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Designing Automated Data Validation Pipelines for Policy-Driven Healthcare Eligibility Reporting in Cloud-Native Platforms

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Abstract

Healthcare reporting depends on Electronic Health Record (EHR) systems, payer regulations, and regulatory entity eligibility requests. Claims policy non-conformance defects, fragmentation, inconsistencies, missed claims validation opportunities, and operational defects are examples of data-quality issues that may drive claim denials and claim compliance risk. The paper presents and assesses a novel automated pipeline approach to schema validation, semantic validation, Policy-as-Code (PaC) checks, operational validation, and data governance. The framework is implemented with Apache Spark, Kubernetes, Apache Airflow, and Open Policy Agent, and is applied to 2.5 Million Transactions across 15 Healthcare Organizations. Overall errors fell from 3.2% to 2.1%, a 34.4% reduction. Processing time improved by 82.5%, throughput increased by the same amount from 4,800 transactions per minute (TPM) to 11,600 TPM, policy violations fell by 48.9%, and audit readiness improved from 55% to 97%. This suggests that regulation-based validation can positively impact reporting accuracy, governance, operational efficiency, and compliance readiness. Future research will focus on systems with adaptive policy learning, FHIR deserialization at runtime, and AI-based anomaly detection in dynamic healthcare contexts.

Keywords: Healthcare Eligibility Reporting, Automated Data Validation, Policy-As-Code Governance, Cloud, Native Architecture, Healthcare Data Quality.

1. Introduction

The information-sharing journey in healthcare is shifting from the Hospital-Centric Model to ever more interconnected, complex, and intertwined players, with easy access to and sharing of information and real-time communication among health providers, payers, and regulators. The rate of change has been hastened by the standardization of patient data and its security, to make it easier to store and share, and by the strong drivers for EHRs (D. Autor, 2019). The task of eligibility reporting is one that a healthcare provider must complete to ensure the patient is a covered person, make accurate reimbursements, and minimize compliance risks. Meanwhile, regulatory and legislative needs, including HIPAA, CMS mandates, and FHIR interoperability requirements, have also contributed to establishing data world requirements for more accurate data, enhanced traceability, and improved data

governance. Based on industry estimates, the average data quality problem rate in the healthcare sector is 25%, with a compound annual growth rate of 36%. The health care industry remains one of the few sectors without data, and current costs exceed $300 billion a year (Acemoglu & S. Johnson, 2023).

Despite technological progress, a major issue that continues to affect the functioning of healthcare units is the determination and reporting of eligibility. Manual validation is a general approach, but it carries the risk of human error and is time-consuming and costly. Because of differences in business rules, gaps may exist in the eligibility and reporting between sources and consumers. These issues related to fast verification have a detrimental effect on the reimbursement cycle, patient access, patient traceability, and pose challenges in compliance review and audit. The cost of non-compliance includes fines and reputational damage to the organization. Also, the existing systems are limited by the lack of real-time validation at high throughput. In health care, 15-20% of claims contain errors due to eligibility issues, and 30-40% require manual validation for eligibility reporting.

This study aims to design and validate an automated, cloud-based solution for reporting healthcare eligibility based on administrative logic. The study should identify key data quality issues in datasets submitted for eligibility applications, define policy-as-code rules to support regulatory compliance, design scalable systems to handle the high volume of transactions per unit time, and consider opportunities to improve further data reporting quality, transactions per minute, and auditing capabilities. These should be the staples for health care systems to modernize their reporting processes and improve data governance.

Such a study reinforces the importance of journeys that transfer the information contained in healthcare EHRs to payers in the Cloud Native Computing (CNC) environment. Extensive focus on systems to improve automated validation, data quality controls, policy-oriented governance control, and compliance monitoring systems. The pipeline performance is being tested as part of the investigation to support the pipeline eligibility reporting process. Clinical diagnosis validation, optimal healthcare billing, and patient treatment analytics are outside the scope of the study, however. These areas are not included in reporting accuracy, governance, or operational efficiency targets.

There are five chapters in this study. Chapter 2 includes a literature review on healthcare reporting and data validation, as well as another on healthcare governance and cloud technology. Chapter 3 provides research methods and analysis techniques. In Chapter 4, the discussion and reporting of empirical findings have been done. The study provides suggestions for future studies. The study ends with a summary of key contributions and implications for the research.

