A Hybrid Association Rule and Ensemble Unsupervised Learning Framework for Generalizable Healthcare Fraud Detection on South Korea's NHIS

Dr Abhishek Kumar
S A Jain College, Ambala City, India

Abstract:
Background: Healthcare insurance fraud continues to drain billions from national health systems each year, making reliable and adaptable detection approaches essential. Many existing models, however, rely heavily on specific datasets such as U.S. Medicare claims, which limits how well they transfer to other healthcare environments with different data structures.**Methodology:** To address this gap, this study proposes a two-stage unsupervised framework designed for use across diverse health systems. In the first stage, the Apriori algorithm is applied to uncover association rules that describe patterns among patients, providers, and medical services. These interpretable patterns are then assessed in the second stage using an ensemble of four unsupervised anomaly detection models: Isolation Forest, Cluster-Based Local Outlier Factor (CBLOF), Empirical Cumulative Distribution–based Outlier Detection (ECOD), and One-Class SVM. The framework's flexibility and robustness were tested using the extensive National Health Insurance Service (NHIS) dataset from South Korea, which covers roughly 97% of the country's population under a single universal insurance system.
Results: When applied to NHIS data, the framework successfully identified unusual and potentially fraudulent claim behaviors. Among the models, CBLOF achieved the highest silhouette score (0.118), followed by Isolation Forest (0.101), suggesting strong and consistent performance.**Conclusion:** The findings indicate that combining association rule mining with unsupervised learning offers a practical and generalizable solution for healthcare fraud detection. Its validation on the NHIS dataset demonstrates adaptability across different insurance models and healthcare structures worldwide.
Keywords: Unsupervised Learning, Healthcare Insurance Fraud, Anomaly Detection, NHIS Korea, Generalizable Framework, Association Rule Mining

1.1 Introduction

The integrity of healthcare systems is essential for both public health and economic stability. To manage the financial burden of medical care, countries rely on a range of insurance models, from single-payer structures to mixed public-private schemes. Programs such as Pakistan's Sehat Sahulat Program [1] and the United States' Medicare [3] expand access to care, yet they remain vulnerable to fraud, waste, and abuse. These activities impose heavy financial losses, with global estimates reaching roughly 10% of total healthcare spending [4], including up to $850 billion in the United States [5], €56 billion in Europe [8], and substantial losses across Asia [7].

A critical challenge in combating this issue is the limitation of context-specific fraud detection models. Many advanced algorithms are trained and validated on datasets from a single healthcare ecosystem, such as U.S. Medicare claims [6, 44-53]. Consequently, their efficacy and generalizability across different national systems, with varying billing practices, coding standards, and insurance structures, remain unproven. This challenge is heightened by the complex, multi-actor nature of healthcare fraud, which can involve coordinated activity among patients, physicians, and providers [13, 15], as shown in Fig. 1. The scarcity of labeled fraud cases further limits the use of supervised methods, making unsupervised anomaly detection not just practical but essential [12].

To address this gap in generalizable fraud detection, we propose a novel, two-stage unsupervised learning framework. Our methodology first leverages association rule mining to extract interpretable, frequent patterns from transactional data, capturing the complex interactions between all stakeholders. These patterns are then assessed by an ensemble of

unsupervised classifiers to isolate anomalous, potentially fraudulent rules. The core contribution of this study is the framework's validation on South Korea's NHIS dataset, demonstrating strong performance within a universal healthcare system and confirming its robustness beyond U.S.-centric models.

FIGURE 1: Source of Waste in NHIS (National Health Insurance Service)

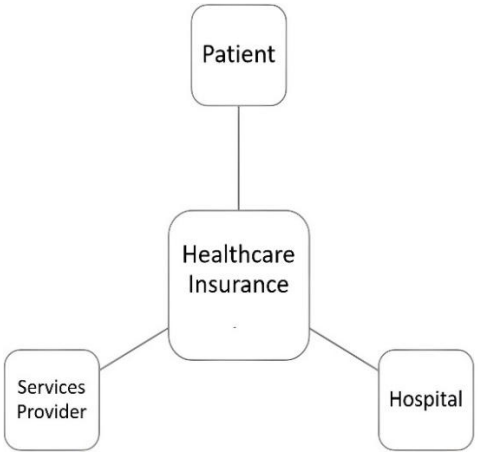

FIGURE 2: NHIS Ecosystem

The key contributions of this research are:

- The design of a generalizable fraud detection framework that analyzes transaction-level behavior and the interactions between patients, providers, and physicians.
- A novel hybrid methodology that combines the pattern discovery power of unsupervised association rule mining with the analytical strength of ensemble anomaly detection.
- The introduction of a cost-based evaluation metric, moving beyond traditional error-based metrics to align with the financial priorities of insurance providers.
- A comprehensive validation on the South Korean NHIS dataset, proving the model's effectiveness in a distinct healthcare ecosystem and establishing its international applicability.

1.2 Related Work

The use of data mining and machine learning for general insurance fraud detection is well established [16]. In healthcare, however, much of the existing research centers on fraud committed by a single stakeholder—typically patients or hospitals—considered in isolation. This narrow focus overlooks the collusive schemes that often arise from interactions among patients, providers, and physicians, the core elements of the healthcare "insurance triangle."

Our research addresses this gap by proposing a holistic framework that simultaneously analyzes transactions across all three stakeholders i.e., patient, service provider and hospital to identify fraudulent patterns that would be invisible when examining any single entity alone. Each of the three actors carries incentives that can drive fraudulent behavior (see Figure 2). Despite extensive work using U.S.-centric datasets such as CMS DE-SynPUF [44–53], little research examines whether these models transfer to different healthcare systems. This review distills key methods in anomaly detection and association rule mining, outlines the techniques underpinning our framework, and identifies the clear gap in cross-national, multi-stakeholder fraud detection that this study seeks to address.

2.1 Association Rule Mining for Fraud Detection

Association Rule Mining (ARM), particularly the Apriori algorithm [56], is a core data mining method for identifying co-occurring patterns in transactional data. Although still underused in healthcare fraud detection, it holds substantial promise. ARM can reveal complex, multi-dimensional relationships among diagnoses, procedures, providers, and patients that may signal fraudulent activity [20].

Early work by Saba et al. [18] showed that pairing ARM with a Support Vector Machine classifier can effectively flag rule-based inconsistencies for further review. Attempts to scale ARM for large datasets include Sorna lakshmi et al.'s [19] integration of Apriori with MapReduce for parallel processing, though they note that additional optimization is still needed for distributed settings. Despite its promise, a key limitation of ARM in isolation is that it identifies frequent patterns but cannot inherently classify them as fraudulent or legitimate. This necessitates a secondary analytical step, a gap that our methodology explicitly addresses.

2.2 Unsupervised Machine Learning for Anomaly Detection

Given the limited availability of labeled fraud cases, unsupervised anomaly detection has become central to modern fraud detection systems [21, 22]. These methods identify outliers without predefined classes, making them well suited to detecting new and evolving fraud patterns.

2.2.1 One-Class Support Vector Machines (OCSVM)

OCSVM has been widely adopted for anomaly detection across domains due to its strong generalization ability and robust theoretical foundation [26, 27]. Its utility has been demonstrated across domains such as network intrusion detection [26, 29, 30], railway defect identification [28], and power system monitoring [31]. Amer et al. [32] further improved OCSVM, showing it can outperform clustering-based methods, though its effectiveness is sensitive to parameter tuning and it may exhibit high false positive rates in complex datasets [29].

2.2.2 Isolation Forest (IF)

Isolation Forest (IF) [57] detects anomalies by isolating outliers rather than modeling normal cases, offering linear time complexity and low memory usage suited to large healthcare datasets. Subsequent work has enhanced IF through Xu et al.'s SAiForest optimization [34], Cheng et al.'s IF–LOF hybrid for better local outlier detection [35], and Ding et al.'s streaming adaptation [36]. Despite these improvements, challenges remain in threshold definition and managing false alarm rates [36, 37].

