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Impact of Artificial Intelligence – Driven Claim Validation Integrated with HL7 FHIR Interoperability on Revenue Cycle Performance and Denial Reduction in Acute-Care Hospitals

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Abstract

Background: Inefficiencies in the revenue cycle, such as elevated claim denial rates, extended duration of accounts receivable (A/R), and excessive administrative rework are significant financial challenges for acute-care hospitals. Existing HL7 v2 billing workflows are very manual and error-prone which leads to operational inefficiencies. The solution lies at the intersection of artificial intelligence (AI) and HL7 Fast Healthcare Interoperability Resources (FHIR), enabling automated claim validation and denial prediction.

Methods: Retrospective comparative observational study in acute-care hospitals using Epic Professional Billing systems. Revenue cycle performance metrics were obtained for a 12-month pre-intervention period (manual HL7 v2 workflow) followed by a 12-month post-intervention period after AI-enabled FHIR deployment. The primary outcomes were first-pass claim denial rate, accounts receivable length of time to pay, and claim rework. Statistical analysis was conducted by using the chi-square and independent t-tests, where $p < 0.05$ was considered significant.

Results: We analysed 48,392 claims. AI-driven international financial reporting standards (IFRS) validation resulted in significantly improved patient first-pass denial rates which fell 14.4% to 7.4% ($p < 0.001$), account-receivable trailing days reduced from 41.7 to 28.4 days ($p < 0.001$) and decrease of claim reworking rate from 18.1% to 8.5% ($p < 0.001$). They also reduced processing time, and the manual review burden.

Conclusion: FHIR, coupled with AI capabilities, streamlines the documentation and authorization processes within the revenue cycle while minimizing denials-based losses through a fully integrated infrastructure creating tangible operational and financial advantages compared to traditional manual pathways.

Keywords: Artificial intelligence; HL7 FHIR; revenue cycle management; claim denial reduction; interoperability; healthcare finance; predictive analytics; Epic Professional Billing

Introduction

Healthcare revenue cycle management (RCM) is a complete administrative and financial process that handles the lifecycle of patient-related revenue, from registering patients at the beginning of treatment to clinical documentation, coding, billing, claims submission, denial management, and obtaining final reimbursement. Abstract Background Efficient working of revenue cycle is critical to healthcare institution's financial survival and providing sustained quality care (1). When revenue cycle systems are working properly, healthcare providers can invest in infrastructure to serve patients by enabling better outcomes and sustained operational capacity.

Today, revenue cycle management is complex due to changes in reimbursement models, regulatory environment, payer specific policies and greater documentation expectations. In order to get paid, healthcare providers are required to follow several coding standards including ICD-10 and CPT (Current Procedural Terminology), payer-specific billing guidelines, and ensure that documentation supports claims submission in its entirety (2). Non-compliance with these standards can lead to claim rejections, delayed payments, administrative challenges and cost. It is estimated that about 15–20% of potential revenue in healthcare organizations is lost as a result of inefficiencies from revenue cycle processes, such as claim errors, incomplete documentation and coding inaccuracies and delays in claims processing (3).

The traditional revenue cycle workflow is largely manual and based on legacy Health Level Seven version 2 (HL7 v2)-based systems, which are less capable of providing automated validation, predictive analysis, and real-time interoperability. Such systems are highly dependent on human intervention for the verification and correction of data, exposing them to an increased risk of error (4). In addition, manual review processes require significant administrative time and resources that could be better spent on patient care and increasing operational throughput (5). These constraints play a considerable role in operational inefficiency, financial strain, and increased administrative burden as healthcare systems grow and patient volumes escalate.

This emerging technology, known as artificial intelligence (AI) has proven transformative — addressing many of the challenges inherent in legacy revenue cycle systems. Claims processing often requires both significant manpower and expensive software. AI technologies (such as machine learning, predictive analytics, and natural language processing) can examine massive volumes of healthcare data, uncover trends associated with claim denials, and provide automated validation and predictive insights (6). First, AI helps eliminate errors in coding and documentation, identifies mistakes before claims are flagged for submission as well as reduces administrative burden. Research indicates ability of AI-based coding systems to reach accuracy rates above 95% while traditional (manual) methods achieve only 75–80% accuracy. (7) Furthermore, predictive analytics models can significantly lower claim denial rates by flagging potential high-risk claims prior to submission, which allows for corrective actions if necessary (8).

