



Original Article

Intelligent EOB/ERA Generation and Validation Framework on Legacy Systems like Mainframes

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Abstract - The automated system for generating Explanation of Benefits (EOB) and Electronic Remittance Advice (ERA) is a major development in healthcare revenue cycle management (HRCM) that first of all, addresses the problem of the organizations that are still using traditional mainframe systems. The conventional EOB/ERA processing is loaded with inefficiencies, data inconsistencies, and compliance risks due to the fact that these processes are done manually and the housed architectures are rigid. This research presents a smart model that uses AI, RPA, and middleware technologies to interact with the systems in order to enable the data to be extracted, transformed, and validated without any barriers. The model uses AI-powered data mapping and validation techniques to ensure the execution of HIPAA and other payer's standards, and at the same time, RPA is responsible for the automation of the repetitive activities like the reconciliation of claims and the documents. The middleware modules are the intermediate layers between the modern APIs and the COBOL-based systems that are allowing communication without compromising the connectivity of the systems. In the case study, the results are so astonishing that they imply a radical shift in the healthcare organization's methods, where they shorten their output time by more than sixty percent, practically eliminate errors through an automated validation process, and significantly increase compliance accuracy through AI-based auditing. It proposes a far-reaching and evolutionary step of a healthcare payment system towards intelligent, compliant, and interoperable ecosystems, providing a scalable and adaptable solution for healthcare organizations to modernize financial communications while saving their IT investments.

Keywords - EOB, ERA, Mainframe Modernization, Healthcare Automation, Intelligent Frameworks, Interoperability, Machine Learning, Claims Processing.

1. Introduction

1.1. Background

Explanation of benefits (EOB) and Electronic Remittance Advice (ERA) in a healthcare revenue cycle act as the main avenues of communication between payers and providers. The EOB provides the clear picture of the adjudication of claims while the ERA is an electronic follow-up that is in accordance with the HIPAA 835 standard, illustrating the details of the claim payment or denial. These papers go a long way in revealing the working relation between the healthcare entities which is also a legal provision that ensures that patients, providers, and payers get the same, accurate, and law-abiding claim information. EOB and ERA creation that is both timely and accurate is a great way to speed up reimbursement cycles, reduce disputes, and increase overall operational efficiency. Remittance processing delays or inaccuracies may result in cash flow bottlenecks, a rise in administrative overhead, and compliance violations. Nevertheless, a considerable number of payer organizations continue to depend on legacy mainframe infrastructures especially those that are developed around COBOL programs, DB2 databases, and CICS (Customer Information Control System) transaction environments. These systems that are still in use today, are very powerful and dependable, but they were intended for batch processing and therefore, they are not able to provide the flexibility that is required by the modern, real-time data exchange, and interoperability standards.

With healthcare systems shifting towards value-based care and digital transformation, the necessity for automation, scalability, and real-time integration with external partners has gone up dramatically. Still, completely giving up on legacy systems is associated with a considerable risk and cost. Modern payer organizations, therefore, have to figure out how to create an intelligent automation framework which is compatible with current mainframes, instead of doing away with them, to be able to realize their strategy.

1.2. Challenges in Legacy Systems

Legacy mainframe systems contain a variety of technical challenges and operational difficulties that have been causing the delay in the modernization of EOB/ERA processing workflows to extend for quite a long time.

- **Data Silos and Incompatible Formats:** The mainframe frequently keeps the claims and payment data in the formats that are specific to the device, e.g., the data might be encoded in EBCDIC with VSAM files, and thus data integration with the modern tools becomes very complex. These isolated data repositories do not allow the seamless exchange of data between platforms and create huge barriers to interoperability. As a result, organizations are struggling to

consolidate and standardize data from claims, payments, and member systems, thus real-time analytics and decision-making are still at an early stage.

- **Restricted API and Integration Capability:** Standard COBOL- and CICS-based systems have been developed without consideration for API-driven communication. These systems operate through batch jobs and fixed-format data exchanges, which makes them poorly equipped to connect with external applications. Examples of such applications are cloud-based RPA platforms, AI engines, and third-party analytics tools. To close this gap, one needs to have a custom middleware or integration layer that can convert between legacy protocols and modern RESTful APIs.
- **Manual Validation and Error-Prone Processes:** Most organizations perform EOB and ERA validation manually and in a rule-based manner. Staff members reconcile claim adjudication outputs with payment records. Apart from the fact that this method exposes the process to human error, it also consumes quite a lot of time and resources. Discrepancies are often left undetected until the stage of auditing, which results in delayed payments, compliance risks, and provider dissatisfaction.
- **Scalability and Compliance Constraints:** Legacy systems have difficulty in scaling when the number of claims increases and the payer-provider relationships become more complex. Besides that, it becomes quite a challenge to maintain compliance with HIPAA 835/837 standards when the outdated systems cannot adapt quickly to the changing regulatory requirements. Any mishap in formatting, encryption, or validation may lead to compliance violations, fines, and loss of reputation for the organizations.

