The Influence Of Artificial Intelligence Auto Verification As An Intervention On Bpjs Claim Output: A Case Study At Murni Teguh Memorial Hospital Medan

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Abstract:

Background: Hospitals are healthcare facilities that provide specialized medical treatment, care, and services to individuals in need of diagnosis, treatment, and recovery from illness, injury, or other health conditions. Hospitals are usually equipped with a variety of medical professionals, including doctors, nurses, and support staff, and offer a wide range of services (Peraturan Menteri Kesehatan Republik Indonesia, 2020). Murni Teguh Memorial Hospital Medan is a leading healthcare facility located in Medan, North Sumatra, Indonesia. Established under the ownership of PT Murni Sadar Tbk, the hospital aims to provide high-quality medical services to the community. For the continuity of health services provided and legal interests, hospitals are required to conduct medical record activities to ensure patient safety. According to the Regulation of the Minister of Health Number 24 of 2022, Medical Records are files containing records and documents on patient data containing patient identity, examination, treatment, actions, and other services that have been provided to patients (Regulation of the Minister of Health of the Republic of Indonesia, 2022). Murni Teguh Memorial Hospital Medan develops electronic medical records to perform official patient documentation. An Electronic Medical Record (EMR) is a digitized version of a patient¹s paper medical record.

Objective: This study aims to analyze the influence of several factors on the output of BPJS claims at Murni Teguh Memorial Hospital Medan, especially in overcoming the problem of pending claims that can hamper hospital cash flow.

Methods: This study used an experimental approach with pre-test and post-test methods to measure the effectiveness of implementing the AI Auto Verification model in overcoming obstacles that cause pending claims on BPJS claims at Murni Teguh Memorial Hospital Medan. This approach was conducted by comparing conditions before and after the use of AI through data collection using a questionnaire before the use of the AI Auto Verification model (control) and a questionnaire after the use of the AI Auto Verification model (experimental). Thus, this study can provide a more in-depth analysis of the extent to which the application of the Auto Verification model

is able to overcome inhibiting factors, such as the completeness of administration/files, errors in coding, and factors related to machines and manpower.

Results: Based on the results of previous research conducted by Cathryn Gabriella (2020) on the factors affecting the return of BPJS claims for inpatients at Fatmawati Government General Hospital in March - May 2020 there were 218 inpatient claim files returned, consisting of three types of returns, namely due to Membership Administration Factors 1.8%, Service Administration Verification 17%, and Service Verification 81.2%.[2] The return factor caused by service verification is the most common return factor at Fatmawati Government General Hospital in 2020. Based on other research at Fatmawati Government General Hospital in 2016 on the return of BPJS claims for inpatients in January - April there were 1719 claims returned, consisting of four categories, namely Administrative Improvements 19%, Borrowed Status 7%, Confirmation of Coding 36%, and Completeness of Resume 38%, of the four factors, the most returns came from the Completeness of Resume category 38%.

Conclusion: This analysis will change the BPJS claim variables after the implementation of the Auto Verification model, to test whether there is an increased impact of file completeness, coding accuracy, and optimization of human and machine resources in the BPJS claim process. The results of the analysis show a significant difference between before and after the implementation of AI, so it can be concluded that the AI Auto Verification model is an effective solution to overcome the various obstacles that cause BPJS claims.

1. Introduction

A hospital functions as a critical healthcare institution tasked with delivering specialized medical care, diagnostics, treatment, and rehabilitative services to individuals confronting diverse health conditions. In accordance with the Regulation of the Minister of Health of the Republic of Indonesia (2020), hospitals are mandated not only to maintain and improve public health but also to provide services that are both effective and efficient. Murni Teguh Memorial Hospital, established under PT Murni Sadar Tbk in Medan, North Sumatra, exemplifies such a commitment by offering patient-centered, high-quality medical services through the integration of advanced technologies and highly qualified medical professionals. To safeguard legal interests and ensure continuity in healthcare delivery, the hospital is required to maintain accurate and comprehensive medical records. In alignment with the Regulation of the Minister of Health Number 24 of 2022, medical records encompass all documents related to patient identification, clinical assessment, treatment, and services rendered. Murni Teguh Memorial Hospital has adopted an Electronic Medical Record (EMR) system to digitize and streamline medical documentation, thereby enhancing accessibility and accuracy in patient care. EMRs play a vital role in enabling authorized medical personnel to efficiently access patient data, reinforcing both clinical decision-making and patient safety.Despite technological advancements, the hospital faces financial strain due to delayed reimbursements from BPJS Health, Indonesia's state-run health insurance provider. These delays, often attributed to administrative deficiencies, coding errors, and incomplete documentation, result in a substantial volume of pending claims, thereby disrupting hospital cash flow. A preliminary survey revealed 94 pending outpatient claims from a total of 15,560 submitted within three months in 2024. Addressing this systemic inefficiency necessitates the deployment of an AI-

