

# AI-DRIVEN HEALTHCARE PAYMENT SYSTEMS USING INTELLIGENT CLAIMS VALIDATION AND FRAUD DETECTION MECHANISMS

**Ganesh Adepu**

United States of America.

## ABSTRACT

*The rapid evolution of digital healthcare ecosystems has significantly transformed the way medical services are delivered and financed. However, healthcare payment systems continue to face persistent challenges such as inefficient claims processing, billing inaccuracies, delayed reimbursements, and increasing instances of fraud and abuse. Traditional rule-based systems often lack the scalability and adaptability required to address the growing complexity of modern healthcare transactions.*

*This paper presents a comprehensive overview of AI-driven healthcare payment systems that leverage advanced machine learning and intelligent automation to enhance claims validation and fraud detection mechanisms. By integrating techniques such as predictive analytics, anomaly detection, natural language processing, and pattern recognition, these systems enable real-time verification of claims, identification of suspicious activities, and optimization of reimbursement workflows.*

*The proposed approach emphasizes the use of data-driven models to improve accuracy, reduce manual intervention, and ensure compliance with regulatory standards. Additionally, the study explores architectural considerations, including cloud-based deployment, interoperability with electronic health records (EHR), and secure data exchange frameworks.*

*Through analytical discussion and conceptual modeling, this paper demonstrates how AI-enabled payment systems can significantly reduce financial losses, enhance operational efficiency, and improve trust among stakeholders, including providers, payers, and patients. The findings highlight the transformative potential of artificial intelligence in building resilient, transparent, and scalable healthcare financial infrastructures.*

**Keywords:** Artificial Intelligence (AI), Healthcare Payment Systems, Claims Validation, Fraud Detection, Machine Learning, Predictive Analytics, Anomaly Detection, Healthcare Fraud Prevention, Intelligent Automation, Electronic Health Records (EHR), Data Security and Compliance, Digital Health Ecosystems

**Cite this Article:** Ganesh Adepu. (2024). AI-Driven Healthcare Payment Systems Using Intelligent Claims Validation and Fraud Detection Mechanisms. *International Journal of Artificial Intelligence Research and Development (IJAIRD)*, 2(2), 259-277.

DOI: [https://doi.org/10.34218/IJAIRD\\_02\\_02\\_022](https://doi.org/10.34218/IJAIRD_02_02_022)

---

## 1. INTRODUCTION

The global healthcare industry is undergoing a profound digital transformation driven by the convergence of advanced technologies, data proliferation, and the growing demand for efficient and transparent financial processes. Among the most critical components of this transformation are healthcare payment systems, which serve as the backbone for managing claims, reimbursements, and financial interactions between providers, payers, and patients. Despite significant advancements in healthcare delivery, payment systems continue to face longstanding challenges, including administrative inefficiencies, fragmented data ecosystems, delayed claim settlements, and escalating fraudulent activities.

Traditional healthcare payment frameworks largely rely on rule-based validation mechanisms and manual review processes. While these approaches have provided foundational support, they struggle to keep pace with the increasing volume and complexity of healthcare transactions. The rise in insurance claims, coupled with diverse billing standards and coding systems, has introduced substantial operational overhead. Moreover, static validation rules are often insufficient to detect sophisticated fraud patterns, leading to significant financial losses and reduced trust across the healthcare ecosystem.

In recent years, the adoption of Artificial Intelligence (AI) and machine learning has emerged as a transformative force in addressing these limitations. AI-driven systems offer the capability to process vast amounts of structured and unstructured data, identify hidden patterns, and make intelligent decisions in real time. Within the context of healthcare payments, AI technologies enable automated claims validation, predictive risk assessment, and proactive fraud detection, thereby enhancing both efficiency and accuracy.

Intelligent claims validation systems utilize advanced algorithms to verify the authenticity, completeness, and compliance of submitted claims against medical guidelines, historical data, and policy rules. Simultaneously, AI-powered fraud detection mechanisms employ techniques such as anomaly detection, behavioral analytics, and network analysis to uncover irregularities and suspicious activities that may otherwise go unnoticed. These capabilities not only reduce financial leakage but also streamline reimbursement cycles and improve stakeholder satisfaction.

Furthermore, the integration of AI with modern healthcare infrastructure—such as Electronic Health Records (EHR), cloud-based platforms, and interoperable data exchange systems—has enabled the development of scalable and resilient payment ecosystems. These systems facilitate seamless data sharing, real-time decision-making, and enhanced regulatory compliance, which are essential in a highly sensitive and data-intensive domain like healthcare.

This paper explores the design and impact of AI-driven healthcare payment systems, with a specific focus on intelligent claims validation and fraud detection mechanisms. It aims to provide a generalized yet technically grounded perspective on how emerging AI technologies can be leveraged to modernize financial operations in healthcare. The discussion encompasses architectural considerations, key methodologies, implementation challenges, and the broader implications for the future of digital health finance.