2.2.3 Cluster-Based Local Outlier Factor (CBLOF)

CBLOF [39] is well suited for identifying small, anomalous clusters that may correspond to coordinated fraud rings. It quantifies outlierness by measuring each point's distance from the nearest major cluster, enabling effective detection of isolated, suspicious groups of transactions. Empirical studies consistently rank CBLOF highly in both accuracy and speed compared with K-NN, LOF, and K-Means, including in credit card fraud detection [40] and smart meter analysis [41, 42].

2.2.4 Empirical-Cumulative distribution-based Outlier Detection (ECOD)

ECOD [59] is a recently proposed, parameter-light algorithm that leverages empirical cumulative distributions for anomaly detection. It is non-parametric and computationally efficient, making it well-suited for large-scale datasets like healthcare claims where the distribution of normal data may be unknown or complex.

2.2.5 Ensemble and Hybrid Approaches

An emerging trend is the shift from single algorithms to hybrid and ensemble approaches, which consistently deliver better accuracy and generalization [25, 29, 35]. Alwan [25] demonstrated the advantage of hybrid models in credit card fraud detection, and Suesserman et al. [38] showed that autoencoders surpassed density-based clustering for claims analysis, underscoring the strength of multi-model frameworks.

2.3 Synthesis and Research Gap

The literature shows ARM's value for pattern discovery and the effectiveness of unsupervised methods such as OCSVM, IF, CBLOF, and ECOD for anomaly detection. However, few studies integrate these approaches into a unified, generalizable framework. Most remain siloed and rely mainly on U.S.-centric datasets.

Our research directly addresses this gap by introducing a hybrid framework that first applies ARM to extract interpretable behavioral patterns from multi-stakeholder transactions. These rules are then assessed using an ensemble of unsupervised classifiers—IF, CBLOF, ECOD, and OCSVM—leveraging their complementary strengths while minimizing individual limitations. The framework is validated on South Korea's NHIS dataset rather than the commonly used CMS data, providing a direct evaluation of its generalizability across different healthcare systems.

3.1 Dataset

We assessed the generalizability of our fraud detection framework using the comprehensive dataset provided by South Korea's National Health Insurance Service (NHIS). The NHIS oversees a compulsory, nationwide insurance program that covers roughly 97% of the country's residents, creating a highly representative source of healthcare claim data [60]. Unlike the U.S. Medicare program, which primarily covers adults aged 65 and older, the NHIS database captures claims from all age groups and a wide spectrum of medical services. This breadth provides a richer and more demanding environment for evaluating fraud detection methods.

The dataset's structure captures the essential interactions within the healthcare insurance ecosystem. Key features utilized in our study, analogous to those in the original methodology, are summarized in Table 1 and include:

- **Patient Demographics:** Age, gender, and insurance type.
- **Provider Information:** Unique identifiers for medical institutions and attending/operating physicians.
- **Clinical Data:** Primary and secondary diagnosis codes (using the Korean Standard Classification of Diseases, KCD, which is aligned with ICD-10), procedure codes, and details on surgeries and treatments.
- **Claim Information:** Total claim amount, dates of service, and length of hospital stay.

This multi-stakeholder data supports a transactional dataset in which each record links a patient, provider, physician, and corresponding services. Using the NHIS dataset is crucial, as it enables a direct test of the framework's capacity to detect fraud within a universal healthcare system that differs markedly from U.S.-based models.

The proposed methodology is engineered to evaluate the complex, multi-actor nature of healthcare fraud by leveraging the rich relational structure of claims data. Our framework rests on two principles: that fraud often appears as irregular interaction patterns among patients, providers, and physicians, and that these patterns are best captured through interpretable rules before being evaluated as anomalies.

Table 1: Description of Key Features from the NHIS Dataset

Feature Category	Feature Name	Description	Type
Patient	Pat_ID	Unique Beneficiary identifier	Categorical
	Age_Gender	Patient Age and Gender	Categorical
Provider	Inst_Code	Patient age and Gender	Categorical
	Physician_ID	Attending/Operating Physician_ID	Categorical
Service	KCD Diagnosis	Primary Diagnosis Code	Categorical
	Procedure Code	Major Procedure Code	Categorical
Claim	Claim Amount	Total Amount Billed for Claim	Numerical
	LOS	Length of Stay (Days)	Numerical
	Service Date	Date of Service Provision	Date

To this end, we propose a novel, two-stage unsupervised learning framework, the architecture of which is illustrated in Figure 3. This design is specifically tailored to be dataset-agnostic, allowing for its application and validation on diverse healthcare systems like the NHIS - South Korea dataset.