driven auto-verification model capable of performing intelligent claims validation, reducing human error, and accelerating the reimbursement cycle thus ensuring financial sustainability and service excellence.

Figure 1.1 Training Model

This study proposes a pioneering intervention through the development and implementation of a self-constructed AI Auto Verification system, designed to mitigate the incidence of pending BPJS claims. It is posited that this technological innovation will significantly expedite the claims disbursement process and enhance the operational efficiency of Murni Teguh Memorial Hospital. Employing an experimental research design, the study utilizes a pre-test and post-test methodology to evaluate the efficacy of the AI system. Data are collected via structured questionnaires administered before (control) and after (experimental) the implementation of the AI model, thereby facilitating a rigorous comparative analysis.

The core objective of this investigation is to empirically assess the extent to which the Auto Verification system addresses critical impediments such as administrative incompleteness, coding inaccuracies, and inefficiencies in human and machine resources. Structural equation modeling, executed via SMARTPLS, is employed to quantify the variance in key variables pre- and post-intervention. Should the results reveal a statistically significant improvement in claims accuracy and

processing speed, the AI Auto Verification system may be regarded as a robust and scalable solution for enhancing the reliability and efficiency of healthcare reimbursement mechanisms in Indonesia.

Figure 1.2 Comparison of PLS

The comparative bar chart elucidates the differential outcomes of the SEM-PLS model metrics between the pre-test (without AI intervention) and post-test (with AI Auto Verification implementation) phases. Four critical model metrics, Factor Loadings, R^2, f-square, and Path Coefficients are examined to assess the efficacy of the AI-enhanced system in improving claim processing performance.

Factor Loadings in the post-test phase approach 0.8, markedly higher than the pre-test value of approximately 0.65. Given that factor loadings exceeding 0.7 are indicative of strong item reliability and convergent validity, the observed post-test enhancement suggests a statistically significant improvement in the measurement model's quality.

The R^2 value, which represents the explanatory power of the model, increases from approximately 0.45 to 0.7. This substantial gain indicates that the AI-driven system enhances the model's capacity to

explain the variance in the dependent constructs underscoring its effectiveness in accounting for the completeness of documentation, coding precision, and optimization of resources in BPJS claims.

The f-square effect size, reflecting the magnitude of change caused by an exogenous construct, also improves from around 0.2 to 0.4. According to Cohen's (1988) criteria, the increase denotes a transition from a small to a moderate effect size, implying a statistically meaningful impact of the AI intervention on model parameters.

The Path Coefficients exhibit an increase from approximately 0.55 to 0.78. This denotes a strengthened causal relationship among latent variables in the structural model post-AI implementation, suggesting a significant enhancement in the predictive validity of the framework.

2. Destination

1) To determine and assess the key elements that cause outstanding BPJS claims at Murni Teguh Memorial Hospital Medan by thoroughly investigating the claim rejection patterns from 2022-2024.

This objective concentrates on methodically classifying the main reasons for delayed claims into three main categories: administrative deficiencies (such as missing or incomplete Participant Eligibility Statement/SEP, unsigned medical resumes, and insufficient supporting documents), coding errors (mainly discrepancies between physician diagnoses and ICD-10 codes or procedural discrepancies with ICD-9 CM standards), and systemic inefficiencies (including communication delays between departments, outdated verification procedures, and limited human resources)1[2].

2. Develop and implement an automated AI verification model

It is specifically designed to address challenges identified in the PBB BPJS process at Murni Tguh Memorial Hospital. This involves creating a machine learning system that integrates natural language processing (NLP) capabilities used to automatically validate the completeness of documents and cross-reference claims submitted for BPJS requirements, a rule-based engine used to verify the accuracy of diagnosis and procedure coding against INA-CBGs standards, and an anomaly detection algorithm to flag potential discrepancies prior to claim submission. The model will be trained with historical claims data for 3 years from 2022 to 2024 to recognize patterns of accepted and rejected claims, with this continuous learning mechanism expected to adapt to evolving BPJS regulations. The implementation will include several stages of testing in hospital billing departments, with performance metrics tracking its ability to reduce common errors that currently lead to claim denials and delays.

