et al., 2022). Similarly, in Malaysia (Nguyen et al., 2022), 74% of reviewed claim documents required adjustments in Malaysian Diagnostic Related Groups (MY-DRG), leading to potential financial losses of RM 654,303.91.

The main causes of coding errors are incomplete clinical records and limited training for coders. Dalal & Roy (2009) emphasized that the lack of standardized documentation often leads to variations in coding. These findings highlight the importance of improving accuracy in both diagnosis and procedure coding, as doing so is critical for strengthening the financial performance of hospitals that depend on casemix funding.

Completeness of Medical Information

Of all claims submitted, only 55% contained complete medical information, meaning nearly half lacked sufficient detail for accurate coding and payment. This gap underscores the importance of stronger documentation processes to prevent claim deductions and ensure compliance with the INA-CBGs model. Key information, such as detailed diagnoses, ongoing care notes, and required lab or imaging results, was often incomplete or missing, particularly in paper-based systems that remain common practice (Thigpen et al., 2015). Missing data leads to ambiguity in code assignment, which can negatively affect reimbursement. Maryati et al. (2021) found that having a complete medical history increased the likelihood of accurate diagnostic coding by 6.663 times. Similarly, other studies confirm (Cheng et al., 2019; Morley et al., 2022) that the quality of supporting documentation is a critical factor in coding reliability and claim validity.

This research underscores that high-quality documentation is vital for accurate clinical coding (Cummings et al., 2011). Clinical notes also play a crucial role in providing both legal and financial support during claims management. When documentation is insufficient or poorly organized, coding errors become inevitable, leading to financial penalties and a higher risk of audits. Addressing this issue requires standardized documentation processes integrated into both medical education and hospital information systems.

Implementation of Electronic Medical Records (EMR)

Electronic Medical Records (EMR) serve as a safeguard in managing claims and protecting hospital revenue. Hospitals that implemented EMR experienced a significantly smaller revenue drop (−47%) compared to those relying on manual processes (−47.92%). EMR systems support well-organized and comprehensive documentation, enable real-time monitoring for data verification, and improve traceability in coding. Research by Kim (2020) and Kim et al. (2011) found that interoperable EMR systems strengthened the link between documentation and billing, thereby reducing errors. Similarly, Liu & Walsh (2018) reported that EMR adoption improved documentation standards, enhanced provider satisfaction, and increased hospital reimbursement rates.

This research highlights that Electronic Medical Records (EMR) are more than just tools for documenting clinical information; they are also valuable resources for managing hospital finances within the INA-CBGs framework(Janssen et al., 2021; Alhur, 2024). By ensuring that data is complete, comprehensive, and consistent, EMR reduces human errors and strengthens the accuracy of claims. However, to achieve these benefits fully, successful implementation requires proper infrastructure, adequate training, and supportive policies to ensure the system matures effectively

CONCLUSIONS

Electronic Medical Records (EMR) are pivotal in improving the quality of clinical documentation, a practice closely tied to accuracy in diagnosis and procedure coding within the INA-CBGs framework. EMR significantly enhance the completeness of medical records, ensuring that all relevant clinical information for coding is systematically documented and easily accessible. Well-organized and comprehensive documentation improves coding accuracy, reducing the frequency of errors and inappropriate DRG assignments. Findings from this study show that hospitals using EMR experienced smaller revenue losses from claims (−23.47%) compared to those relying on paper records (−47.92%). Even with these reductions, EMR-supported hospitals still achieved net profits under the national casemix-based payment system

To encourage wider adoption of Electronic Medical Records (EMR), several targeted interventions are recommended. The Ministry of Health and the Health Insurance Administration Agency should provide financial support to private and smaller hospitals to facilitate EMR adoption. All JKN-affiliated hospitals should be required to implement a standardized EMR system. National standards should mandate training on EMR use and coding for both coders and healthcare providers. A centralized monitoring system should be established to ensure that EMR implementation does not negatively affect coding accuracy or hospital revenue claims. These measures highlight that EMR adoption is not only a step toward improving the quality of medical care but also a cost-saving strategy that deserves priority on Indonesia's health policy agenda

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