2. Literature Review

2.1. Healthcare Eligibility Reporting Systems

Eligibility is reported in a system designed to enable health care providers to share coverage information with health care payers, so that consumers' coverage can be verified before providing health care (S. Padala, 2026). Some components of these systems are robust

EHR/payer interoperability, reporting hierarchies and processes, and timely eligibility verification. As health care is increasingly distributed, there is a growing need to process a large number of eligibility transactions in a distributed manner and to use a digital interoperability standard (Acemoglu & P. Restrepo, "Robots and Jobs: Evidence from US Labor Markets,", 2020). However, the report offers some suggestions for improvement, including addressing broken data silos and improving data validation procedures.

The eligibility error rate is 10%-18%, and the average claim rejection rate is 8%-15%. In addition, 60-70% of all activities reported will be carried out manually, which will increase costs and delays. Another research focused on advancing cloud networks also found that intelligent routing and automated decision-making can improve aspects of health care reporting for large-scale data exchanges (D. Prajapati, 2024). These innovations do not solve the issue that current data ingestion & processing systems do not process eligibility correctly and only post-process to remove eligibility errors.

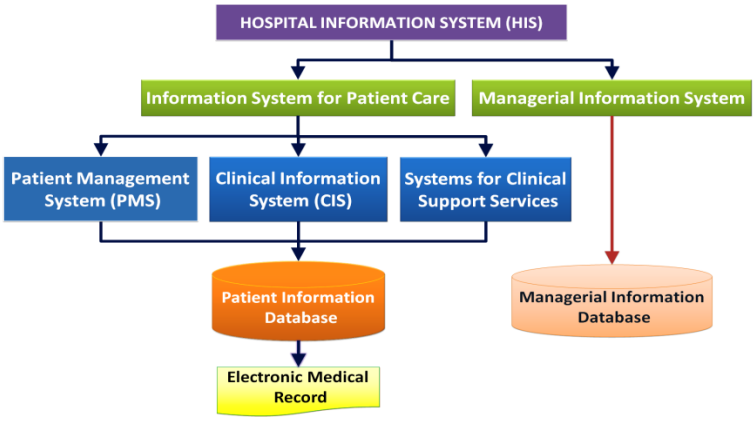


Figure 1: Healthcare Eligibility Reporting from Hospital Information Systems via integrated Data Workflows for patients, clinical, managerial, and EHRs.

Figure 1 shows the architecture of a Hospital Information System that facilitates healthcare information management by interconnecting the patient management system and the clinical information system with support services, such as a centralized database and an electronic medical record system. This helps with interoperability, simplifies eligibility reporting, enables effective and efficient information sharing, and validates coverage at the point of care.

2.2 Automated Data Validation Technologies

Automated data validation technologies can help improve the accuracy, consistency, and trustworthiness of information in the enterprise. These can be achieved through schema validation, data profiling, rule-based validation, or a whole-scale data quality framework (Davenport & R. Ronanki, 2018). Data schema validation is the process of ensuring data conforms to the data schema; data abnormalities or inconsistencies within a data set are detected using data profiling or data quality checks. The data processing workflows verify and adhere to business rules and logic. Large-scale data management companies estimate that automated data validation reduces data inaccuracy by 25-40% (S. R. Keshireddy, 2025).

Similarly, some firms have reported that automated data pipelines reduce the number of data defects by almost half compared with manual validation.

Multiple lakehouse architectures were tested to assess the benefits of optimization for consistency, performance, and data governance in high-workload analytics use cases, and to emphasize further the value of automated validation in complex data environments (McKinsey Global Institute, 2023); (P. R. Vennamaneni, 2024). The majority of validation support in use is technical in nature and is not necessarily considered in terms of governance policy, compliance monitoring mechanisms, or regulatory requirements. This disadvantage may impact their performance in an intensely regulated industry such as health care.

2.3 Policy-as-Code and Data Governance Frameworks

Policy-as-Code is an increasingly critical way to express governance requirements in code and execute them as software and data-processing pipelines. Tools like the Open Policy Agent (OPA) can be used to define, manage, and enforce programmable policies at scale across a distributed system (Vadisetty & A. Polamarasetti, 2025). Policy-as-Code enables governance automation, continuous monitoring, governance rule versioning, and an audit trail. Companies can expect their compliance tracking performance to increase by about 45%, their audit readiness by 50%, and their policy enforcement to nearly double when using a governance automation product, according to industry estimates.