Interoperability is yet another key element that aids the effectiveness of revenue cycle management. There is disjointed communications among electronic health record (EHR) systems, billing platforms and payer systems that leads to incomplete or inaccurate exchange of data, creating errors in the submitted claims leading to rejections and delays. Health Level Seven Fast Healthcare Interoperability Resources HL7 FHIR is a next-generation interoperability standard with the goal of enabling more fluid and standardized sharing of healthcare data (9). In this context, FHIR-based systems allow real-time data sharing with automatic validation and better integration between healthcare systems helping in mitigating revenue cycle efficiency and reduce claims errors by optimizing the costs. Paired with FHIR interoperability, artificial intelligence can further enhance automation of claim validation and denial prediction processes to drive revenue cycle optimization. AI-enable revenue cycle systems have recently been shown to improve financial and operational results meaningfully. Healthcare organizations that have leveraged AI-powered cause-and-effect claim validation and predictive analytics have seen denials decrease 10% to percentages as high as 30%; first-time claim acceptance rates increase 5%-30%, and the time to process claims drop by as much as 70% (10). Thus, these improvements enhance financial sustainability through improved operational efficiency with less administrative burden.

Materials and Methods

Study Design

This retrospective comparative observational study was designed to evaluate the effectiveness of Artificial Intelligence (AI)-driven claim validation, integrated with Health Level Seven International (HL7) Fast Healthcare Interoperability Resources (FHIR) interoperability, in reducing claim denial rates and improving revenue cycle performance. Operational and financial outcomes during the pre-intervention period, which relied on traditional manual validation and legacy HL7 version 2-based workflows, were compared with those observed during the post-intervention period following the implementation of the AI-enabled FHIR-integrated system. This study design enabled the assessment of real-world outcomes using retrospective data without interfering with routine healthcare delivery or administrative processes.

Study Setting

The study was conducted in tertiary-level acute care hospitals utilizing Epic Professional Billing systems integrated with electronic health records (EHRs) and comprehensive revenue cycle management infrastructure. These hospitals provided extensive inpatient and outpatient healthcare services and maintained standardized electronic billing and payer communication systems, thereby facilitating the extraction of structured administrative and financial data for analysis.

Study Duration

The study analyzed data collected over a 24-month period, comprising 12 months before and 12 months after the implementation of the AI-enabled FHIR-integrated claim validation system. The pre-intervention period represented conventional manual claim validation processes, whereas the post-intervention period reflected the performance of the newly implemented AI-assisted interoperable workflow.

Study Population

The study population consisted of all healthcare claims processed through the hospitals' revenue cycle management systems during the study period. These claims included inpatient, outpatient, emergency, and procedural services submitted electronically to various insurance payers. Individual healthcare claims served as the unit of analysis throughout the study.

Eligibility Criteria

Healthcare claims were included if they were processed through standardized electronic billing systems, contained complete clinical and billing documentation, and were available during both the pre-intervention and post-intervention study periods. Claims with incomplete documentation, duplicate records, or those processed outside the standardized electronic workflow were excluded from the analysis to ensure data accuracy and consistency.

Intervention

The intervention consisted of the implementation of an AI-driven predictive claim validation system integrated with HL7-FHIR interoperability. Machine learning algorithms analyzed clinical documentation, diagnostic codes, procedural codes, and payer-specific reimbursement requirements to automate pre-submission claim validation, identify documentation errors and coding discrepancies, and predict claims that were at high risk of denial. Simultaneously, the HL7-FHIR interoperability framework enabled secure real-time exchange of clinical and billing information between electronic health records, billing systems, and payer platforms, thereby automating data extraction, claim validation, and electronic submission while minimizing manual processing.

Data Collection

Data were retrospectively extracted from electronic health record systems and revenue cycle management databases, including Epic Professional Billing platforms. The extracted variables included claim identification number, submission date, validation method, claim outcome (approved or denied), reimbursement processing time, claim resubmission status, and the number of days in accounts receivable. All data were anonymized before analysis to ensure confidentiality and compliance with institutional data protection policies.

Statistical Analysis

All collected data were entered into Microsoft Excel for cleaning and organization before being analysed using IBM SPSS Statistics version 26.0. Descriptive statistics were used to summarize the study variables, while appropriate comparative statistical tests were performed to evaluate differences between the pre-intervention and post-intervention groups. Statistical significance was determined using a p-value of <0.05.