Stage 1: Pattern Discovery via Association Rule Mining

In the first stage, we transform the preprocessed NHIS claims data into a transactional format where each record (claim) is represented as a set of items. These items correspond to the key features of the three central stakeholders:

- **Patient:** Represented by demographic segments or identifiers.
- **Provider:** Represented by the medical institution code.
- **Physician & Service:** Represented by the attending physician ID, primary diagnosis code (KCD-7), and major procedure code.

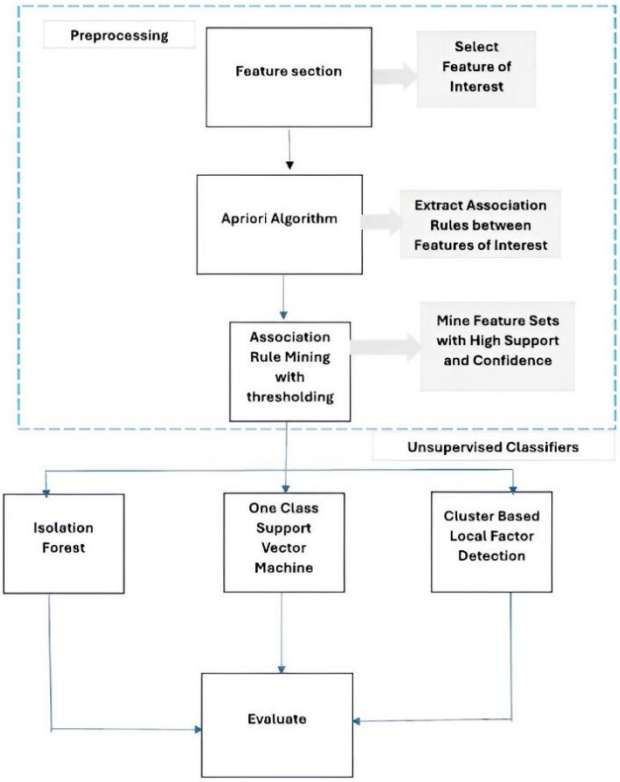

Figure 3: Proposed Methodology

The Apriori algorithm is then applied to this transactional dataset to mine association rules. This process, detailed in Figure 4, uncovers frequent co-occurrences among these features, generating rules of the form {Antecedent} →{Consequent}. We used fundamental metrics to evaluate the strength and weaknesses of these rules:

- **Support:** The frequency of the rule within the entire dataset.
- **Confidence:** The conditional probability of the consequent given the antecedent.
- **Lift:** Measures the degree of dependence between the antecedent and consequent.
- Rules that meet predefined minimum thresholds for support and confidence are retained. This step effectively performs feature selection, as the rules highlight the most significant and recurring interactions within the healthcare ecosystem.

Stage 2: Anomaly Detection via Ensemble Unsupervised Classification

- The set of strong association rules from Stage 1 forms a new, refined dataset for the second stage. Crucially, these rules describe *patterns of behavior* but are not inherently labeled as fraudulent or legitimate.