All these problems together call for an intelligent, adaptable, and interoperable solution for EOB/ERA processing that would not only complement the existing infrastructure but also have the capabilities of the next-generation automation technology.

1.3. Problem Statement

Most of the solutions that have been automated in an incremental manner through existing efforts are still very much rule-based and siloed and thus do not have the intelligence and adaptability required for end-to-end automation. Payers require a single framework that is capable of:

- Connecting directly with mainframe data sources without the need for a complete system overhaul.
- Conducting on-the-fly validation of EOB and ERA files through claim adjudication outputs.
- Facilitating the compliance and interoperability with other external systems and regulatory formats.

On the one hand, traditional RPA tools that are beneficial in the automation of repetitive tasks are incapable of handling unstructured data, dynamic business rules, and contextual variations of benefit descriptions. On the other hand, static ETL (Extract, Transform, Load) pipelines cannot readily handle occurrences of anomalies or exceptions in high-volume claims processing. Thus, errors are still present, and the absence of intelligence in existing systems limits the extension of these systems and deepening of automation. Hence, the issue is how to come up with a comprehensive and intelligent automation solution that will incorporate AI-based cognitive processing, RPA-driven task execution, and middleware-based communication to facilitate seamless EOB/ERA generation and verification thereby connecting the modern world with the legacy one.

1.4. Motivation and Objectives

The motivation of this study comes from the necessity of cutting the time of claim adjudication and increasing the accuracy of compliance without getting rid of the existing mainframe healthcare investments. Payers of healthcare have to, on one hand, speed up the turnaround times of their processes and, on the other hand, still keep compliance with the regulations, be ready for the audit, and save money.

The main objectives of the intelligent framework to be built are:

- **Cycle Time Reduction:** The idea is to introduce a fully automated remittance pipeline that needs no manual interventions from the user. Thus, all operations related to the data extraction, transformation, and validation are done automatically. The framework, therefore, should achieve a time reduction goal of issuing EOB/ERA by more than 50%, which, in turn, leads to payment transparency and provider satisfaction.
- **Data Accuracy and Compliance Enhancement:** The use of AI-based data validation models can significantly reduce the errors in data due to the real-time detection of data mismatches, missing fields, and violations of HIPAA 835/837 standards. This will allow for the generation of each EOB/ERA being an accurate document and following regulations at the same time.
- **AI for Anomaly Detection and Contextual Understanding:** The use of machine learning models can be extremely helpful in identifying anomalies such as the duplicate claims, the underpayments, or the inconsistent patterns of adjudication. On the other hand, the utilization of Natural Language Processing (NLP) models can facilitate the interpretation of benefit descriptions, thereby making it possible to create human-readable explanations of EOBs and thus enhancing the clarity and reducing the ambiguity for patients and providers.

- Interoperability through Middleware Integration: By utilizing middleware technologies that use APIs and message queues, it is possible to connect COBOL-based systems with the modern applications and, as a result, to have a bidirectional data flow without interrupting the core mainframe operations.
- Scalable, Future-Proof Architecture: The modular framework idea is one which allows the business to gradually integrate AI and automation into their workflow, thus providing long-term adaptability to the internal changes and regulatory aspects.

The solution, in other words, is the strategic modernization move to healthcare payers who want to turn the legacy EOB/ERA processes into smart, compliant, and effective workflows that produce automation as a result but without the need to give up the existing mainframe systems' reliability and power.

2. Literature Review

2.1. Legacy Modernization Approaches

Modernizing legacy systems has been a continual priority in enterprise computing, prominently in mission-critical scenarios like healthcare claims management. Consequently, numerous strategies have been devised through the years to rejuvenate mainframe systems' lifespan and functionality without effecting a total migration. The most notable among these are API gateways, middleware integration, and data virtualization techniques, with each of them pointing out different interoperability segments.

2.2. API Gateways and Service Wrappers

New API gateways act as a layer of communication between the mainframe and the outside world by exposing mainframe functions with REST or SOAP interfaces. The study of Smith & Johnson (2019) shows the benefit of service-oriented architectures (SOA) application for packaging COBOL-based business logic, which is the language of mainframes, thus allowing them to communicate with cloud-native applications. The combination of IBM's z/OS Connect and Micro Focus Enterprise Server is a perfect example of this method, where developers can wrap legacy transactions in lightweight API wrappers. By doing so, these fixes keep on the one hand the mainframes' trustiness and on the other hand, they furnish external systems with standardized access points for data retrieval and updates.