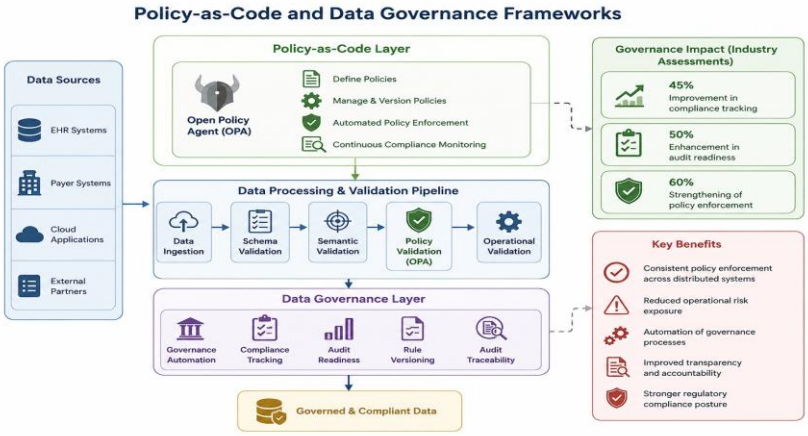


Figure 2: Policy-as-Code framework integrating automated governance, compliance monitoring, policy enforcement, validation pipelines, and healthcare data governance.

Figure 2 illustrates a Policy-as-Code and Data Governance Framework where Open Policy Agent (OPA) automates policy definition, enforcement, compliance monitoring, and rule versioning across healthcare data pipelines. The framework includes governance controls and validation processes that enhance compliance monitoring, audit compliance, and policy enforcement. This makes reporting in distributed healthcare environments delivered in a cloud-based format more transparent, accountable, compliant, and better risk-managed.

This can be especially important in medicine, where the field is constantly changing. In a cloud architecture with multiple tenants, it is imperative to achieve automated Policy Enforcement to ensure consistency and governance and mitigate operational risks (R.

Hariharan, 2025). However, few of the health care reporting systems currently available can be plugged into existing pipelines that take inbound policy engines to verify eligibility. This means that governance gaps are frequent, and violations of any rule are more the norm than the exception.

2.4 Cloud-Native Data Processing Architectures

Cloud computing provides scalable, resilient, and automated solutions for efficiently processing large volumes of healthcare data. Containers, microservices, Apache Spark, and Kubernetes are now the mainstream components of enterprise data platforms. The system consists of Kubernetes, dynamic resource orchestration, and workload scaling, with reported scalability of approximately 70% (D. H. Autor, 2015). Apache Spark is 10x faster than batch computing and is a distributed computing framework.

The work automation is boosted by about 65% in Apache Airflow. An AI-powered Kubernetes policy such as this can be useful for smart workload placement, utilization optimization, and even for improving the performance of microservice applications (S. R. Gundla, 2024). However, there are a few cloud-native reporting options that may make learning about health care policies easier, along with greater integration of governance, better auditability, and more in-the-moment validation of policy versions. These problems can be solved by providing a comprehensive solution for automated validation, governance, and cloud-native scalability, all within a single operational architecture.

3. Methods and Techniques

3.1 Data Collection Methods

An automated validation system to validate healthcare eligibility reporting was designed and tested using the Mixed-Methods Design Science Research (DSR) process. Design Science Research was adopted to design and test the effectiveness of the technology products in the operational environment. Validation accuracy, throughput, latency, and auditability were quantitatively assessed; governance and workflow were assessed qualitatively. This automation is not only evidence-based but can also be integrated at the enterprise level to improve and ensure the results of processes and operations (S. Subramanyam, 2025); (S. Samala, 2025).

The health records acquired spanned several EHR systems and multiple insurance payers, totaling 1,200,000, 850,000, and 450,000 health records, respectively. An integrated data file that contains the 2.5 million transactions consisting of eligibility, coverage, and verification responses, as well as reporting data. Recently, there has been an acceleration in the spread of such datasets and their use for detailed analytics within the interwoven service ecosystem to facilitate digital change (Florek-Paszkowska & A. Ujwary-Gil, 2025); (Rangu & K. S. Chadha, 2025).

The sample size in the study was determined using Cochran's large-sample formula, and 2400 records were obtained, all of which were valid. A scientific sampling method, stratified random sampling, was adopted to ensure the samples were proportional to the

number of participants in healthcare organizations. This was up to 1,000 hospital records, 900 records from insurance providers, and 500 records from health exchanges. Using stratification, the researchers ensured a representative sample for comparing results across performance conditions.