3. Evaluated the performance of the automated AI verification system with a rigorous benchmarking study to measure key performance indicators in the implementation. Using pre-test and post-test experimental tests, the study measured improvements across dimensions such as a repeat of the average claims processing time, a decrease in the percentage of claims returned for correction, an increase in first-stage approval rates, and a reduction in time spent by staff performing manual verification tasks. The evaluation also continued for 6 months after implementation with weekly performance tracking and monthly comparative analysis against baseline metrics established during the pre-intervention phase.

4. To assess the impact of AI integration on the hospital's operational efficiency by examining changes in several operational parameters. This includes analyzing departmental workflow shifts, measuring time savings in claims processing flow, evaluating changes in permanent productivity and job satisfaction, and assessing the system's impact on the hospital's overall financial performance. The assessment will utilize time movement studies to measure efficiency improvements, staff to measure user experience with the new system, and financial analysis to measure improved accounts receivable turnover[14].

5. To investigate the role of AI in reducing the gap between medical professionals and BPJS verifiers by analyzing how the system impacts coding consistency and interpretation differences. This research was conducted specifically by examining cases where physician documentation has traditionally conflicted with BPJS coding requirements, such as in the setting of initial procedures for debridement or other frequently disputed treatments. By comparing the level of limb-related disputes before and after AI implementation, this study determined whether the core recommendations in the AI system standards helped to align clinical documentation with BPJS requirements.

2. Methods

This study utilizes a comprehensive mixed-methods research approach to rigorously examine the application as well as the impact of artificial intelligence automated verification technology on patient satisfaction of BPJS claims at Murni Teguh Memorial Hospital Medan. The methodology was carefully designed to obtain quantitative performance metrics, as well as qualitative operational understanding throughout their management cycle. The design starts from the initial documentation to the final reimbursement.

Table 2.1 Concepts and Operational Variables (Experimental)

Variables	Conceptual Definition	Indicator	Variable Operationalization	Scale and Source
Full File (X1)	Completeness of BPJS claim documents submitted using AI and its impact on claim processing. (Farhansyah et al., 2024)	IF1: Completeness of BPJS claim documents using AI IF2: Delays due to completeness of AI-based claim documents IF3: Hospital efforts in ensuring document completeness with AI IF4: Delay in payment caused by the completeness of documents submitted with AI IF5: Effectiveness of the hospital system in verifying claim documents using AI	1. I feel that by using AI, the hospital ensures that my BPJS claim documents are complete. 1. Using AI, I often experience delays in BPJS claims due to document completeness. 2. The hospital has a good system using AI to check the completeness of documents before they are submitted to BPJS. 3. I feel that delays in payment of BPJS claims occur due to the completeness of documents submitted through AI.	Interval (Farhansyah et al., 2024)
Code Accuracy (X2)	The accuracy of diagnosis and medical procedure codes in BPJS claims using AI and its effect on claim approval (Farhansyah et al., 2024).	CI1: Accuracy of diagnosis and procedure codes with AI CI2: AI coding errors affecting claims payment CI3: AI-based hospital verification system for coding errors ean CI4: Collaboration between physicians and coders in AI-based coding CI5: Claim denial due to AI-based coding errors	1. I am confident that by using AI, the diagnosis and medical procedure codes in my BPJS claims are correct. 2. I have experienced lower claim payments due to coding errors using AI. 3. The hospital has an AI-assisted verification system that can detect coding errors.	Interval, (Farhansyah et al., 2024)
Machine (AI in BPJS Claims) (X3)	The role of AI in the BPJS claims process, including error detection, process efficiency, and claim accuracy (Farhansyah et al., 2024).	M1: AI detects BPJS claim document errors M2: AI speeds up BPJS claim verification M3: AI reduces pending claims M4: AI improves coding accuracy M5: AI speeds up claims processing	1. I feel that the AI system helps detect errors in my BPJS claim documents. 2. With AI, the verification process of BPJS claims has become faster. 3. Since AI was implemented, the	Interval, (Farhansyah et al., 2024)

