

AGENTIC AI FRAMEWORK FOR AUTOMATED CLINICAL CLAIMS VALIDATION AND DECISION SUPPORT

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Abstract

Healthcare organizations process millions of clinical insurance claims every day to support patient care, reimbursement, hospital operations, and regulatory compliance. The increasing complexity of healthcare services, evolving insurance policies, changing clinical guidelines, and diverse coding standards have significantly increased the challenges associated with manual claims validation. Traditional claims review processes rely heavily on human auditors who examine clinical documentation, diagnosis codes, procedure codes, insurance eligibility, policy coverage, medical necessity, and reimbursement rules before approving or rejecting claims. These manual workflows are time-consuming, expensive, inconsistent, and susceptible to human error, resulting in delayed reimbursements, claim denials, administrative burden, financial losses, and reduced operational efficiency. Recent advances in Artificial Intelligence have enabled intelligent automation of healthcare administrative processes through machine learning, natural language processing, knowledge graphs, and large language models. More recently, Agentic Artificial Intelligence has emerged as a transformative paradigm in which autonomous AI agents collaborate, reason, plan, retrieve knowledge, and execute complex tasks while interacting with multiple healthcare information systems. This paper

proposes an Agentic AI framework for automated clinical claims validation and decision support that integrates autonomous reasoning agents, clinical knowledge retrieval, policy interpretation, electronic health records, insurance databases, medical coding systems, and intelligent workflow orchestration into a unified decision-support architecture. The proposed framework continuously analyzes clinical documentation, diagnoses, treatment procedures, laboratory reports, physician notes, insurance policies, reimbursement guidelines, historical claim outcomes, and regulatory compliance requirements before generating evidence-based validation decisions. Multiple specialized AI agents collaborate to perform eligibility verification, medical necessity assessment, coding validation, fraud detection, policy compliance evaluation, reimbursement estimation, and recommendation generation. Contextual reasoning and explainable decision-making enable healthcare professionals and insurance reviewers to understand the rationale behind each validation outcome. Experimental evaluation using representative healthcare claim scenarios demonstrates that the proposed Agentic AI framework significantly improves claims validation accuracy, reduces processing time, minimizes false claim denials, enhances coding consistency, supports regulatory compliance, and

accelerates reimbursement workflows compared with conventional rule-based and manually supervised claims review systems. The proposed architecture provides a scalable, secure, and intelligent solution suitable for hospitals, insurance providers, healthcare administrators, government healthcare programs, and digital health ecosystems seeking to modernize clinical claims management through trustworthy autonomous artificial intelligence.

Keywords: Agentic Artificial Intelligence, Clinical Claims Validation, Healthcare Decision Support, Electronic Health Records, Medical Coding, Insurance Claims, Intelligent Agents, Explainable AI, Clinical Informatics, Healthcare Automation.

1. Introduction

Healthcare organizations process an enormous number of insurance claims every day to support reimbursement, regulatory compliance, hospital revenue management, and patient care. Clinical claims validation is a critical administrative function that determines whether submitted healthcare services satisfy medical necessity, insurance eligibility, clinical documentation requirements, reimbursement policies, and healthcare regulations. As healthcare delivery becomes increasingly complex with expanding electronic health records, evolving payer policies, multiple coding standards, and growing patient populations, traditional manual claims validation has become time-consuming, expensive, and prone to inconsistencies. Consequently, intelligent automation has become essential for improving the efficiency and reliability of modern healthcare claims management [1], [2].

Conventional clinical claims validation primarily relies on manual review performed by medical coders, insurance specialists, physicians, and healthcare administrators. Reviewers examine physician documentation, diagnosis codes, procedure codes, laboratory reports, imaging findings, medication histories, insurance policies, reimbursement rules, and regulatory guidelines before approving or rejecting claims. Although manual validation provides clinical oversight, differences in reviewer expertise, increasing workload, policy complexity, and continuously changing reimbursement requirements often result in coding errors, delayed reimbursements, unnecessary claim denials, administrative costs, and operational inefficiencies. Rule-based automation has improved workflow efficiency but remains limited when interpreting complex clinical narratives and dynamically evolving healthcare policies [3], [4].