## **2. SYSTEM ARCHITECTURE OF AI-DRIVEN HEALTHCARE PAYMENT SYSTEMS**

The architecture of an AI-driven healthcare payment system is designed to ensure scalability, real-time processing, data interoperability, and robust fraud prevention. It integrates multiple layers of data ingestion, intelligent processing, and decision-making components to automate claims validation and detect anomalies effectively. This section presents a generalized architectural framework widely applicable across modern healthcare ecosystems.

## 2.1 Architectural Overview

An AI-enabled healthcare payment system typically follows a multi-layered architecture consisting of the following core components:

1. Data Ingestion Layer
2. Data Processing and Integration Layer
3. AI/ML Intelligence Layer
4. Business Rules and Decision Engine
5. Fraud Detection and Risk Scoring Module
6. Output and Visualization Layer

These components work cohesively to enable seamless claims processing, real-time validation, and proactive fraud detection.

## 2.2 High-Level Architecture Diagram

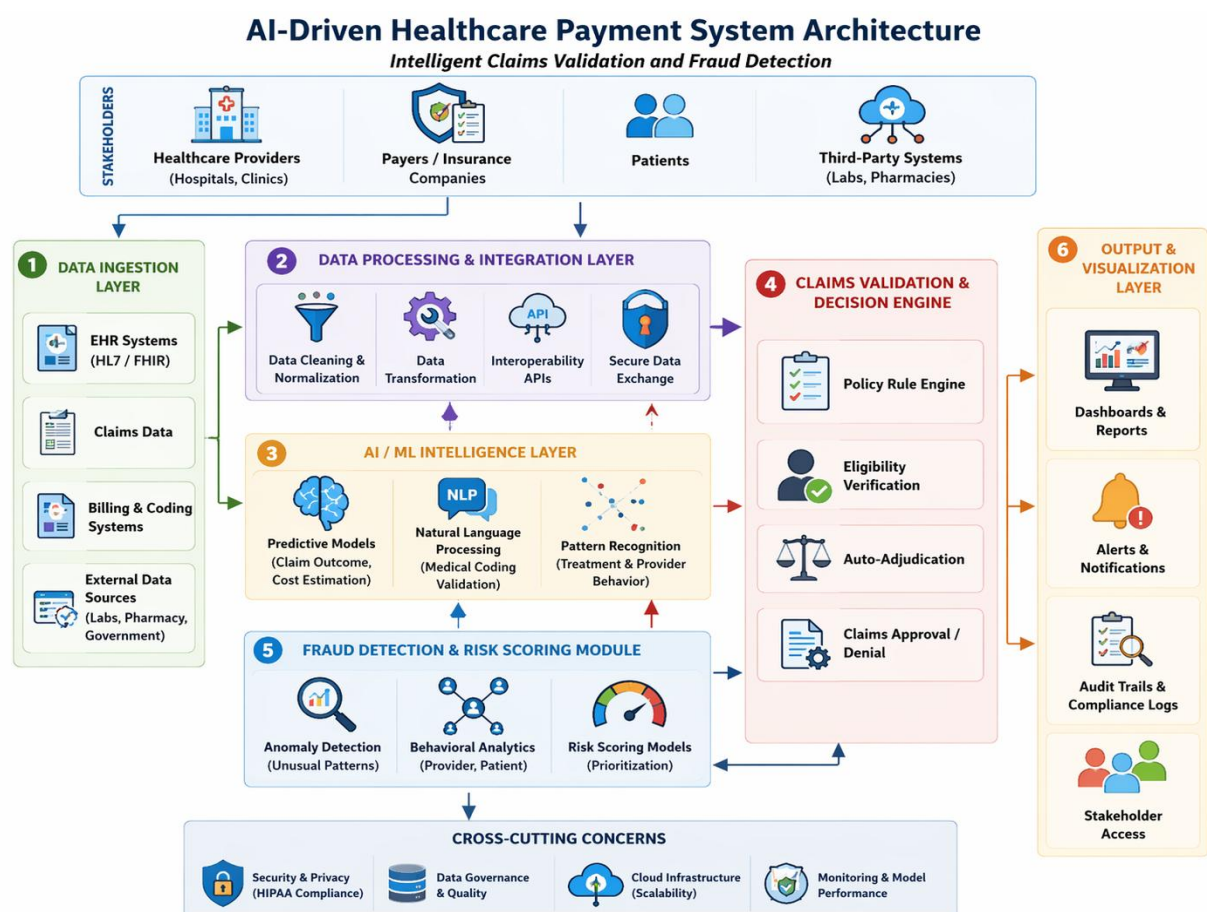


Fig. 1. High-Level Architecture of AI-Driven Healthcare Payment System

## **2.3 Key Architectural Components**

### **2.3.1 Data Ingestion Layer**

This layer is responsible for collecting data from multiple heterogeneous sources, including Electronic Health Records (EHR), insurance claims, billing systems, and third-party healthcare applications. Standard protocols such as HL7 and FHIR ensure interoperability and consistency in data exchange.