			number of pending claims has decreased significantly.	
Machine (AI in Klai m BPJS) (X3)	The role of AI in the BPJS claims process, including error detection, process efficiency, and claim accuracy (Farhansyah et al., 2024).	M1: AI detects BPJS claim document errors M2: AI speeds up BPJS claim verification M3: AI reduces pending claims M4: AI improves coding accuracy M5: AI speeds up claims processing	1. I feel that the AI system helps detect errors in my BPJS claim documents. 2. With AI, the verification process of BPJS claims has become faster. 3. Since AI was implemented, the number of pending claims has decreased significantly.	Interval, (Farhansyah et al., 2024)
BPJS Claim Output (Y)	Efficiency and financial impact of BPJS claims processing after AI implementation. (Farhansyah et al., 2024)	BO1: Improved accuracy of claim coding with AI BO2: Faster BPJS claim submission with AI BO3: Reduction of pending claims with AI BO4: Optimization of hospital revenue due to AI-based claims processing BO5: Improved efficiency in BPJS claims management after AI implementation	1. Since AI was implemented, the accuracy of diagnosis codes in my BPJS claims has improved. 2. I feel that BPJS claims are submitted faster using AI. 3. The number of pending claims has decreased since the hospital implemented AI.	Likert 1-5 (Farhansyah et al., 2024)

This study focused on the hospital's BPJS KM management system as the main unit of analysis, with particular emphasis on four important operational domains: claims verification process, medical record argumentation, diagnostic and procedural coding accuracy, and calculation management oversight. These domains collectively have an overarching workflow that determines the efficiency and success rate of insurance claim submissions. Hospitals serve as ideal research sites. This is due to the large volume of claims processed by BPJS, approximately 5000 claims per month, and the challenges faced, which are common to all health care institutions in Indonesia that participate in the national insurance program. In collecting data, this study utilized a longitudinal observational design incorporating multiple controlled intervention trials[15].

The baseline phase involved a 6-month retrospective analysis of claims processing data from January to June 2024; examining approximately 30,000 claim submissions to determine current benchmarks. This was complemented by a 3-month perspective intervention period on how the AI automated verification system was implemented in parallel with existing manual processes, which aided direct comparison between traditional and technology-enhanced workflows.

The study population included all full-time staff directly involved in BPJS claims processing across the hospital's administrative and clinical departments. This included 21 claims verification specialists, 10 medical records technicians, 49 coding and billing staff, and 6 healthcare administrators. Rather than using sampling methods that may lead to biasing, the study used all personnel in the role to ensure a comprehensive representation of the operational perspective and to capture the full spectrum of workflow variations. The study also collected primary data using complementary instruments. A structured electronic survey using a validated 5-point Likert scale measured staff perceptions across 35 operational dimensions related to claims processing efficiency[16].

Simultaneously, direct workflow observations should be in place while capturing quantitative performance metrics including average inspection time per claim, error rates at various stages of labor and claim surface frequency. My microstructured interviews with key companies from each department provided qualitative depth to query process challenges and opportunities for improvement.

The AI automated verification intervention itself came from a custom machine learning system layered on 3 years of historical claims data from 2021 to 2023 covering over 180,000 claims processed.

The system integrates natural language processing for document analysis, computer vision for form recognition, as well as rule-based validation. For data analysis, this study used advanced statistical modeling techniques based on partial least quadratic structure equation (PLS-SEM) modeling. This multivariate approach is well suited to the context of the study as it can analyze the complex relationships between multiple independent variables such as documentation completeness, coding accuracy, and staff competency, and dependent variables such as claim approval rate and processing time, while accounting for the moderating effects of AI interventions.

This measurement model incorporates 127 observable indicators in 12 latent constructs, each of which has been rigorously tested for validity and reliability. Convergent validity is determined through Average Variance Extracted (AVE) scores that exceed the 0.5 threshold, while discriminant validity is corroborated using the Fornell-Lacker criterion. Internal consistency reliability was verified through composite reliability values above 0.8 and Cronbach's alpha values exceeding 0.7 for all contracts. The structural model evaluation used several criteria to assess predictive power and practical significance. The R^2 value measures the proportion of variance explained in the main outcome variable, with additional analysis of effect size (f^2) and predictive relevance (Q^2) using the blinfolding[18] procedure. Path coefficients were tested for statistical significance through bootstrapping with 5,000 repeated samples to ensure robust estimation of the impact of AI systems.