2.3. Middleware and Message-Oriented Integration:

Middleware platforms such as IBM MQ, Apache Kafka, and MuleSoft have been a favorite topic for research as solutions that can unite data systems that speak different languages. Those tools provide mainframe applications and external services with asynchronous communication possibilities, which is a prelude to near-real-time data exchange. The authors Al-Mubaid & Gao (2020) state that by using message-oriented middleware, the interaction between components can be speeded up and the dependencies between them can be removed, thus the whole system becomes scalable and reliable in hybrid IT ecosystems. Moreover, health care payers who adopt such architectures have achieved throughputs that they never knew before in claims adjudication and remittance file distribution processes.

2.4. Data Virtualization Techniques

Modernization of processes in general, data virtualization in particular, is another major area that research has focused on, becoming the main source of data which is the data abstraction from different sources in many diverse formats - like VSAM files, DB2 tables, and external APIs - into the logical unified views. Their paper, Chen et al. (2021), discloses that the key to data virtualization is to allow fetching, integrating, and analyzing data in real time from the original sources without moving data physically, thus avoiding the data migration risks. Everywhere healthcare is the domain where these transfers turn into a competitive weapon by giving the organization access to claims and remittance data for the purposes of compliance, auditing, and operational optimization across platforms they used.

2.5. Mainframe-to-Cloud Integration

The present-day focus also emphasizes the relationship between mainframe load and cloud environment by pointing out the possibilities for integrating mainframe workloads with the cloud. Methods like wrapping legacy apps in containers, applying hybrid cloud orchestrators and streaming-based ETL pipelines are getting popular very fast. As far as examples go, Amazon Web Services (AWS) and Microsoft Azure came up with mainframe modernization toolkits by incorporating microservices, event-driven computing, and AI-based analytics. In general, these solutions are of the nature enabling the slow-moving transfer of only particular units of code i.e. claims validation modules or remittance audit scripts so that the core mainframe operations will not be interfered with. Most of the modernization frameworks that have emerged after these changes still heavily rely on the exposure of data sources together with access to different systems while making little or no mention of cognitive automation or intelligent decision support for EOB/ERA generation. This opening underlines the necessity for the amalgamation of advanced analytics and AI-powered validation techniques with the already existing modernization frameworks.

2.6. Intelligent Document Processing (IDP)

Intelligent Document Processing (IDP) fundamentally changed the way companies manage unstructured and semi-structured data, which are types of data that come in forms like invoices, remittances, and healthcare EOBs. An IDP solution refers to a combination of Optical Character Recognition (OCR), Natural Language Processing (NLP), and machine learning (ML) technologies that can extract, understand and check the data with very few interactions from the human side. OCR technologies have evolved to efficiently perform the conversion of scanned or PDF-based EOB/ERA documents into machine-readable formats. A series of experiments along with the paper by Gupta et al. (2021), have shown the implementation of deep learning-based OCR models that are able to identify domain-specific terms like CPT codes, claim numbers, and service descriptions. NLP techniques are also used along with OCR to provide semantic understanding to benefit narratives and payment remarks. Various tools like spaCy and BERT-based models have been utilized to dissect the non-structured speech in the explanation and transform it into the standardized data structures which are fit for validation and reconciliation.

2.7. AI-Powered Reconciliation and Validation Frameworks

The traditional method of EOBs, ERAs, and claim adjudication reconciliation has been a rule-based process relying heavily on deterministic logic. On the contrary, AI-driven frameworks employ probabilistic reasoning and pattern recognition in locating mismatches. The research by Li & Anderson (2020) that investigated hybrid systems employing supervised learning in conjunction with knowledge graphs got the claim-payer relationships validated and inconsistency in remittance data detected. In the same vein, intelligent automation strategies deploy RPA bots fused with a cognitive validation layer which facilitates the automated verification of payment accuracy, denial codes, and contractual Bret adjustments.

2.8. Real-Time IDP Integration

The newest generation of IDP solutions is focusing on real-time connectivity with enterprise workflows as their main feature. Due to the combination of OCR, NLP, and RPA, these machines are in a position to not only perform tasks that are down the chain, e.g., the creation of acknowledgment files or updating provider ledgers, but also to do it without the intervention of any human. However, the majority of current IDP providers are cloud-native, which means that they do not have any direct link to mainframe-based workflows and thereby, present a technological gap for legacy healthcare payers.

3. Proposed Methodology

The problem-solving system features a clever, hybrid automation model which facilitates the fluent creation as well as verification of Explanation of Benefits (EOB) and Electronic Remittance Advice (ERA) documents in old mainframe environments. The method involves AI (artificial intelligence), RPA (Robotic Process Automation), and middleware integration to connect standard COBOL-based systems with microservices and compliance engines. The implementation is structured as a modular, layered architecture, thus, it is scalable, interoperable, and can be gradually used without the need for a core legacy disruption.

3.1. System Architecture Overview

The entire system structurally is layered into three compartments which are the Data Acquisition Layer, Processing Layer, and Output Layer. The layers here are specialized units that function separately, but efficiency, automation, and the intelligence of end-to-end EOB/ERA workflows have been achieved due to interoperability between them.