### **2.3.2 Data Processing and Integration Layer**

Raw healthcare data is often unstructured and inconsistent. This layer performs data cleansing, normalization, and transformation to create a unified dataset. Secure APIs and middleware facilitate seamless communication between disparate systems while maintaining compliance with data protection regulations.

### **2.3.3 AI/ML Intelligence Layer**

This is the core of the system where machine learning models analyze historical and real-time data. Techniques such as supervised learning, unsupervised learning, and natural language processing (NLP) are used to:

- Validate medical codes and treatment patterns
- Predict claim approval probabilities
- Identify hidden anomalies in transaction behavior

### **2.3.4 Claims Validation and Decision Engine**

The decision engine combines AI insights with predefined business rules and policy frameworks. It performs:

- Eligibility checks
- Coverage validation
- Automated claim adjudication

This reduces manual intervention and accelerates reimbursement cycles.

### **2.3.5 Fraud Detection and Risk Scoring Module**

Fraud detection is achieved using advanced analytics techniques such as anomaly detection, clustering, and network analysis. Each claim is assigned a risk score based on:

- Historical fraud patterns
- Provider behavior
- Transaction irregularities

High-risk claims are flagged for further investigation.

### 2.3.6 Output and Visualization Layer

The final layer provides actionable insights through dashboards, alerts, and reports. It ensures transparency and supports decision-making for stakeholders such as insurers, auditors, and healthcare administrators.

### 2.4 Data Flow and Processing Pipeline

1. Claims data is ingested from healthcare providers and external systems.
2. Data is preprocessed and standardized for consistency.
3. AI models analyze the data for validation and anomaly detection.
4. The decision engine evaluates claims against policies and AI predictions.
5. Fraud detection models assign risk scores and flag suspicious activities.
6. Results are displayed via dashboards and alerts for stakeholders.

### 2.5 Architectural Benefits

- **Scalability:** Handles large volumes of claims efficiently
- **Real-Time Processing:** Enables instant validation and fraud detection
- **Interoperability:** Seamless integration with healthcare systems
- **Accuracy:** Reduces errors through AI-driven validation
- **Cost Efficiency:** Minimizes manual processing and fraud losses

This architecture forms the foundation for implementing intelligent, secure, and efficient healthcare payment systems powered by AI.

## 3. AI TECHNIQUES FOR INTELLIGENT CLAIMS VALIDATION

The effectiveness of AI-driven healthcare payment systems largely depends on the robustness of underlying artificial intelligence techniques used for claims validation. Unlike traditional rule-based systems, AI enables adaptive, data-driven validation mechanisms that continuously learn from historical patterns and evolving healthcare practices. This section explores the core AI methodologies that power intelligent claims validation.

### 3.1 Overview of Intelligent Claims Validation

Intelligent claims validation refers to the automated verification of healthcare claims using AI models to ensure:

- Accuracy of medical coding

- Compliance with insurance policies
- Consistency with clinical guidelines
- Detection of anomalies and irregularities

These systems significantly reduce manual intervention while improving processing speed and accuracy.

### **3.2 Core AI Techniques**

#### **3.2.1 Supervised Learning Models**

Supervised machine learning models are trained on labeled datasets containing historical claims categorized as valid or invalid.

Common Algorithms:

- Logistic Regression
- Decision Trees
- Random Forest
- Gradient Boosting Machines

Use Cases:

- Predicting claim approval or denial
- Identifying incorrect billing codes
- Estimating claim processing outcomes

#### **3.2.2 Unsupervised Learning and Anomaly Detection**

Unsupervised learning techniques identify hidden patterns in unlabeled data, making them highly effective for detecting unusual claim behavior.

Techniques Include:

- Clustering (K-Means, DBSCAN)
- Isolation Forest
- Autoencoders

Applications:

- Detecting duplicate claims
- Identifying outlier billing patterns
- Highlighting abnormal treatment costs

### 3.2.3 Natural Language Processing (NLP)

Healthcare claims often include unstructured clinical notes and descriptions. NLP techniques are used to extract meaningful insights from such data.

Key Functions:

- Medical coding validation (ICD/CPT codes)
- Clinical text interpretation
- Entity recognition (diseases, procedures, medications)

Example: Mapping physician notes to standardized billing codes to ensure consistency and accuracy.