Recent advances in Artificial Intelligence (AI), Large Language Models (LLMs), Natural Language Processing (NLP), Retrieval-Augmented Generation (RAG), and autonomous intelligent agents have significantly enhanced healthcare administrative automation. Unlike conventional machine learning systems that perform isolated prediction tasks, Agentic Artificial Intelligence enables multiple specialized autonomous agents to collaborate, reason, retrieve external knowledge, execute sequential workflows, and communicate across heterogeneous healthcare information systems. These intelligent agents can independently analyze physician notes, validate medical coding, interpret insurance policies, estimate

reimbursements, detect fraudulent claims, and generate explainable recommendations while coordinating their reasoning to produce accurate evidence-based decisions [5], [6].

Modern healthcare ecosystems require interoperability among Electronic Health Records (EHRs), Hospital Information Systems (HIS), Laboratory Information Management Systems (LIMS), Pharmacy Information Systems, insurance management platforms, clinical knowledge repositories, and regulatory databases. Secure API communication, cloud-native architectures, intelligent workflow orchestration, and explainable artificial intelligence enable autonomous agents to exchange information securely while maintaining regulatory compliance and protecting sensitive healthcare information. These technologies support scalable, transparent, and trustworthy decision-making throughout the clinical claims validation lifecycle [7], [8].

Although previous studies have investigated healthcare artificial intelligence, clinical decision support, natural language processing, healthcare automation, and large language models independently, comparatively limited research has integrated autonomous reasoning agents, collaborative workflow orchestration, contextual knowledge retrieval, medical coding validation, reimbursement estimation, fraud detection, and explainable decision support into a unified framework for clinical claims validation. Therefore, this research proposes an **Agentic AI Framework for Automated Clinical Claims Validation and Decision Support** that integrates collaborative intelligent agents, contextual reasoning, secure enterprise communication, healthcare knowledge retrieval, and explainable

decision-making to improve claims validation accuracy, reduce administrative workload, accelerate reimbursement processing, strengthen regulatory compliance, and enhance intelligent healthcare administration [9], [10].

2. Literature Survey

Pokala (2023) proposed a production-ready Retrieval-Augmented Generation and Agentic AI framework for healthcare claims processing and prior authorization. The study demonstrated that integrating autonomous reasoning with knowledge retrieval significantly improves healthcare administrative automation, reduces processing delays, and enhances evidence-based decision support. These concepts provide a strong foundation for collaborative Agentic AI systems supporting automated clinical claims validation [11].

Gummadi (2021) proposed a secure API lifecycle management framework integrating MuleSoft Secrets Manager for enterprise data protection. The research emphasized secure authentication, authorization, centralized credential management, and lifecycle governance across distributed enterprise applications. These concepts strengthen secure communication among autonomous healthcare agents, electronic health record systems, insurance platforms, and clinical knowledge repositories within the proposed framework [12].

Akinapalli (2024) introduced a predictive workload intelligence framework for optimizing large-scale cloud data warehousing environments. The study demonstrated that intelligent workload management improves computational efficiency, resource allocation, and distributed workflow execution. Similar

concepts support scalable orchestration of multiple autonomous AI agents operating simultaneously across complex healthcare information systems [13].

Kavuri (2023) investigated machine learning approaches for identifying software security vulnerabilities through intelligent behavioral analysis. Although developed for software security, the study emphasized continuous anomaly detection, adaptive learning, and intelligent monitoring. These concepts support secure deployment of Agentic AI systems responsible for handling sensitive healthcare information and automated administrative workflows [14].

Pokala (2022) proposed a practical MLOps framework for production-ready healthcare claims processing and revenue cycle optimization within payer organizations. The research demonstrated that continuous model monitoring, lifecycle management, automated deployment, and intelligent workflow optimization substantially improve operational efficiency and model reliability. These concepts directly support deployment of collaborative Agentic AI architectures in healthcare claims validation environments [15].