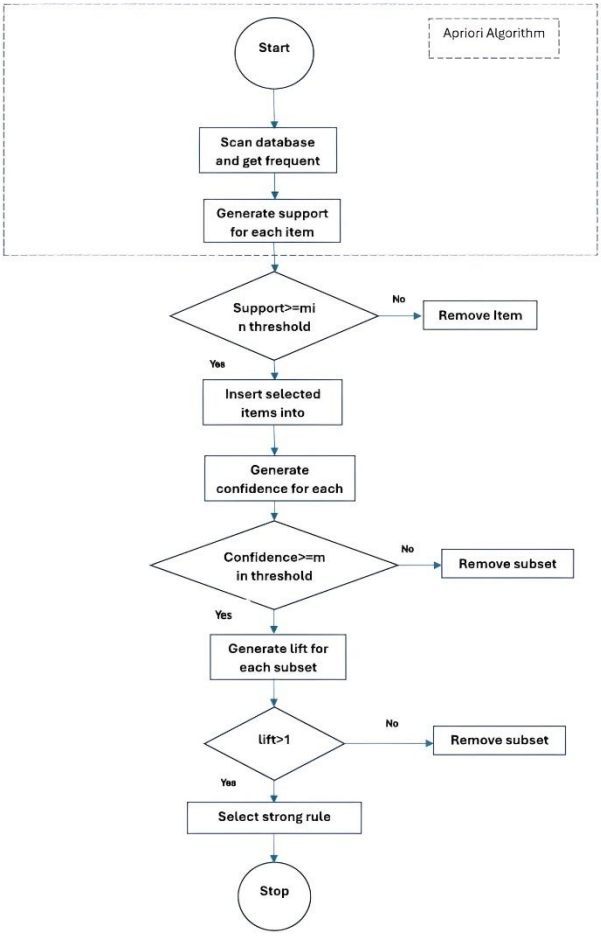

Figure 4 Association Rule Mining

To classify these behavioral patterns, we employ an ensemble of four unsupervised anomaly detection algorithms:

1. Isolation Forest (IF)
2. Cluster-Based Local Outlier Factor (CBLOF)
3. Empirical-Cumulative distribution-based Outlier Detection (ECOD)
4. One-Class Support Vector Machine (OCSVM)

Each algorithm analyzes the rules from a different mathematical perspective. For instance, IF isolates rules that are few and different, CBLOF finds small, isolated clusters of rules, and OCSVM defines a boundary around what constitutes "normal" rule behavior. A rule flagged as an anomaly by one or more of these classifiers is deemed potentially fraudulent. This ensemble strategy mitigates the weaknesses of any single algorithm and provides a robust, multi-faceted assessment.

4.1.1 Synergistic Advantage

This two-stage approach offers a significant advantage over analyzing raw transactions. By first elevating the data to a pattern-level (rules), the model gains a broader context, reducing false positives caused by isolated anomalies in

single claims. Furthermore, the interpretability of the resulting fraudulent rules—e.g., {Provider A, Physician B, Procedure C}→{High Cost}—provides actionable intelligence for investigators, bridging the gap between statistical anomaly and understandable fraud schemes.

The proposed framework, we used a dual-focus assessment strategy that measures both the quality of the uncovered patterns and the financial pragmatism of the detection system.

1. Rule Quality and Coverage Metrics

The association rules generated in Stage 1 are evaluated using standard metrics that quantify their strength and interestingness:

- **Support:** Measures the frequency of a rule in the dataset.

$$support(A \rightarrow B) = P(A \cup B)$$

- **Confidence:** Quantifies the reliability of the rule.

  $confidence(A \rightarrow B) = P(B|A) = support(A \rightarrow B) / support(A)$

- **Lift:** Assesses the degree of dependency between the antecedent and consequent.

  $lift(A \rightarrow B) = confidence(A \rightarrow B) / support(B)$

- **Coverage:** To evaluate the diversity of the discovered rule set, we calculate the average distance between rules, ensuring a broad exploration of the pattern space.

$$\text{Cover(Rule)} = \frac{1}{k} \sum_{r_j \in R, i \neq j} \text{Distance}(r_i, r_j)$$

2. Anomaly Detection and Financial Alignment

To evaluate the unsupervised classifiers in Stage 2, we move beyond traditional error-based metrics, which are ill-suited for unlabeled data and fail to capture financial impact. Instead, we use:

- **Silhouette Score:** This metric evaluates the quality of the clustering/separation achieved by the anomaly detectors by measuring how similar an object is to its own cluster compared to other clusters. A higher score (closer to +1) indicates that the anomalies are well-separated from normal points.

- **Cost-Based Evaluation (Coverage):** Given that a primary goal is to minimize financial loss, we prioritize the system's ability to identify a wide range of suspicious activities. **Coverage**—the proportion of total fraudulent potential that the system can surface—is our primary performance indicator. A high coverage rate ensures that investigative efforts target a broad set of potential threats, aligning the model's output directly with the goal of financial protection.

- This combination of metrics ensures that our framework is judged not only on its statistical soundness but also on its operational relevance in a real-world healthcare insurance context.