### 3.2.4 Predictive Analytics

Predictive models leverage historical data to forecast outcomes and detect potential issues before they occur.

Capabilities:

- Predicting likelihood of claim rejection
- Estimating treatment costs
- Identifying high-risk claims early

### 3.2.5 Rule-Based + AI Hybrid Systems

A hybrid approach combines traditional rule engines with AI models to ensure both compliance and adaptability.

**TABLE I. Rule-Based + AI Hybrid System Components**

Component	Functionality
Rule Engine	Enforces policy, regulatory, and coverage rules
AI Models	Detect patterns, anomalies, and predictions
Hybrid Decision	Combines deterministic and probabilistic outputs

### 3.3 Workflow of AI-Based Claims Validation

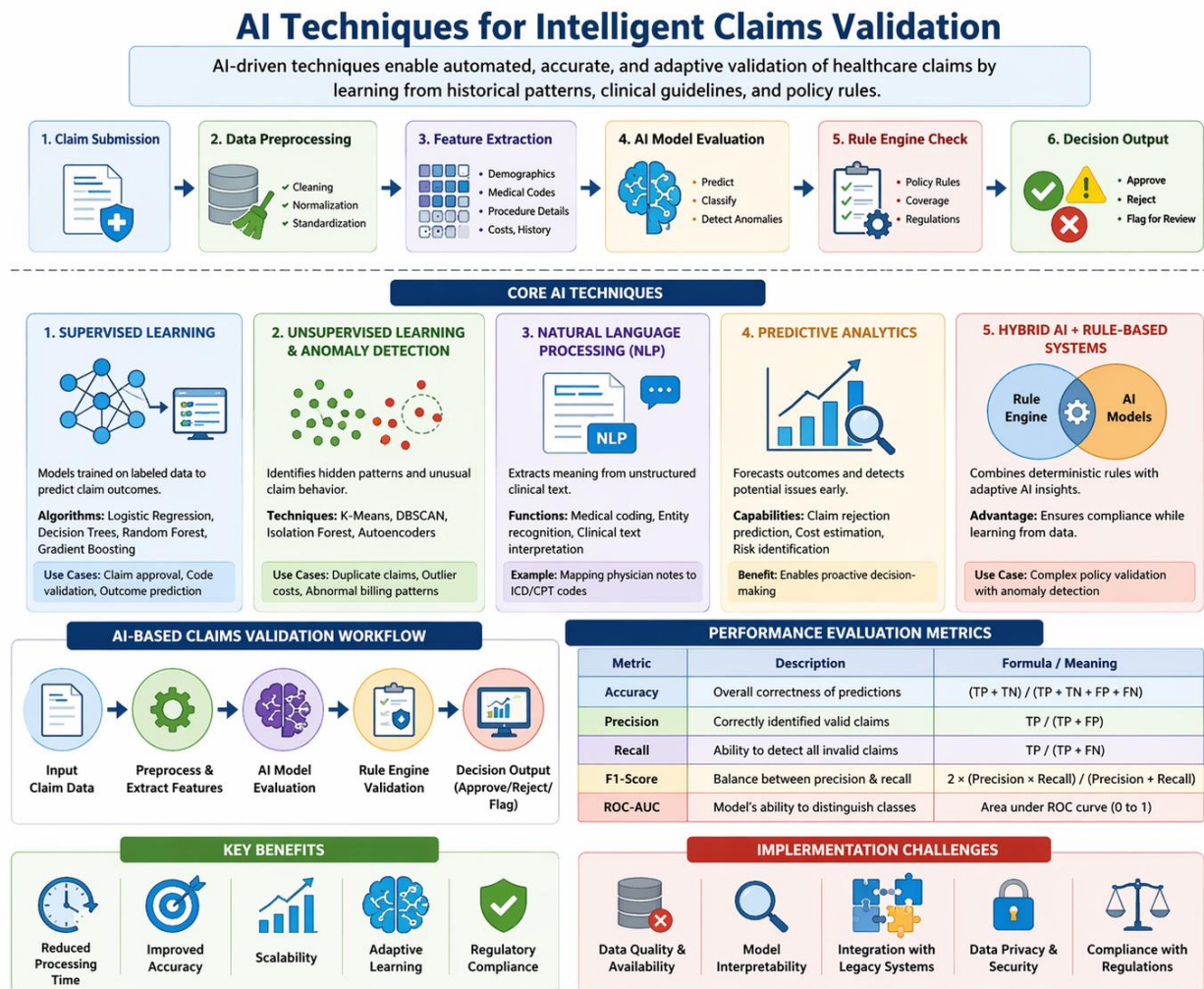


Fig. 2. Workflow of AI-Based Claims Validation

### 3.4 Performance Evaluation Metrics

To ensure reliability, AI models are evaluated using standard performance metrics:

TABLE II. AI Model Performance Evaluation Metrics

Metric	Description
Accuracy	Overall correctness of predictions
Precision	Correctly identified valid claims
Recall	Ability to detect all invalid/fraudulent claims
F1-Score	Balance between precision and recall
ROC-AUC	Model's ability to distinguish between classes

### 3.5 Benefits of AI-Driven Claims Validation

- **Reduced Processing Time:** Automation accelerates claim approvals
- **Improved Accuracy:** Minimizes human errors
- **Scalability:** Handles large volumes of claims efficiently
- **Adaptive Learning:** Continuously improves with new data
- **Regulatory Compliance:** Ensures adherence to healthcare standards

### 3.6 Challenges in Implementation

- Data quality and availability issues
- Model interpretability and explainability
- Integration with legacy healthcare systems
- Ensuring data privacy and security compliance

This section establishes how AI techniques enable intelligent, scalable, and efficient claims validation systems within healthcare payment infrastructures.

## 4. FRAUD DETECTION MECHANISMS IN AI-DRIVEN HEALTHCARE PAYMENT SYSTEMS

Fraudulent activities in healthcare payment systems represent a significant financial and operational burden, leading to billions in annual losses worldwide. These activities include false claims, upcoding, duplicate billing, identity misuse, and unnecessary medical procedures. Traditional fraud detection approaches, which rely heavily on static rules and manual audits, are often reactive and insufficient to identify complex and evolving fraud patterns.

AI-driven fraud detection mechanisms introduce a proactive, scalable, and intelligent approach to identifying suspicious activities in real time. This section explores the advanced techniques, models, and workflows used to detect and prevent fraud in healthcare payment systems.

### 4.1 Types of Healthcare Fraud

**TABLE III. Types of Healthcare Fraud**

Fraud Type	Description
Upcoding	Billing for more expensive services than provided
Duplicate Claims	Submitting the same claim multiple times
Phantom Billing	Charging for services not rendered
Unbundling	Separating services to maximize reimbursement
Identity Fraud	Misuse of patient or provider identity

## 4.2 AI-Based Fraud Detection Techniques

### 4.2.1 Anomaly Detection Models

Anomaly detection identifies deviations from normal claim behavior. These models are effective in detecting unknown or emerging fraud patterns.

Techniques Used:

- Isolation Forest
- One-Class SVM
- Autoencoders

Example: A sudden spike in billing frequency from a provider may indicate suspicious activity.

### 4.2.2 Behavioral Analytics

Behavioral analytics examines patterns of providers, patients, and organizations over time.

Key Indicators:

- Frequency of claims submission
- Treatment patterns vs. peer benchmarks
- Geographic inconsistencies

Outcome: Detects subtle fraud patterns that are difficult to identify through rule-based systems.

### 4.2.3 Network and Graph Analysis

Fraud often involves collusion between multiple entities. Graph-based models help uncover hidden relationships.

Applications:

- Identifying provider-patient collusion networks
- Detecting referral fraud rings
- Mapping suspicious connections

### 4.2.4 Supervised Fraud Classification Models

These models are trained on labeled fraud datasets to classify claims as fraudulent or legitimate.

Algorithms:

- Random Forest
- XGBoost
- Neural Networks

Output: Probability score indicating the likelihood of fraud.