To address potential confounding factors, the study design incorporated several control mechanisms. Case-mix adjustment accounted for variation in claim complexity, while interrupted time-series analysis helped distinguish the effects of AI interventions from secular trends. Staff members were randomly assigned to continue traditional processes or practices on the AI system to control for individual performance differences.

The methodology also includes a comprehensive economic evaluation component. Time-based activity-based costing measures the difference in resource utilization between manual and AI-assisted processes, while return on investment calculations project the financial implications of full-scale implementation.

Sensitivity analyses tested how results varied across different scenarios and operational assumptions. Ethical considerations were maintained through institutional review board approval, consent procedures for all participants, and strict data anonymization protocols. Hospital management also continued the most effective processes identified by this study regardless of the results, to ensure that the findings of this study would result in practical improvements[19].

This robust methodology was designed to not only evaluate the direct impact of AI automated verification on claims processing efficiency, but also to generate transferable insights on technology adoption in healthcare administration, a combination of quantitative and qualitative approaches, coupled with rigorous experimental controls and advanced statistical analysis, to ensure scientifically valid and operationally relevant findings for healthcare institutions across the BPJS Indonesia ecosystem.

3. Results

This study on the implementation of AI auto verification in the BPJS claims process at Murni Teguh Memorial Hospital Medan provides a comprehensive overview of digital transformation in the health administration sector. Through a rigorous quantitative approach using SmartPLS analysis of data from 86 respondents, the study successfully uncovered various dimensions of change that occurred after the implementation of AI technology in claims submission.

The demographics of the respondents show a balanced and representative composition. The majority of staff involved in the claims process are at a productive age, between 31 and 50 years old with quite varied work experience. The distribution of respondents' professions reflects the actual BPJS claims workflow, ranging from medical record staff who prepare documents, the coding team responsible for the accuracy of diagnosis and procedure codes, verifiers who check the completeness of files, and management who oversee the entire process. This diversity explains that the data collected is able to present various perspectives on the claims system.

In the early stages of the research before the implementation of AI, previous findings had revealed some crucial challenges in the manual claims process. Document completeness was often an obstacle with many imperfect files causing delays in the claims process. This problem arose due to human error and a sub-optimal monitoring system. The accuracy of diagnosis and procedure coding was also quite weak, with frequent errors in the application of ICD-10 and ICD-9 CM codes. The technology system used prior to the implementation of AI was considered unable to provide maximum support with various limitations in function and integration[20]. However, the overall performance of the claims process was still quite adequate, albeit with considerable room for improvement in various aspects.

The implementation of AI auto verification brings fundamental changes to the entire BPJS claims management ecosystem. The new system is designed with machine learning capabilities that can adapt to hospital work patterns. The developed auto verification algorithm not only checks the completeness of documents mechanically, but is also able to understand the clinical context of each claim file. This is reflected in the significant increase in document checking accuracy, where the system is able to identify 32 completeness parameters that were previously missed in the manual process.

In terms of diagnosis and procedure coding, the integration of the latest ICD database into the AI system has resulted in a marked improvement in precision. The system not only matches codes literally, but also understands the clinical relationship between diagnosis and action, thus providing more comprehensive coding recommendations[21]. This natural language processing capability is particularly helpful in the system reading and extracting information obtained from unstructured medical records, then mapping it to the appropriate codes.

The most striking transformative impact is seen in the changing role of human resources. With the automation of routine administrative tasks, staff have the opportunity to shift their focus to aspects that require human judgment and clinical expertise. The coding team is now more of a quality control and case exception watchdog, while verifiers can concentrate on analyzing claim patterns and improving systems. This role shift not only improves efficiency, but also creates a much more meaningful work environment for staff.

From an organizational performance perspective, the implementation of AI has resulted in improvements in various key indicators. Claim cycle time has been significantly reduced, from an average of 48 hours to just 18 hours. The claim rejection rate by BPJS has decreased dramatically, while the value of fully approved claims increased by almost 20%. These efficiencies have a direct impact on the hospital's financial health by improving cash flow and reducing administrative costs.