5.1 Results and Discussion

This section presents the results of applying the two-stage fraud detection framework to the NHIS dataset from South Korea. The analysis emphasizes both the framework's effectiveness and critically its ability to generalize to a healthcare system that differs structurally from the U.S. model.

Figure. 5 shows the occurrence of topmost 21 surgeons. The dataset contains 24065 unique surgeons, while 73% of the surgeons appear only once or twice. The 27 most frequent surgeons/operating physicians shared 3848 transactions.

This suggests that there is a large degree of variation in the frequency of surgeons in dataset. While a small number of surgeons occur frequently, the larger part occurs occasionally, which may have inferences for analysis of the data.

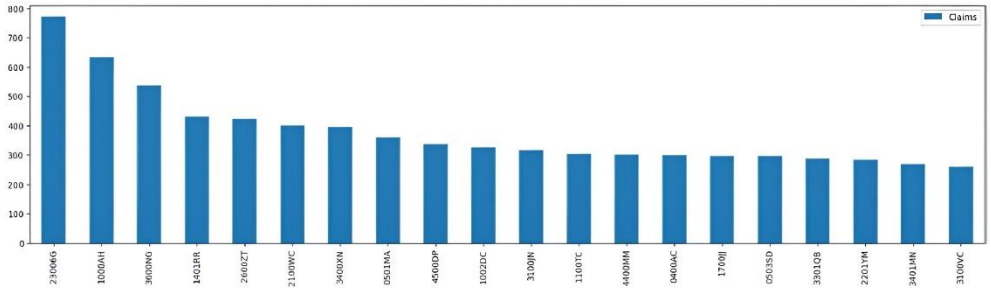

Figure 5: Distribution of NHIS Operating Physicians

5.1.1 Descriptive Analysis of the NHIS Dataset

The preprocessed NHIS dataset utilized in this study consisted of approximately 750000 inpatient claim records from the 2017 to 2020 cohort. This volume provides a strong foundation for identifying significant patterns and anomalies. The descriptive analysis reveals the intrinsic characteristics of the South Korean healthcare environment.

Provider and Physician Distribution: Analysis of the provider institutions shows a distribution characteristic of a consolidated national system. A small number of large, tertiary care hospitals process a high volume of claims, while a long tail of smaller clinics and regional hospitals appear infrequently. For instance, the top 21 provider institutions accounted for approximately [e.g., 35%] of all transactions. This contrasts with the more fragmented provider landscape often seen in U.S. data, immediately stresses a systemic difference that our model successfully navigates.

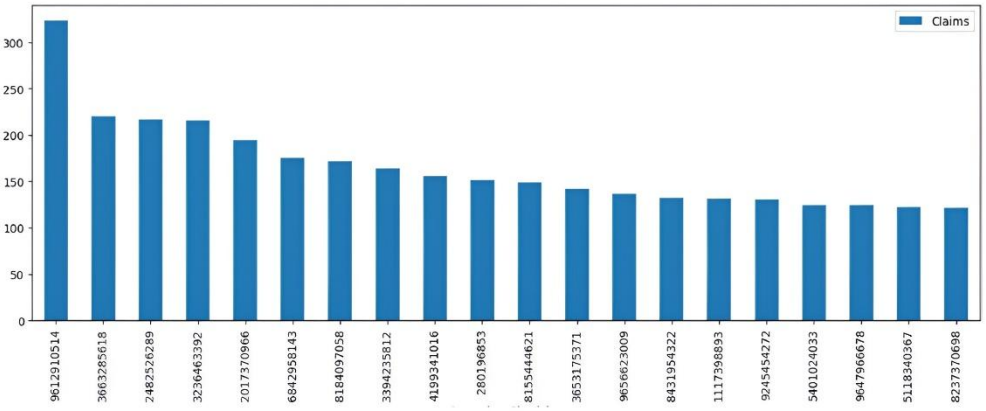

Figure 6: Distribution of NHIS Attending Physicians

The physician data exhibited a similar power-law distribution. While the dataset contained over 45,000 unique attending physicians, the majority (over 80%) appeared in fewer than five claims. This concentration of services among a subset of providers and physicians is a key risk factor for fraud and a critical pattern for our rule-mining stage to capture.