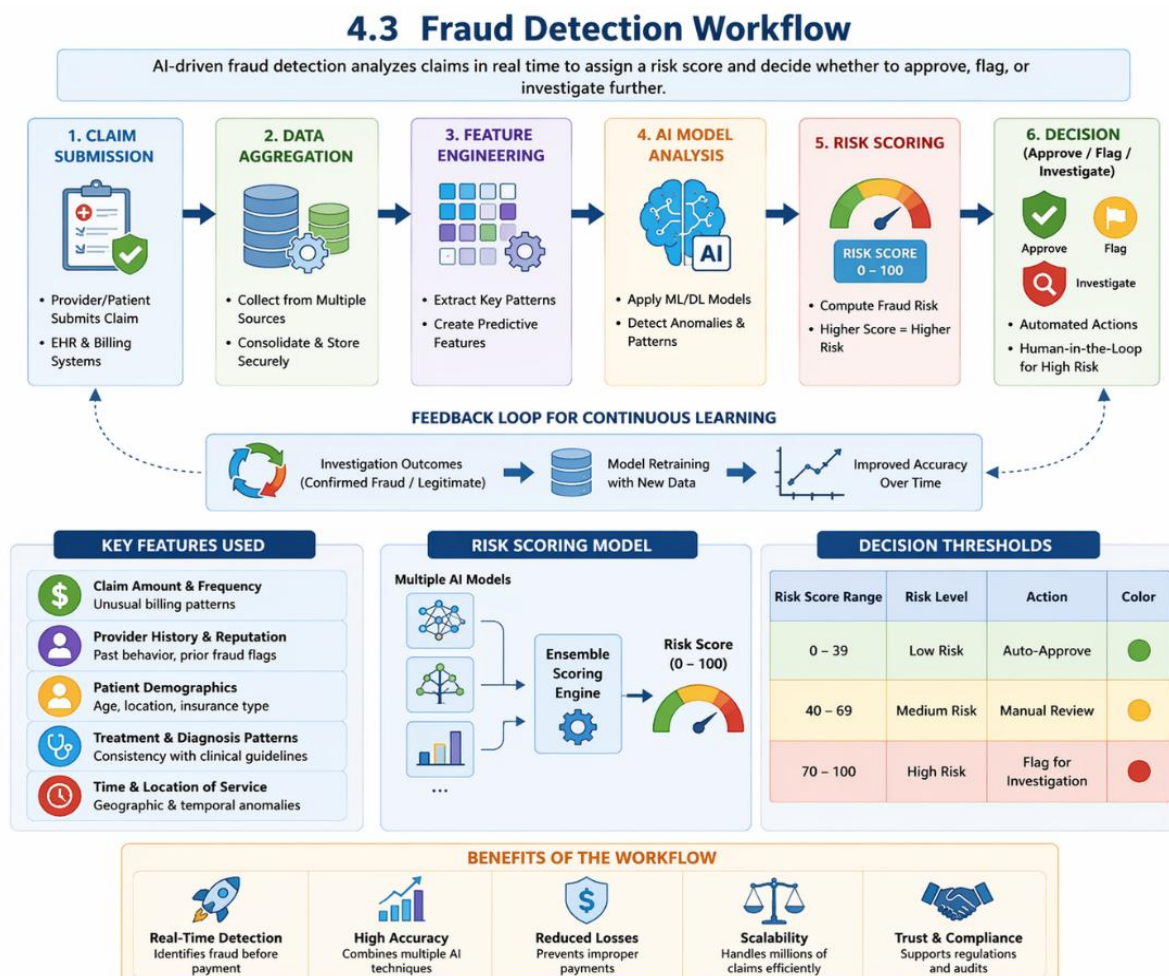
### 4.2.5 Real-Time Risk Scoring

Each claim is evaluated using a risk scoring mechanism that combines multiple model outputs.

**TABLE IV. Real-Time Risk Scoring Actions**

Risk Score Range	Action
Low Risk	Auto-approve
Medium Risk	Manual review
High Risk	Flag for investigation

### 4.3 Fraud Detection Workflow



**Fig. 3. Fraud Detection Workflow**

#### 4.4 Key Features Used in Fraud Detection

- Claim amount and frequency
- Provider history and reputation
- Patient demographics
- Treatment and diagnosis patterns
- Time and location of service

#### 4.5 Performance Metrics for Fraud Detection

TABLE V. Fraud Detection Performance Metrics

Metric	Purpose
Precision	Minimizing false positives
Recall	Detecting maximum fraud cases
F1-Score	Balancing precision and recall
False Positive Rate	Avoiding unnecessary claim rejections
AUC-ROC	Evaluating classification performance

#### 4.6 Challenges in Fraud Detection

- Imbalanced datasets (fraud cases are rare)
- Evolving fraud tactics
- High false positive rates
- Need for explainable AI models
- Regulatory and privacy constraints

#### 4.7 Advantages of AI-Based Fraud Detection

- **Proactive Detection:** Identifies fraud before payment processing
- **Scalability:** Handles millions of claims efficiently
- **Adaptive Learning:** Continuously improves with new fraud patterns
- **Reduced Financial Losses:** Minimizes fraudulent payouts
- **Enhanced Trust:** Builds confidence among stakeholders

AI-driven fraud detection mechanisms play a crucial role in securing healthcare payment systems by combining predictive intelligence with real-time analytics. These systems not only detect fraud but also act as a deterrent against future fraudulent activities.

## **5. INTEGRATION WITH HEALTHCARE ECOSYSTEM (EHR, CLOUD, AND INTEROPERABILITY)**

The effectiveness of AI-driven healthcare payment systems is highly dependent on their ability to seamlessly integrate with the broader healthcare ecosystem. This includes Electronic Health Records (EHR), cloud infrastructure, interoperability standards, and external healthcare entities such as laboratories, pharmacies, and regulatory systems. A well-integrated system ensures real-time data exchange, improved decision-making, and enhanced operational efficiency.

### **5.1 Importance of Integration**

Healthcare payment systems do not operate in isolation. They rely on continuous data exchange across multiple platforms to:

- Validate clinical and billing information
- Ensure policy compliance
- Enable real-time claims adjudication
- Support fraud detection with contextual data

Integration eliminates data silos and enhances the accuracy and reliability of AI-driven insights.