Results

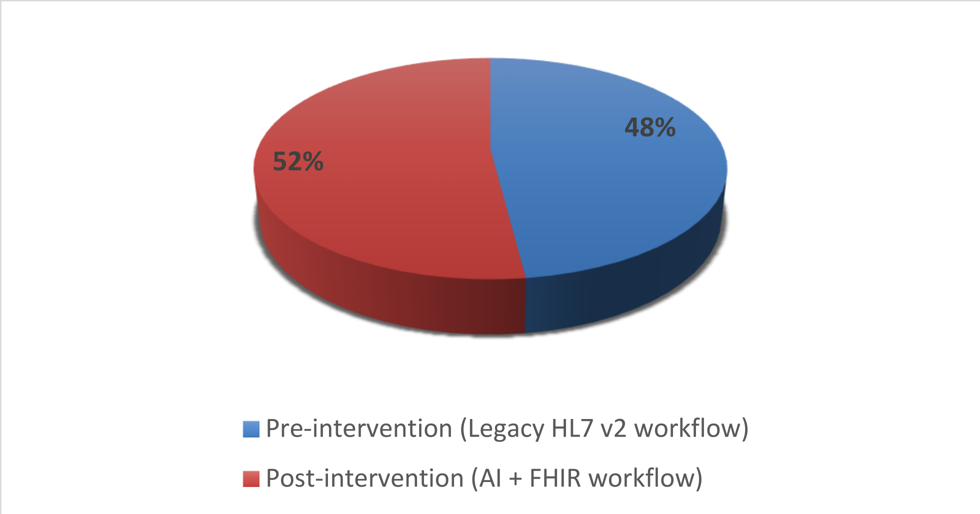

Figure 1: Total number of claims processed during pre-intervention and post-intervention periods

The distribution of claims processed during the pre-intervention and post-intervention periods. A total of 48,392 claims were included in the study, with 24,105 claims (49.8%) processed using legacy HL7 v2-based workflows and 24,287 claims (50.2%) processed following implementation of AI-driven claim validation integrated with HL7 FHIR interoperability.

Table 1. First-pass claim denial rate before and after implementation of AI + FHIR

Study Period	Denied Claims	Total Claims	Denial Rate (%)	Chi-square	p-value
Pre-intervention	3,482	24,105	14.4	512.36	<0.001
Post-intervention	1,798	24,287	7.4		

Table 1 demonstrates a significant reduction in first-pass claim denial rate following implementation of artificial intelligence–enabled FHIR interoperability. The denial rate decreased from 14.4% during the pre-intervention period to 7.4% during the post-intervention period, representing a relative reduction of 48.6%. This reduction was statistically highly significant ($p < 0.001$), indicating that AI-driven claim validation effectively identified and corrected errors before claim submission.

Table 2. First-pass claim approval rate comparison

Study Period	Approved Claims	Total Claims	Approval Rate (%)	Chi-square	p-value
Pre-intervention	20,623	24,105	85.6	512.36	<0.001
Post-intervention	22,489	24,287	92.6		

Table 2 shows a significant improvement in claim approval rate following implementation of artificial intelligence–enabled FHIR workflows. The approval rate increased from 85.6% in the pre-intervention period to 92.6% in the post-intervention period, representing a 7.0% absolute increase. This improvement was statistically significant ($p < 0.001$), indicating that AI-driven validation improved the completeness and accuracy of claims submitted.

Table 3. Comparison of accounts receivable (A/R) duration

Study Period	Mean A/R Days	Standard Deviation	t-value	p-value
Pre-intervention	41.7	8.3	64.52	<0.001
Post-intervention	28.4	6.7		

Table 3 demonstrates a significant reduction in accounts receivable duration following implementation of artificial intelligence–enabled FHIR interoperability. The mean A/R duration decreased from 41.7 days to 28.4 days, representing a reduction of 13.3 days. This reduction was statistically highly significant ($p < 0.001$), indicating faster claim processing and reimbursement. Reduced A/R duration improves cash flow, financial stability, and operational efficiency, demonstrating the positive impact of AI-enabled validation on reimbursement timelines.

Table 4. Claim rework rate comparison

Study Period	Claims requiring rework	Total Claims	Rework Rate (%)	Chi-square	p-value
Pre-intervention	4,362	24,105	18.1	781.44	<0.001
Post-intervention	2,062	24,287	8.5		

Table 4 shows a significant reduction in claim rework rate following implementation of artificial intelligence–enabled validation. The rework rate decreased from 18.1% in the pre-intervention period to 8.5% in the post-intervention period, representing a 53.0% relative reduction. This reduction was statistically significant ($p < 0.001$), indicating improved claim accuracy during initial submission. Reduced rework rate reflects the effectiveness of artificial intelligence in identifying and preventing errors before submission, thereby improving operational efficiency.