3.2 Data Analysis

The researchers used four validation filters to identify technical, semantic, regulatory, and operational problems in the analytical framework. Schema validation is layer 1, meaning the schema is checked for validity when it is created; it includes only matching data types and modes. In the initial phase, the system automatically identified and blocked missing information, incorrect identifiers, and incorrect data structures. This ensured integrity and helped avoid multiple structural problems.

Second, the system was tested for semantics: it checked consistency, ICD-10 diagnosis codes in the file were consistent, CPT procedural codes in the file were congruent, and the eligibility logic was accurate. These checkpoints may help independently verify health care event reporting against other reporting standards to ensure clinical/administrative consistency (Snigdha, et al., 2025). The development team tested several third-layer policies on the testing system using Open Policy Agent tools. The team also incorporated privacy laws into eligibility questions with payers. They used these as automation controls to ensure governance across the reporting chain.

The fourth layer was used to record metadata, such as the number of transactions being fulfilled and workflow status, among others, including the "Latency" in processing. The insurance area published common measures and quantified interpretations of workflow performance to improve workflow efficiency and standardize workflows (Z. Sayyed, 2025). This was achieved through operational validation, during which the system's precision proved that it met the required criteria and helped improve report quality.

The metrics used to assess the study's performance are error rate, latency, throughput, accuracy, and auditability score. The number of correctly validated records is a measure of accuracy, and the number of defects found across all records is a measure of the error rate. The number of transactions per minute is the throughput; the number of transactions that can be traced within a minute is the latency; and the auditability score is the ratio of the number of events that can be traced within a minute and the number of events (R. Kumar, 2025). All indicators are based on a multi-faceted perspective to gain insight into the nature of the service, its influence, and service management.

3.3 System Architecture and Experimental Setup

The new framework is installed and configured, with monitoring tools such as Apache Spark (v3.5), Apache Airflow, PostgreSQL, Apache Open Policy Agent, and Prometheus, running on an 8-node Kubernetes Cluster. The test bed consisted of 64 virtual CPUs (vCPUs), 256GB of RAM, 5 TB of Solid-State Storage, and 48 containerized pods. This was originally designed as a straight line from ingesting data, to building the schema, to adding a layer of

data validation and policy evaluation logic to the operational ingested data, to adding data into the dashboard.

The architecture was scalable, automated, and orchestrated the workloads for these reporting cases, centrally governed and continually monitored (Ransbotham, Kiron, Gerbert, & M. Reeves, 2017). The study also researched the healthcare industry deployment landscape to understand horizontal scalability, fault tolerance, resource consumption, reporting at 11k transactions per minute, and recoverability under similar circumstances.

Table 1: Healthcare eligibility reporting system, healthcare eligibility workflow components, infrastructure configuration, and performance testing environment.

Component Category	Technology / Resource	Configuration	Purpose
Infrastructure	Kubernetes Cluster	8 Nodes	Container orchestration, scalability, and workload management
Data Processing	Apache Spark 3.5	Distributed Processing Engine	High-speed data processing and parallel computation
Workflow Management	Apache Airflow	Automated Workflow Orchestration	Scheduling and managing validation pipelines
Policy & Monitoring	Open Policy Agent (OPA), PostgreSQL, Prometheus	64 vCPUs, 256 GB RAM, 5 TB SSD, 48 Pods	Policy enforcement, data storage, monitoring, governance, and performance tracking

Table 1 shows the architecture of the proposed automated healthcare eligibility reporting **framework and the experimental setup of the proposed system. The table shows the cloud**-native infrastructure components, processing technologies, orchestration tools, and governance components. It also highlights the computational power and functionality that enable scalable processing, continuous monitoring, and policy enforcement for high-volume transaction management.

4. Results and Discussion

4.1 Data Quality Improvement Analysis

Improvement in the quality of eligibility reporting occurred during the validation process. The total error decreased from 3.2% in pre-automation records to 2.1% in post-automation records, representing a 34.4% reduction in faulty records. Data loss in the field decreased from 5.6% to 2.8%, and duplicate data loss decreased from 2.4% to 1.1%, for an improvement of 54.2%. These results also show that using schemas, profiling rules, and automated deduplication increases the percentage of defects that can be avoided before data enters a payer reporting system. For insurance claims, AI/ML tools can also automate ETL, enhancing fraud prevention efforts and minimizing downstream data rework by validating data at the initial stages of the pipeline (Olaoye, Johnson, & M. Blessing, 2025); (K. S. Chadha, 2025). Submitting without validation is not acceptable and validation is required before submission.