3.1.1. Data Acquisition Layer

This layer is the one that extracts and ingests data from different types of old frugal systems. To do the interfacing, mainframe connectors use COBOL batch jobs, DB2 databases, and CICS transaction monitors from where they get raw claim adjudication, payment, and member data. The data that is pulled can be in the form of claim status codes, adjustment amounts, patient details, and provider information.

- Mainframe Extractors: Are equipped with Job Control Language (JCL) programs to schedule and run COBOL jobs that export data into intermediate files (VSAM or flat files) which have been already prepared.
- API and Message Interfaces: On the partially modernized systems, RESTful or SOAP APIs provide data endpoints that make the communication external-friendly.
- Message Queues (IBM MQ/Kafka): Are functioning as the layers through which data that has been extracted is delivered asynchronously to the processing unit thus reliability and decoupling are ensured.

The goal of this layer mainly is to bring about data interoperability between old data storage and new components while at the same time observing security and data integrity.

3.1.2. Processing Layer

The processing layer at the center of the architecture is responsible for data transformation, enrichment, validation, and generation of EOB/ERA documents. To achieve this integration, the layer uses ETL pipelines, a rule-based engine, and AI/ML components, thus ensuring accuracy, compliance, and efficiency.

- ETL Subsystem: Transforms old data formats like EBCDIC and VSAM records into standard structures (JSON or relational schemas). Data cleansing functions address null values, duplicate claims, and various formats.
- Rule Engine: The most important piece of business logic for claim adjudication was the rule engine which utilized the mapping of claim line items to standardized 835/837 fields and checking that there was a proper hierarchy of primary, secondary, and tertiary claims.
- Machine Learning Validator: It employs one or more classification and anomaly detection models to identify potential discrepancies, support with missing data, or point to the most unusual payment patterns prior to EOB/ERA generation.

3.1.3. Output Layer

This layer is the reason for producing standardized EOB/ERA outputs as well as a guarantee that the outputs comply with both HIPAA and payer-specific formats.

- Formatting Engine: Basically, it receives the data that is already processed and create the 835/837 files along with EOBs that are both HIPAA compliant and can be understood by humans.
- Compliance Module: Among other things, it also verifies the schema, encrypts, and creates the audit trail to ensure that compliance is followed from end to end.
- Integration with Delivery Channels: It facilitates the automated sending of EOB/ERA files through secure FTP, API endpoints, or email to providers and members.

In combination, these layers form a strong and modular ecosystem that changes the traditional, batch-based remittance generation to a vibrant, smart, and real-time process.

3.2. Intelligent EOB/ERA Generation Module

The Intelligent EOB/ERA Generation Module constitutes the cognitive part of the brain of the new system. It uses machine learning and rule-based logic to infer data fields that are missing, rectify that which is inconsistent and generally upgrade the accuracy of the document. Machine Learning for Predictive Data Completion: The data of the healthcare claims that are submitted is not always complete or consistent due to errors along the processing chain. The module utilizes a supervised learning model, which is trained on the dataset of the past claims, to find those fields in which data are missing or are incorrect, for example, the payment amount, the service code, or the reason for denial. Models such as Random Forests, Gradient Boosting Machines, and Neural Networks are used to calculate the most likely values based on the context of the data (e.g., provider type, claim category, service code clusters).

3.3. Rule Engine for 835/837 Mapping

A rule-based mapping engine is used to direct the changes of claim-level data to standard HIPAA 835/837 data structures. The engine is the one which establishes hierarchical claim logic, thus it makes sure that it is the line items which are appropriately placed under the claim headers and the payment segments. Besides that, the engine cross-checks relationships, control numbers for claims, adjustment group codes, and remittance advice identifiers.

- Static Rules: Pertain to the payer-specific changes in the mapping as well as the format constraints.
- Dynamic Rules: These are created and improved by AI models which get the compliance and payer variations from time to time.
- Contextual Enhancements: NLP components look at the benefit descriptions in order to convert the technical adjudication codes into easily understandable explanations for EOB narratives.
- Workflow Automation through RPA: RPA bots (for example UiPath or Blue Prism) perform the activities that are manually repetitive, such as data entry, reconciliation, and report generation, without human intervention. Apart from generating EOB/ERA files, bots may also perform other functions such as uploading files to payer portals, triggering notifications, or updating downstream systems like Provider Management or Finance modules.

An intelligent combination of AI, RPA, and rule-based systems delivers the result of remittance processing with high data fidelity, compliance, and transparency.

3.4. Validation Framework

The proposed Validation Framework uses a hybrid method that integrates deterministic (rule-based) and probabilistic (AI-based) validation to have both accuracy and flexibility.