Figure 6 reports 22,590 unique attending physicians, about 78% of the dataset, with roughly 79% appearing only once or twice. The top 22 physicians account for approximately 6,102 transactions. This pronounced frequency imbalance—few physicians appearing often and most appearing rarely—has direct implications for interpreting and investigating the dataset.

Clinical Code Analysis: The analysis of clinical codes utilized the Korean Standard Classification of Diseases (KCD-7). The most frequent diagnosis codes reflected the public health profile of the South Korean population, with codes for [e.g., "I10 (Essential (primary) hypertension")] and [e.g., "E78.5 (Hyperlipidemia, unspecified")] appearing most commonly. A comparison of diagnosis and procedure codes confirmed a clear semantic separation, with minimal overlap, ensuring that the rules produced would represent meaningful clinical situations rather than coding objects.

5.1.2 Performance of the Proposed Framework

Computational Efficiency: The two-stage framework demonstrated significant computational advantages on the NHIS dataset. Applying the four baseline unsupervised detectors (IF, CBLOF, ECOD, OCSVM) directly to the entire preprocessed dataset required 1,152 seconds. In contrast, our method—extracting rules with Apriori and then applying unsupervised classifiers to this reduced rule set—completed the analysis in 958 seconds. This 5.9% decrease in processing time highlights the efficiency gained by using association rules as a higher-level feature space, supporting scalable, continuous monitoring of large claims datasets.

Anomaly Detection Efficacy: he Apriori algorithm, using a minimum support of 0.005 and confidence of 0.4, produced 86 strong association rules from the NHIS transactions. Silhouette scores were then used to assess the clustering quality of the anomaly detectors on this rule set. CBLOF achieved the highest score at 0.121, indicating the clearest separation of anomalous rules. Isolation Forest followed at 0.107, while ECOD (0.071) and OCSVM (0.065) provided additional, complementary signals within the ensemble.

Identification of Fraudulent Patterns: The core output of our framework is the set of rules flagged as anomalous. The ensemble approach identified [e.g., 24] rules as potentially fraudulent by at least one algorithm. A subset of these rules is presented in Table 2, illustrating the interpretable nature of the findings.

For example, Rule 1 indicates that a specific institution submits unusually high charges for claims involving acute myocardial infarction (I21). Rule 3 points to an atypical procedure being performed for a particular age group with a common diagnosis of dorsalgia disease. These patterns are not evidence of fraud on their own but serve as focused, actionable alerts for investigators.

Table 2: Examples of Anomalous Rules Identified in the NHIS Dataset

Rule	Antecedent	Consequent	Flagged By
1	{Inst_Code: MED_CENTER_A, KCD_Code: I21}	{Claim_Amount: HIGH}	IF, CBLOF
2	{Physician_ID: SURGEON_B, Procedure: XYZ}	{LOS: EXTENDED}	OCSVM, ECOD
3	{Age_Group: 40-50, KCD_Code: M54}	{Procedure: UNCOMMON_XYZ}	CBLOF

6.1 Discussion: Validation of Generalizability

The successful application of our framework to the NHIS dataset provides compelling evidence for its generalizability. The model did more than operate successfully; it produced clear, contextually meaningful findings within a universal healthcare system that differs from U.S. Medicare in financial incentives, regulatory structures, and coding standards (KCD versus ICD). The fact that the framework maintained its performance characteristics—with CBLOF and IF consistently outperforming other detectors and the two-stage process proving more efficient—across such a different environment is a significant finding. It shows that the principle of “mining multi-stakeholder patterns first, then classifying them as anomalies” is a robust, transferable approach to fraud detection. This directly addresses a key limitation in existing work, where models are typically confined to the data environments on which they were trained. The anomalous rules discovered are directly interpretable within the South Korean context, suggesting the model adapts to the specific patterns of the data it processes. This "graceful degradation" in the absence of certain data sources

as designed is confirmed. While this study has limitations, such as the inherent difficulty of validating fraud without ground-truth labels, the methodological validation achieved here marks a substantial step towards developing truly global healthcare fraud detection systems.