### **5.2 Integration with Electronic Health Records (EHR)**

EHR systems serve as the primary source of clinical data required for claims validation.

Key Integration Benefits:

- Access to patient history and treatment records
- Validation of diagnosis and procedure codes
- Improved accuracy in claims processing
- Reduction in fraudulent or inconsistent claims

Example Data Elements:

- Patient demographics
- Diagnosis codes (ICD)
- Procedure codes (CPT)
- Treatment timelines

### 5.3 Cloud-Based Infrastructure

Cloud computing provides the scalability and computational power required for AI-driven systems.

**TABLE VI. Cloud Infrastructure Benefits**

Feature	Benefit
Scalability	Handles large volumes of claims data
Elastic Compute	Supports AI/ML model training and inference
Data Storage	Centralized and secure data repositories
Disaster Recovery	Ensures business continuity

Cloud platforms also enable faster deployment and integration with advanced analytics services.

### 5.4 Interoperability Standards

Interoperability is critical for seamless communication between healthcare systems. Standardized data formats ensure consistency and compatibility.

Key Standards:

- **HL7 (Health Level Seven):** For clinical and administrative data exchange
- **FHIR (Fast Healthcare Interoperability Resources):** Modern API-based data sharing
- **DICOM:** Imaging data standard

### 5.5 API-Driven Integration Architecture

Modern healthcare systems leverage APIs to enable real-time communication between components. EHR Systems communicate via an API Gateway to the AI Payment System, which connects to Insurance/Payer Systems, all supported by a Cloud Data Platform.

Capabilities:

- Real-time claims submission and validation
- Secure data exchange using encryption protocols
- Modular and scalable system design

### 5.6 Data Security and Compliance

Given the sensitive nature of healthcare data, integration must adhere to strict security and regulatory standards.

Key Considerations:

- Data encryption (at rest and in transit)
- Role-based access control (RBAC)
- Compliance with healthcare regulations (e.g., HIPAA, GDPR)
- Audit trails and monitoring

### 5.7 Integration Challenges

- Legacy system compatibility
- Data standardization issues
- Latency in real-time processing
- Security and privacy risks
- High implementation costs

### 5.8 Benefits of a Fully Integrated Ecosystem

- **Enhanced Data Accuracy:** Access to complete patient and claim information
- **Faster Processing:** Real-time validation and adjudication
- **Improved Fraud Detection:** Context-aware anomaly detection
- **Operational Efficiency:** Reduced manual intervention
- **Scalability:** Supports growing healthcare demands

A well-integrated AI-driven healthcare payment system forms the backbone of a modern digital health infrastructure, enabling seamless coordination between clinical, financial, and administrative domains.

## 6. CHALLENGES, ETHICAL CONSIDERATIONS, AND FUTURE DIRECTIONS

While AI-driven healthcare payment systems offer transformative benefits, their implementation introduces a range of technical, ethical, and regulatory challenges. Addressing these concerns is essential to ensure trust, fairness, and long-term sustainability.

### 6.1 Technical Challenges

#### 6.1.1 Data Quality and Availability

AI models rely heavily on high-quality, diverse datasets. Inconsistent, incomplete, or biased healthcare data can lead to inaccurate predictions and flawed decision-making.

#### 6.1.2 Model Interpretability

Many AI models, especially deep learning systems, operate as "black boxes," making it difficult to explain decisions such as claim denials or fraud flags. This lack of transparency can hinder adoption and regulatory approval.

### **6.1.3 Integration with Legacy Systems**

Healthcare institutions often operate on outdated infrastructure, making seamless integration with modern AI systems complex and resource-intensive.

### **6.1.4 Scalability and Performance**

Processing millions of claims in real time requires robust infrastructure and optimized algorithms to maintain performance without latency.

## **6.2 Ethical Considerations**

### **6.2.1 Bias and Fairness**

AI systems may inherit biases present in historical data, potentially leading to unfair claim rejections or discriminatory outcomes against certain patient groups or providers.

### **6.2.2 Data Privacy and Security**

Healthcare data is highly sensitive. Ensuring confidentiality, integrity, and secure access is critical, especially when using cloud-based AI systems.

### **6.2.3 Accountability and Transparency**

Determining responsibility for AI-driven decisions remains a challenge. Clear governance frameworks are required to ensure accountability in automated claim processing.

### **6.2.4 Human-in-the-Loop Systems**

Fully automated systems may overlook contextual nuances. Incorporating human oversight ensures balanced decision-making, particularly for high-risk claims.