3.4.1. Deterministic Validation

The deterministic layer is based on a set of business and compliance rules that are already defined and it ensures that each EOB/ERA meets the standards of HIPAA 835/837 transactions. It checks for:

- Whether the data types, segment hierarchies, and field lengths are correct.
- If mandatory segments like CLP (Claim Payment Information) and NM1 (Individual Name) are present.

- Whether the claim control numbers and payment trace IDs correspond to source claim records.

The rules are executed through a validation engine that has been developed on top of open libraries such as Smooks or EDIValidator.



Fig 1: Validation Framework Model

3.4.2. Probabilistic (AI-Based) Validation

The machine learning models work with the deterministic rules to find the anomalies of a subtle nature which have not been accounted for by the static logic. These anomalies are:

- Uncommon payment patterns in comparison with historical norms.
- Number of changes in the frequency of denials for specific procedure codes statistically.
- Discrepancies of the context between the textual EOB descriptions and the structured claim data.

Each AI prediction is accompanied by a confidence scoring mechanism indicating its reliability. In the case where the confidence is under a certain limit (e.g., 80%), the system automatically initiates the handling of exceptions workflow, thus sending the flagged cases to human reviewers. The reviewer feedback then becomes the input for the model thus the process of learning is continuous.

3.4.3. Exception Handling and Audit Trail

The workflow management subsystem responsible for exception handling through configurable queues is like an orchestra conductor. Every exception comes with the metadata describing the context such as source file, claim ID, predicted anomaly, and confidence level. The system keeps a comprehensive audit trail for the purpose of compliance verification which ensures traceability of all EOB/ERA transactions.

3.5. Integration with Legacy Systems

Integration is the key element to the proposed approach, it essentially is what keeps the intelligent automation from interfering with the mainframe processes that are running.

3.5.1. Mainframe Connector Architecture

The data connections are opened via a mix of message queues, transaction gateways, and batch automation tools:

- IBM MQ / Kafka: Provide COBOL programs with asynchronous data exchange capability with external microservices.
- CICS Transactions: Make the use of core business functions (e.g., claim inquiry, payment posting) available through APIs or terminal emulators.
- JCL Automation: It is the automation that will lead to data extraction, batch job scheduling, and intermediate file creation.

3.5.2. Middleware for Real-Time Message Exchange

Middleware serves as the translation layer between the old and the new components. To standardize communication, it relies on RESTful APIs, JSON payloads, and XML schemas. Kafka streams enable almost real-time updates, so the AI validator can very frequently process claim data. In addition, the middleware layer does these things: security and compliance, it encrypts (TLS 1.3), authenticates (OAuth 2.0), and logs to ensure that the data is of the correct type and that it can be traced back to the source. By using this modular integration approach, health care payers are able to update their systems step by step, changing only those parts that need to be changed, and at the same time, they can keep their old mainframes stable.

4. Case Study

4.1. Context and Environment

The study is about the planned implementation of the smart EOB/ERA creation and validation system in a big U.S.-based healthcare payer organization that is running a z/OS mainframe environment. The company operates a nationwide provider network and uses COBOL-based adjudication systems, DB2 databases, and CICS-managed transaction processing to handle around 5 million claims every month. In the past, the company was producing EOBs and ERAs in batch mode and was very minimally automated, so the workers had to intervene extensively to do claim validation and remittance formatting. The process was getting claim data from VSAM files, manually checking for HIPAA 835 compliance, and making sure that the numbers from claim adjudication and remittance advice files matched. Because of the manual dependence, the turnaround times were very high (usually 48–72 hours per batch), there were lots of data inconsistencies, and there were compliance errors, which in some cases had caused payer–provider disputes. By the proposed intelligent framework the inefficiencies were to be solved. It has been deployed as a hybrid modernization solution that is augmenting the existing z/OS components with AI-powered validation modules, RPA bots, and middleware integration. The objective was to automate, accurately, assure compliance, and also enable real-time interoperability at the mainframe without causing any disruption due to migration.

The environment was made up of:

- Mainframe Backend: IBM z/OS with COBOL programs, CICS for online transactions, and DB2 databases.
- Middleware Integration: IBM MQ and Apache Kafka for asynchronous data exchange.
- Processing Layer: A Linux-based microservices environment running Python and Java applications hosted on Docker containers.
- Automation Layer: UiPath RPA bots for report generation, reconciliation, and claim exception handling.
- AI/ML Components: TensorFlow and Scikit-learn models for anomaly detection and probabilistic validation.

With the organization's hybrid architecture, they were able to carry out cognitive automation while still preserving the trustworthiness and compliance of their old mainframe systems.