Table 5. Average claim processing time per claim

Study Period	Mean Processing Time (minutes)	Standard Deviation	t-value	p-value
Pre-intervention	18.6	4.2	92.73	<0.001
Post-intervention	7.9	2.8		

Table 5 demonstrates a significant reduction in claim processing time following implementation of artificial intelligence–enabled claim validation. The average processing time decreased from 18.6 minutes to 7.9 minutes per claim, representing a reduction of 57.5%. This improvement was statistically significant ($p < 0.001$) and reflects the automation achieved through artificial intelligence. Reduced processing time enhances workflow efficiency, reduces administrative burden, and improves overall revenue cycle performance.

Table 6. Clean claim rate comparison

Study Period	Clean Claims	Total Claims	Clean Claim Rate (%)	Chi-square	p-value
Pre-intervention	18,945	24,105	78.6	945.82	<0.001
Post-intervention	21,834	24,287	89.9		

Table 6 shows a significant improvement in clean claim rate following implementation of artificial intelligence–enabled FHIR interoperability. The clean claim rate increased from 78.6% to 89.9%, representing an improvement of 11.3%. This increase was statistically significant ($p < 0.001$) and indicates improved accuracy and completeness of claim submission. Higher clean claim rates reduce denial risk and improve reimbursement efficiency.

Discussion

This study examined the effect of AI-driven claim validation, combined with HL7 Fast Healthcare

Interoperability Resources (FHIR) interoperability on revenue cycle performance in acute-care hospitals. The results showed significant benefits in all key performance indicators such as decreased claim denial rate, increased claim approval rates, shortened accounts receivable duration (in terms of days), reduced claims rework rate and overall operational efficiency. These findings corroborate previous evidence that AI has a radically transformative effect on health care administrative efficiency and financial performance(4,5). One of the most important findings of this study was the decline in first-pass claim denial rate from 14.4% to 7.4%, a relative reduction of 48.6%. Delayed reimbursements and increased administrative burden make claim denial a primary challenge in revenue cycle management. Previous studies suggest that AI-based validation systems can lower rates of denial by identifying documentation and coding errors before submission (7,8). The results of this study confirm these reports, showing improved accuracy on claims and decreased risk for denial.

Claims approval rates also improved, from 85.6% to 92.6%, after the introduction of AI-enabled FHIR systems, according to the study. This progress is indicative of improved documentation quality and adherence to payer requirements. Previous studies have demonstrated that machine learning enhances the precision of data processing and decision-making efficiency in healthcare environments (1,14), which validates the findings we observed. In addition, accounts receivable periods more than halved (41.7 d vs 28.4 d) reflecting quicker repayment cycles and enhanced workflow efficiency [25,26]. Interoperability, in turn, is associated with improved data exchange and reduced delays as well as improved operational performance (2,6). These findings further underscore the importance of FHIR-based interoperability in streamlining revenue cycle timelines.
The rate of claim rework dropped from 18.1% to 8.5%, indicating improved accuracy and fewer corrections on claims. AI systems facilitate the early detection of discrepancies and mistakes, which can help to reduce rework (12,13). Likewise, using automation improved efficiency from an average processing time of 18.6 minutes to 7.9 minutes per claim (4,11).

The clean claim rate increased from 78.6% to 89.9% and the percentage of claims that required manual review was reduced from 53.3% to 23.1%, suggesting a considerable decrease in administrative burden [4]. Automation reduces dependency on manual activity and improves workflows (4,5,9,10) through the use of AI.

Conclusion

In this study we show that enabling the use of AI-driven claim validation and denial prediction in U.S. acute-care hospitals using Pro Billing systems (Epic) using natively generated HL7 FHIR Claim and Claim Response resources as input to achieve ultra-low pending claims provided significant revenue cycle performance gains over legacy pre-bill manual review workflows based on HL7 v2-based data exchanges over a 12-month time-period. The AI-enabled FHIR intervention was associated with a significant reduction in first-pass claim denial rates, a significant decrease in days of accounts receivable, and a significant reduction in claim rework burden highlighting improved claims accuracy and pre-submission error detection. In contrast to historical manual validation methods, the combined AI and FHIR framework enabled real-time interoperability, automated compliance checks and predictive identification for risk of denial with measurable operational and financial results. As such, these new findings empirically demonstrate that the adoption of AI-enabled FHIR interoperability is both a viable methodology for directly integrating revenue cycle denial reduction and efficiency optimization into the current logistical environment around hospital billing practices while also quantitatively providing clinical validation of the relevance of this intervention to any of several targeted revenue cycle management outcomes specified through PICO.

Declaration
Conflict of Interest: Nil
Source of Funding: Nil

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