From a theoretical perspective, the findings of this study successfully reinforce some basic principles in the digital transformation literature. The high level of user acceptance of the new system is more consistent with the Technology Acceptance Model, where perceived usefulness and ease of use are key predictors of implementation success. Within the Resource Based View framework, AI automated verification has evolved into a more strategic resource and provides a competitive advantage for hospitals.

In addition, the practical implications of this study are multidimensional. That is, for hospitals, the findings provide a roadmap to develop digital staff competencies and require the application of AI to

other areas such as inventory management or patient scheduling. For BPJS Kesehatan, the results offer valuable insights to develop AI-based verification standards and improve system integration.

4. Discussion

The influence of factors related to BPJS claims such as file completeness, code accuracy, machine use, and human involvement on BPJS claim outcomes showed significant changes with and without AI model intervention. This study discusses the results of hypothesis testing conducted to examine the influence of these factors on BPJS claim outcomes, both before and after the implementation of the AI model.

Without AI intervention, the hypothesis test results show that the file completeness factor has a significant influence on BPJS claim outcomes. This is reflected in the high T-statistic value of 3.306, with a P-value of 0, which indicates that complete files have a significant effect on claim outcomes. Previous research by Christy et al. (2023) also revealed that complete and accurate medical files are an important factor in accelerating the health claims process and improving the quality of hospital services. In this case, file incompleteness that can be caused by a lack of information or documents that are not in accordance with BPJS procedures will cause claims to be delayed or even rejected which ultimately affects the efficiency of the overall health claims system.

In addition to file completeness, the machine usage factor also shows a significant influence on BPJS claims. The results of hypothesis testing show that the use of machines in the BPJS claim process has a T-statistic of 1.999 and a P-value of 0.023, which means that there is a significant influence on claim output. Research by Burri et al. (2019) and Orji & Ukwandu (2024) underscores the important role of technology, particularly machine learning, in improving the accuracy and efficiency of medical cost predictions and reducing errors that occur during the claims process. Machines, in this case, serve to identify certain patterns in claims that can speed up the verification process and improve the accuracy of diagnosis and coding of medical services, which previously often resulted from human error[23].

Human involvement in the BPJS claims process also shows significant influence. Although the use of machines can speed up and simplify claims verification, human involvement is still needed in some aspects, especially in assessing more complex cases or those that require in-depth understanding of the medical context. In the hypothesis testing results, the T-statistic for human involvement is 1.709 with a P-value of 0.044 which indicates a significant effect. Mohammed et al., (2011) research emphasizes that although technology plays an important role in improving claims efficiency, human supervision is still needed to verify and confirm the claim results generated by the automated system[5].

However, the code accuracy factor does not show a significant effect on BPJS claims without an AI model. The hypothesis test results for this variable show a T-statistic value of 1.265 and a P-value of 0.103, which means that code accuracy does not significantly affect the results of BPJS claims at the 0.05 significance level. Accuracy in coding medical diagnoses and procedures is often one of the causes of errors in claims, causing invalid claims or rejected claims. Nurwahyuni's research (2019) states that accuracy in diagnosis coding can affect overall claim results, but its effect can be minimized by applying more accurate technology.

However, In the model with AI intervention, the effect of code accuracy on BPJS claims became insignificant with a P-value of 0.21. This indicates that AI plays a role in improving code accuracy and minimizing errors in coding that could previously cause incorrect or delayed claims. In contrast, the factors of file completeness, machine use, and human involvement still showed a significant influence on BPJS claims with P-values of 0.008, 0, and 0, respectively. This indicates that although AI can improve the efficiency of the claims process, other factors still play an important role in ensuring the accuracy and completeness of claims.

Overall, the application of AI in the BPJS claims model has a positive impact on improving the efficiency and accuracy of claims. AI can optimize the relationship between variables affecting claims, such as file completeness, inaccurate codes, and machine usage, by reducing errors that previously occurred due to human factors. AI helps in identifying patterns in claims that can speed up the verification process and ensure that the claims submitted meet the established requirements. In this regard, these results are in line with the findings expressed by Rawat[24] and Robinson[14] who stated that technology can improve predictive decisions in the health insurance industry.

Thus, it can be concluded that the application of AI models in the BPJS claims process can help minimize errors in coding and speed up the claims verification process, which will ultimately improve efficiency and accuracy in managing health claims. This technology can be an important tool in improving the quality of health services and provide great benefits to the BPJS system as a whole.

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