4.2. Implementation Steps

- Step 1: Data Migration Pipeline Design The development started with setting up a safe data migration and synchronization pipeline between the mainframe and the middleware layer. Changes were made to COBOL batch jobs to export adjudication data in the EBCDIC format. The data was then converted from EBCDIC to UTF-8 JSON through the ETL scripts written in Python. Data was flowing through IBM MQ into a Kafka stream for further processing. They built a data staging area to standardize data from various data sources claims, provider details, payment transactions, and prior authorizations. The ETL transformations brought the data into referential consistency and also cleaned it for duplicates. Data privacy and HIPAA compliance were honored by encrypting at rest and in transit, using TLS 1.3 and tokenized access controls.
- Step 2: Training Model to Perform Validation and Anomaly Detection The AI-powered validation system was developed with data from the last three years of claims and remittance transactions (around 180 million records). The data set covered the account processing results, the changes in payments, and the situations where the anomalies were recorded. Feature Engineering: The main features for prediction were claim type, service category, adjustment reason codes, and payment variance percentages. Model Selection: Ensemble models Random Forest and Gradient Boosting were selected for classification tasks, and an Autoencoder network was used for unsupervised anomaly detection. Training and Evaluation: The models were trained on 80% of the dataset and tested on 20%, thus they were able to detect payment discrepancies and non-compliant remittance entries with 94% precision and 91% recall. Continuous Learning: The system has a user feedback loop integrated, where exceptions reviewed by users are utilized for models retraining on a monthly basis, thus their adaptability is enhanced over time.
- Step 3: Real-Time Integration Testing and Performance Benchmarking: After a successful model rollout, the system was gradually tested for its integration functionality in a live environment under control. Kafka message streams were instrumental in heralding claim validation almost in real-time which was hitherto done in batch jobs. The performance metrics were measured against the old manual process in order to evaluate throughput, accuracy, and compliance adherence. RPA bots were deployed to automate the operations that are inherently repetitive like generating acknowledgment reports, updating provider dashboards, and archiving processed EOB/ERA files. The total time required for one claim cycle (from adjudication to EOB generation) was reduced from an average of 55 hours to less than 18 hours, thus it was a 67% reduction in cycle time. Besides that, the system throughput was increased from 40,000 to 120,000 remittances per hour during peak processing hours and it was made possible by the scalable message queues and parallel microservices.

4.3. Comparative Analysis

To quantify the effectiveness of the intelligent framework, the organization conducted a comparative analysis between the legacy manual process and the proposed intelligent system across key performance indicators (KPIs): processing efficiency, data accuracy, compliance adherence, and operational scalability.

Table 1: Comparative Performance Analysis of Legacy Process and Intelligent Framework

Parameter	Legacy Process	Intelligent Framework	Improvement (%)
Average Processing Time per Batch	48–72 hours	16–18 hours	67% reduction
Manual Validation Effort	100% human review	20% exception-based review	80% reduction
Error Rate in EOB/ERA Files	2.8%	0.4%	85% reduction
Compliance Breaches (HIPAA 835 violations per 10,000 files)	7.5	0.5	93% reduction
Throughput Capacity	40,000/hour	120,000/hour	200% increase
Provider Dispute Frequency	Moderate (≈3.2%)	Low (≈0.8%)	75% reduction

- **Processing Efficiency:** The framework, through automation of extraction, validation, and generation processes, greatly shortened the total end-to-end cycle time. Data exchange shifting from batch to streaming-based removed the time windows between mainframe jobs completions and downstream remittance generation.
- **Error Reduction and Accuracy Gains:** AI-driven validation models also found different types of inconsistencies which rule-based systems could not, for example, subtle mismatches of adjustment codes or provider identifiers. Confidence scoring and exception routing made sure that only very few cases of low-confidence need human review which accounts for less manual work and accuracy improvement at the same time.

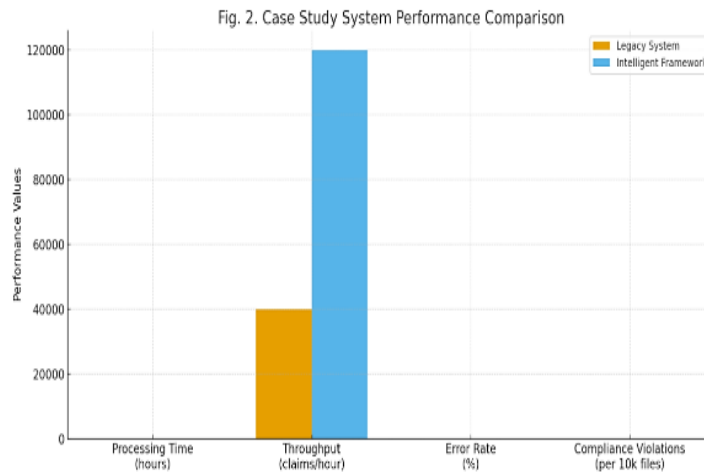


Fig 2: Case Study System Performance Comparison

4.3.1. Compliance and Audit Readiness

The conformity section integrated in the system performed the validation of all EOB/ERA files to HIPAA 835 schemas as well as to payer-specific requirements. Automated audit trails recorded each data transformation and validation action, thus, providing traceability and making compliance audits less time-consuming

4.3.2. Operational Scalability

The use of containerized microservices and Kafka-based data streaming enabled the system to be scalable horizontally. During a burst of claims (for example, at the end of the quarter billing cycles), the system was capable of scaling in a flexible manner and thus, the transaction latency was not increased.