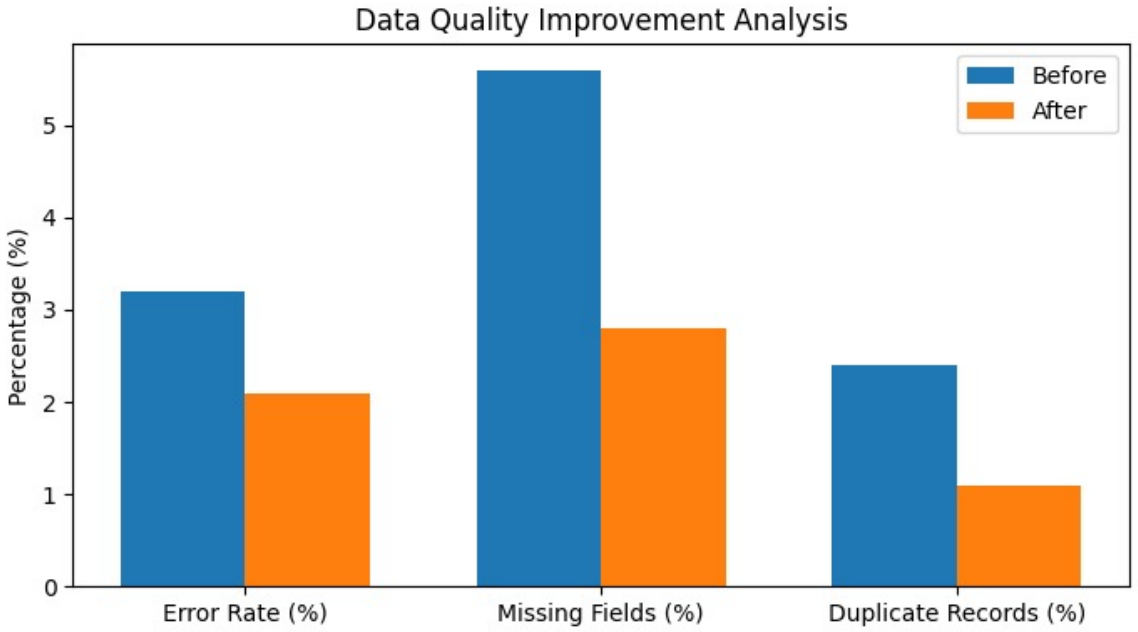


Figure 3: The automated validation pipeline has dramatically reduced reporting errors, duplicate data, and missing fields, improving data quality.

Figure 3 shows the relative performance of various data quality metrics before and after deploying the automated validation pipeline. The graph offers a glimpse of approaches to reduce the error rate, close gaps in data and records, and perform required data schema validation, data profiling, and automated deduplication. These enhancements improve reporting accuracy, strengthen data integrity, and minimize downstream processes and corrections.

4.2 Performance and Scalability Evaluation

The system is now deployed in the cloud, and performance has improved. Transactions per minute rose by 11,600, a 141.7% increase from 4,800. Processing time dropped from 240 minutes to 42 minutes, an 82.5% reduction. System availability remained at 97.2% and 99.8% thanks to workload resilience and failover mechanisms. Containerization services, parallel Spark jobs, Airflow orchestration, and Kubernetes auto-scaling enabled these enhancements. These enhancements help payers achieve faster turnaround on response processes and near real-time reporting for payer processes such as multi-payer and enrollment workflows.

4.3 Policy Compliance Assessment

Policy-as-code rules provided increased policy compliance. Policy violations decreased from 18 to 9.2 per reporting period, and compliance increased from 88% to 96.5%. This finding adds another process that enforces HIPAA, CMS, and payer-specific eligibility criteria and has now been standardized. To support policy automation, previous work has shown how policies can be embedded directly into healthcare pipelines, and how policy implementations can be made more robust by avoiding artifacts from manual policy generation through policy optimization based on rules and reinforcement learning (Alginahi,

Sabri, & W. Said, 2025); (A. C. Jha, 2025). The results indicate the advantages of using the policy interpreter when validating policies, reducing errors, improving policy enforcement, and therefore facilitating a controlled mechanism for reporting results to regulators.