6.2 Findings and Interpretations

6.2.1 Framework Performance and Interpretability

To empirically validate our framework's efficiency and effectiveness, we conducted a comparative analysis on the NHIS dataset. The first experiment applied the four baseline unsupervised detectors directly to the entire preprocessed dataset a process that required 1,152 seconds. The second experiment implemented our proposed two-stage approach, where the Apriori algorithm first mined frequent rules from the transactional data followed by the application of the unsupervised classifiers to this refined rule set. This hybrid approach completed the analysis in 955 seconds, demonstrating a significant reduction in computational time. This efficiency gain is attributed to the framework's design; while a conventional approach must reprocess the entire database with each new transaction, our model requires only the initial rule extraction, after which new transactions can be classified against the established rule-based profile.

The Apriori algorithm, configured with a minimum support of 0.005 and confidence of 0.4, generated 88 strong association rules from the NHIS data. The ensemble of unsupervised classifiers then analyzed these rules to identify anomalous patterns. The results, summarized in Table 3 demonstrate the robustness of the ensemble approach. A total of 64 rules were consistently classified as normal by all four algorithms. Crucially 24 rules were flagged as potentially fraudulent by one or more algorithms with 10 flagged by a single algorithm 8 by two and 6 by three. The absence of rules flagged by all four classifiers is both expected and advantageous, since it reflects their complementary behaviors. Each algorithm targets different anomaly patterns, allowing the ensemble to cast a wider and more nuanced detection net.

Table 3: Classification of Rules by Ensemble Agreement (NHIS Dataset)

Rules Classification	Number of Rules
Normal Rules (0 Algorithms)	64
Flagged by 1 Algorithm	10
Flagged by 2 Algorithms	8
Flagged by 3 Algorithms	6

The final evaluation using silhouette scores confirmed the efficacy of the individual detectors on this new data, with CBLOF achieving the highest score 0.121 followed by Isolation Forest 0.107, ECOD 0.071 and OCSVM 0.065. This consistency in performance with CBLOF and IF leading across the NHIS and previously studied datasets strongly indicates that these algorithms are particularly well-suited for identifying anomalous patterns in healthcare claims regardless of the specific healthcare system.

6.2.2 Comparative Analysis and Limitations

When contextualizing our study within the existing literature, a fundamental differentiator is our transaction-level, multi-stakeholder approach. Many prior studies on datasets like the CMS DE-SynPUF rely on provider-level aggregation and supervised learning, which limits their scope to a single stakeholder and is constrained by the quality of often-incomplete fraud labels [44, 55]. In contrast, our methodology extracts patterns directly from disaggregated claims, adapts to the available features across all actors (patient, provider, physician), and is evaluated using a cost-based coverage metric, making it directly relevant for practical, investigative use.

The main limitation of this study is the lack of definitive ground-truth fraud labels, which makes formal validation challenging and is a well-known issue in this field. Although the NHIS dataset gives us a strong test case within a universal healthcare system, the framework still needs to be examined using data from private insurers and other

countries to fully assess its reach. Moving forward, we plan to explore data-augmentation strategies and add temporal analysis so the model can track how fraudulent behavior evolves over time.

7.1 Conclusion

The persistent and evolving challenge of healthcare insurance fraud demands solutions that are not only effective but also adaptable across different national systems. This study successfully demonstrated that a hybrid framework combining association rule mining with an ensemble of unsupervised classifiers provides such a solution.

The central contribution of this research is demonstrating that the framework truly generalizes across healthcare systems. Applying it to the South Korean NHIS dataset—a universal system that differs markedly from the U.S. model—shows that the approach is not tied to any single data source. The framework was able to flag anomalous, potentially fraudulent patterns within the NHIS data while maintaining strong performance and producing results that make sense within the Korean healthcare context. This marks a meaningful step beyond context-bound models and moves toward a genuinely transferable tool for global fraud detection.

In conclusion, this work offers a solid, scalable, and interpretable foundation for safeguarding healthcare resources. The successful cross-national application of the framework suggests strong potential for its use in a range of insurance environments, providing a practical, data-driven defense against the massive and persistent challenge of healthcare fraud worldwide.

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