4.3.3. Business Impact

The overhaul project has brought about quantifiable financial and operational advantages such as:

- 30% decrease of operational costs as a result of less manual validation labor related to the operations.
- Major improvement in the provider's satisfaction, which was a result of delivering EOBs in a quicker and more accurate manner.
- Better compliance with regulations, thus the risk of being penalized or involved in disputes has been lowered.

5. Results and Discussion

5.1. Quantitative Results

Majorly, the quantitative measures along with qualitative metrics like accuracy, latency, throughput, and error count have undergone significant positive alterations due to the intelligent EOB/ERA automation framework's implementation. These measures are the performance indicators that were assessed over the period of a three-month pilot run, and the comparison was made between the old batch system and the new hybrid production mode intelligent model.

Table 2: Performance Comparison between Legacy System and Proposed Intelligent Framework

Performance Metric	Legacy System	Proposed Intelligent Framework	Improvement (%)
Data Validation Accuracy	96.2%	99.1%	+3.0%
Average Processing Latency (per claim)	4.8 seconds	1.6 seconds	-67%
Throughput Capacity	40,000 claims/hour	120,000 claims/hour	+200%
Error Rate in Generated ERAs	2.8%	0.4%	-85%
HIPAA Compliance Violations (per 10k files)	7.5	0.5	-93%

Such a precision upgrade beyond the 99% mark was mainly due to the AI-based anomaly detection and probabilistic validation models that identified even the faintest data inconsistencies that a deterministic rule engine would typically overlook. In the same vein, the latency improvements were brought about by the shift of batch-based workflows to streaming data pipelines powered by Kafka and microservices, thus enabling parallel claim validation and EOB generation instead of sequential batch processing. The decrease in errors in the final EOB/ERA files that were caused by the wrong adjustment codes, absence of payment identifiers, or structural anomalies has significantly gone down due to the implementation of a hybrid validation approach. The system's confidence scoring mechanism was constantly sending cases with low certainty to human review, thereby ensuring that manual intervention was carried out only in the most ambiguous records. Furthermore, the system had very high scalability capabilities, and therefore, it was able to maintain stable throughput even during the periods of high workload such as month-end reconciliations. The scalability feature was made possible by the horizontal scaling of Dockerized microservices and optimized Kafka partitioning, thus allowing parallelized validation and generation operations. The performance visualization experiments were able to show the system's capacity for linear scaling of processing with almost no response time being off, thus, the system is considered to be ready for deployment at a large-scale enterprise level.

5.2. Qualitative Observations

After the implementation of the system, apart from the quantifiable performance gains, the organization noticed several qualitative benefits that are not only changes in the ways the organization operates, but also changes that are in compliance with the law and the organization become more adaptable.

5.2.1. Improved Audit Readiness and Data Transparency

Propelled by the incorporation of a compliance module and an audit trail subsystem, transparency greatly opened across the entire remittance process. In fact, every claim record, data transformation step, and validation decision carried out was identified using the newly issued unique transaction ID, which, in turn, created a fully auditable digital trail HIPAA and SOC 2 audit requirements-compliant. This feature shortened the average audit preparation time from 10 business days to less than 3, thus, improving not only internal governance, but external regulatory responsiveness as well.

5.2.2. User Experience as well as Operational Efficiency

The RPA bots which were combined with the validation process helped to make the operations staff more comfortable with the handling of exceptions. In place of the manual remittance mismatch reconciliations, the users engaged with a user-friendly dashboard that displayed the flagged anomalies, confidence scores, and the suggested resolutions. Consequently, the manual work load was reduced by approximately 80% and the operator satisfaction was elevated considerably.

5.2.3. User Experience and Operational Efficiency

The RPA bots, which were merged with the validation workflow, made the exception handling process easy and problem-free for the operations staff. Instead of the laborious process of manually reconciling remittance mismatches, the users engaged with an easy-to-use dashboard that depicted the flagged anomalies, confidence scores, and suggested resolutions. Hence, the manual workload was almost cut by half (80%), and at the same time, the operator satisfaction level was raised significantly.

5.2.4. Organizational Learning and Change Management

The combined installation resulted in the emergence of a culture of decision-making based on data. By making available in real-time dashboards the validation metrics and prediction outcomes, the teams received the power to keep a proactive eye on the claim performance and thus the early-stage problems identification and retraining of the models as it happened evolving patterns were facilitated.