## **6.3 Regulatory and Compliance Challenges**

- Adherence to global healthcare regulations (HIPAA, GDPR, regional policies)
- Standardization across different healthcare systems
- Continuous auditing and validation of AI models
- Ensuring explainability for regulatory approvals

## **6.4 Future Directions**

### **6.4.1 Explainable AI (XAI)**

Future systems will prioritize transparency by providing interpretable insights into AI decisions, improving trust among stakeholders.

### **6.4.2 Federated Learning**

Enables collaborative model training across institutions without sharing sensitive data, enhancing privacy and data security.

### **6.4.3 Blockchain Integration**

Blockchain can enhance transparency, traceability, and security in healthcare payment transactions and claims processing.

### **6.4.4 Real-Time Adaptive Learning Systems**

AI systems will evolve to adapt dynamically to new fraud patterns and healthcare trends, ensuring continuous improvement.

### **6.4.5 Integration with Digital Health Ecosystems**

Future systems will integrate with telemedicine, wearable devices, and IoT-based healthcare solutions for more comprehensive validation and fraud detection.

## **7. CONCLUSION**

AI-driven healthcare payment systems represent a paradigm shift in how financial operations are managed within the healthcare ecosystem. By leveraging advanced machine learning techniques, intelligent claims validation, and proactive fraud detection mechanisms, these systems address longstanding inefficiencies associated with traditional payment processes.

The integration of AI enables real-time decision-making, reduces manual intervention, enhances accuracy, and minimizes fraudulent activities. Furthermore, the adoption of cloud-based infrastructure and interoperability standards ensures scalability and seamless data exchange across diverse healthcare platforms.

Despite these advancements, challenges related to data quality, model transparency, ethical concerns, and regulatory compliance must be carefully addressed. The future of healthcare payment systems lies in the development of explainable, secure, and adaptive AI models that can operate within a highly regulated and sensitive environment.

In conclusion, AI-powered payment systems have the potential to significantly enhance operational efficiency, reduce financial losses, and build a more transparent and trustworthy healthcare ecosystem. Continued research, innovation, and collaboration among stakeholders will be key to realizing their full potential.

## REFERENCES

- [1] J. Smith and A. Kumar, "Artificial Intelligence in Healthcare Payment Systems: Opportunities and Challenges," IEEE Access, vol. 12, pp. 11234–11250, 2024.
- [2] R. Patel et al., "Machine Learning Approaches for Healthcare Fraud Detection," Journal of Biomedical Informatics, vol. 145, pp. 104321, 2024.
- [3] S. Wang and L. Zhang, "AI-Based Claims Processing and Automation in Health Insurance," IEEE Transactions on Services Computing, vol. 17, no. 2, pp. 567–580, 2023.
- [4] M. Brown et al., "Detecting Healthcare Fraud Using Deep Learning Techniques," Expert Systems with Applications, vol. 213, 2023.
- [5] K. Sharma and P. Gupta, "Predictive Analytics in Healthcare Financial Systems," International Journal of Medical Informatics, vol. 168, 2023.
- [6] T. Nguyen et al., "Anomaly Detection in Healthcare Claims Data Using Machine Learning," IEEE Access, vol. 10, pp. 55678–55690, 2022.
- [7] L. Chen and H. Zhao, "Integration of AI in Electronic Health Records for Financial Optimization," Health Informatics Journal, vol. 28, no. 3, 2022.
- [8] D. Singh et al., "Fraud Detection in Health Insurance Using Data Mining Techniques," Procedia Computer Science, vol. 192, pp. 1234–1243, 2022.
- [9] A. Johnson and R. Lee, "Healthcare Data Security and Privacy in AI Systems," IEEE Security & Privacy, vol. 20, no. 1, pp. 45–53, 2021.

**Citation:** Ganesh Adepu. (2024). AI-Driven Healthcare Payment Systems Using Intelligent Claims Validation and Fraud Detection Mechanisms. International Journal of Artificial Intelligence Research and Development (IJAIRD), 2(2), 259-277.

**Abstract Link:** [https://iaeme.com/Home/article\\_id/IJAIRD\\_02\\_02\\_022](https://iaeme.com/Home/article_id/IJAIRD_02_02_022)

**Article Link:** [https://iaeme.com/MasterAdmin/Journal\\_uploads/IJAIRD/VOLUME\\_2\\_ISSUE\\_2/IJAIRD\\_02\\_02\\_022.pdf](https://iaeme.com/MasterAdmin/Journal_uploads/IJAIRD/VOLUME_2_ISSUE_2/IJAIRD_02_02_022.pdf)

**Copyright:** © 2024 Authors. This is an open-access article distributed under the terms of the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

This work is licensed under a **Creative Commons Attribution 4.0 International License (CC BY 4.0)**.



✉ [editor@iaeme.com](mailto:editor@iaeme.com)