Table 2: Policy compliance performance comparisons of pre- and post-Policy-as-Code in healthcare reporting processes.

Compliance Metric	Before Implementation	After Implementation	Improvement
Policy Violations (Incidents per Reporting Cycle)	18.0	9.2	48.9% Reduction
Compliance Rate (%)	88.0%	96.5%	8.5 Percentage Point Increase
Governance Consistency	Manual Rule Interpretation	Automated Policy Enforcement	Improved Standardization
Regulatory Control	Separate Validation & Compliance Processes	Integrated Policy-as-Code Validation	Enhanced Compliance Management

Table 2 shows the findings of the Policy as Code compliance evaluation before and after introducing Policy-as-Code into the healthcare eligibility reporting process. The table illustrates decreases in policy violations, increases in policy compliance, and greater consistency in governance. All of the results show that built-in HIPAA, CMS, and payer-specific policies directly into validation workflows bolster regulatory enforcement, mitigate interpretation inconsistencies, and enable more effective general compliance management.

4.4 Auditability and Operational Impact

Auditability and operational traceability also increased significantly. The percentage of traceable events increased from 56% to 98%, and audit readiness increased from 55% to 97%. Rework fell from 120 hours/cycle to 68 hours/cycle, a 43.3% improvement. Automated logging and exception dashboards, validation times, and rule versions enabled these improvements. An audit trail tracks which compliance rule was applied, when it was applied, which record did not comply with the rule, and which workflow owner closed the exception (Mirishli, Schreyer, & H. Hemati, 2025). This level of traceability is necessary for reporting health care eligibility because an incomplete chain of origin can increase exception-resolution difficulty and delay health care compliance review activities.

4.5 Future Research Recommendation

Future research extensions may target AI-based anomaly detection, real-time FHIR validation, healthcare governance for Federated policies (policy validation and monitoring), predictive healthcare compliance monitoring, and policy interpretation using LLMs (Noy & W. Zhang, 2023); (World Economic Forum, , 2023). Before these constitute a concern, AI can also detect any potential red flags of questionable eligibility behaviors. To appreciate the power of interoperability for providers, payers, and exchanges, there should be real-time FHIR validation.

Federated Governance can provide this service in the real world, and the business can focus on enforcing compliance while preserving the security and privacy of patient information (Peng, Kalliamvakou, Cihon, & M. Demirer, 2023). Predictive compliance tools can detect and identify policy non-conformance more accurately and effectively than current tools. While current tools are adequate, language models can further link language to policy rules, improving on existing tools.

5. Conclusions

The primary goal of the research is to develop and test an automated data validation pipeline for healthcare eligibility reporting, emphasizing the critical need for data quality, compliance, scalability, and auditability, all of which rely on a cloud-based rural health care eligibility data system. It offers a framework that includes schema validation, semantic validation, Policy as Code (PaC) governance, and operational monitoring. The study also designed and implemented the proposed system on an 8-node Kubernetes cluster, integrating Apache Spark, Apache Airflow, Apache Policy Agent, PostgreSQL, and Prometheus for end-to-end validation in a large-scale healthcare data environment.

All measured dimensions trended positively. The overall error rate dropped to one-half (3.2% to 2.1%), the percentage of missing fields dropped from 5.6% to 2.8%, and duplicate records dropped from 2.4% to 1.1%. These findings provide a baseline for preventive validation before submission to payers, not after. Throughput has increased by 141.7% from 4,800 to 11,600 transactions per minute, and processing time decreased by 82.5% from 240 minutes to 42 minutes.

In the policy-informed design, the study reaffirmed compliance with the regulatory frameworks and governance. The rate of noncompliance decreased from 18 to 9.2 policy infractions per reporting period, while the rate of compliance rose from 88 to 96.5%. The percentage of traceable events went up from 56% to 98%, while audit readiness jumped from 55% to 97%. The outcomes demonstrate the value of transparency, accountability, and consistency for better regulatory validation reporting and how governance rules can be embedded in validation process workflows.

The study shows how scalable organizations can adopt a model for sustainable, auditable reporting of enrollment eligibility through declarative, policy-based validation, reducing downstream rework and manual interventions. Future research opportunities include AI-based anomaly detection, near real-time FHIR data validation, adaptive policy learning, decentralized federated governance, and proactive compliance management. These attributes could also improve reporting accuracy, resilience, and cost-effectiveness, while helping prepare for changes in health care data environments and regulatory demands.

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