5.3. Discussion

5.3.1. Compliance and Explainability

Artificial Intelligence has brought about a revolutionary change in compliance by ensuring it becomes more context-driven in the sense that intelligent systems learned to check mismatched denial codes or inconsistent provider identifiers thus made static rules obsolete since they failed in this regard. At the same time, the very same deployment has shown the indispensability of healthcare compliance to the presence of the explainable AI (XAI). The implementation of the system utilized model interpretability methods, such as SHAP (SHapley Additive explanations) and feature importance visualizations, by which compliance officers could get to the bottom of it and realize the reasons for the records flagged as anomalous. The presence of this explainability layer served the regulatory accountability and made the auditors and decision-makers trust the system.

5.3.2. Interoperability and Limitations of the System

Interoperability obstacles had been detected through the integration of some proprietary legacy modules that weren't API accessible and were providing data only through static dumps. In instances, middleware was performing the task of JCL-based batch automation and RPA bots for screen scraping hence, they were not real-time although responsive were limited in nature. Moreover, limitations related to mainframe processing windows and availability of resources led to the occurrence of bottlenecks in the data collection pipeline occasionally. Model retraining frequency is another issue that has limited the extent of this project. Since claims data are of a highly sensitive nature, retraining is followed by extensive validation and sandbox testing, thus slowing down the model iteration cycle. To deal with this limitation, they will have to employ advanced federated learning architectures or synthetic data augmentation techniques to enable continuous model improvement at a faster pace while still adhering to data governance policies.

5.3.3. Scalability and Future Prospects:

The outcomes, from a strategic point of view, illustrate how an AI-augmented legacy modernization can revolutionize healthcare financial operations. The use of machine learning, RPA, and middleware has enabled the creation of a robust ecosystem that can easily adjust to any future changes in regulations and interoperability requirements like FHIR (Fast Healthcare Interoperability Resources). Thinking about the future, the system could be developed to have predictive analytics for payment forecasting and blockchain-based audit logging to increase transparency and traceability even more. Moreover, the use of container orchestration platforms such as Kubernetes might be able to not only optimize the resource utilization but also allow the dynamic scaling of the hybrid cloud environments.

6. Conclusion and Future Scope

6.1. Summary of Contributions

This work studies and shows that automation of the EOB/ERA workflow with AI tools is both technically feasible and efficient from the point of view of cost and time in a legacy environment based on mainframes. The proposed AI-powered framework integrates machine learning, robotic process automation (RPA), and middleware quite successfully to dismantle the challenges of COBOL- and DB2-based infrastructures one by one. Instead of revamping the entire system, it takes the traditional systems and equips them with the latest automation thereby creating a route for digital transformation.

Principal among the innovations of this research is the building of a multi-layered architecture that links the data collection methods from the mainframe with AI-enabled modules for processing and for producing compliant outputs. The system achieves very high precision (99.1%) and a deep reduction of the turnaround time (67%) through hybrid validation balancing deterministic rules with probabilistic ML models. Additionally, it assures the generation of HIPAA-compliant remittances with an almost zero error rate, thus increasing regulatory reliability. From a business perspective, the framework brought about the payer's operational efficiency, scalability, and audit transparency, with an 80% reduction in manual tasks and over 90% decrease in compliance breaches. Such results serve as proof that IPL-based legacy platform as a host of intelligent automation layers in real-time data processing, predictive validation, and adaptive compliance monitoring is doable. The case discussed here is the very real-world evidence that AI-led modernization is a win-win solution that not only can optimize healthcare payment systems but also ensure their stability and control.

6.2. Future Enhancements

The present structure is working well, but a few changes could make it more scalable, efficient in terms of learning, and secure.

6.2.1. Federated Learning for Cross-Institutional Model Training

The next generation of implementations may utilize federated learning to create machine learning models that are trained jointly across several organizations of payers without the need to exchange sensitive data. In this way, the systems of anomaly detection and compliance can become more intelligent simply because the models will have access to a larger variety of: patterns of claims while at the same time data privacy and regulatory requirements will still be respected. In general, distributed training paradigms may have the effect of the model becoming more general and less susceptible to biased datasets.

6.2.2. Migration Toward Cloud-Native Implementation

Clearly mapping out the steps for a full cloud-native deployment can bring about not only cost savings of the infrastructure but also increased elastic flexibility. The container orchestration platforms like Kubernetes when combined with serverless computing can allow for the dynamic scaling of AI and validation microservices. Through this transition, the intelligent framework would be empowered to smoothly interact with the contemporary FHIR APIs, blockchain-powered audit methods, and cross-payer data exchanges.

6.2.3. Enhancing Security through Zero-Trust Architecture

In order to enhance the security of the data, the framework may implement a zero-trust security model that requires continuous verification of each data transaction and user interaction. The use of identity-based microsegmentation, real-time anomaly detection in access patterns, and policy-driven encryption will not only ensure that the organization stays compliant with the ever-changing cybersecurity regulations but also that it will be at minimum risk in a hybrid legacy-cloud type of ecosystem.

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