Kumar (2018) proposed a machine learning framework for optimizing manufacturing process parameters using intelligent predictive analytics. Although developed for manufacturing applications, the study demonstrated the effectiveness of machine learning for modeling complex relationships and supporting adaptive decision-making. Similar analytical principles can be extended to healthcare claims validation involving multidimensional clinical and administrative information [16].

Jiang, Huang, and Chen (2023) proposed a multi-agent artificial intelligence framework for clinical decision support in healthcare environments. Their study demonstrated that collaborative intelligent agents outperform isolated predictive models by coordinating reasoning across multiple healthcare tasks, improving decision consistency, transparency, and workflow efficiency. These concepts strongly support the proposed collaborative claims validation framework [17].

Zhang, Liu, and Wang (2024) investigated autonomous AI agents for intelligent healthcare workflow automation using coordinated planning, contextual reasoning, and adaptive execution. Experimental results demonstrated that autonomous collaboration among specialized agents significantly improves administrative efficiency, reduces manual intervention, and enhances decision quality within complex healthcare environments [18].

Singhal, Patel, and Verma (2024) presented an explainable artificial intelligence framework for automated clinical claims validation and fraud detection. Their research demonstrated that transparent AI-generated explanations improve reviewer confidence, facilitate regulatory auditing, and support reliable reimbursement decisions while maintaining accountability throughout healthcare administrative workflows [19].

Chen, Zhao, and Xu (2024) proposed an Agentic Large Language Model framework supporting intelligent healthcare administration through collaborative reasoning, contextual knowledge retrieval, secure enterprise integration, and adaptive workflow execution. Their research demonstrated that multiple specialized AI

agents significantly improve healthcare decision support compared with conventional standalone language models. The proposed framework extends these concepts by integrating clinical documentation analysis, medical coding validation, insurance policy interpretation, fraud detection, reimbursement estimation, explainable reasoning, and secure multi-agent collaboration into a unified architecture for automated clinical claims validation and decision support [20].

3. PROPOSED METHODOLOGY

The proposed Agentic AI framework is designed as an intelligent, collaborative, and context-aware architecture that automates clinical claims validation and supports evidence-based reimbursement decisions across modern healthcare ecosystems. Unlike traditional claims processing systems that depend on static business rules and sequential manual verification, the proposed framework employs multiple autonomous artificial intelligence agents that collaborate to analyze clinical documentation, validate medical coding, interpret insurance policies, verify patient eligibility, detect fraudulent activities, and generate transparent decision recommendations. Each intelligent agent performs a specialized responsibility while sharing contextual knowledge with other agents to produce accurate and explainable claim validation outcomes. The framework combines autonomous reasoning, healthcare knowledge retrieval, clinical workflow orchestration, and continuous decision monitoring to improve operational efficiency and reduce administrative complexity throughout the claims management lifecycle. The design of the proposed architecture begins with the observation that clinical

claims validation is a multidisciplinary decision-making process rather than a single administrative activity. Every healthcare claim contains multiple interconnected components, including patient demographics, physician documentation, diagnosis codes, procedure codes, laboratory findings, medication records, insurance eligibility, authorization status, reimbursement policies, and regulatory compliance requirements. These components cannot be evaluated independently because the validity of one element often depends upon information contained within several other clinical records. Consequently, the proposed framework adopts a collaborative multi-agent architecture where autonomous AI agents continuously exchange information and coordinate their reasoning before generating a final validation decision. The architecture consists of several interconnected operational layers that collectively support intelligent claims processing. The first layer represents the healthcare data acquisition environment, where clinical information is collected from Electronic Health Records, Hospital Information Systems, Laboratory Information Management Systems, Radiology Information Systems, Pharmacy Information Systems, insurance management platforms, physician documentation repositories, and patient registration systems. These healthcare information sources provide structured and unstructured clinical data required for comprehensive claims validation. Every claim contains associated patient identifiers, diagnosis information, treatment records, laboratory reports, clinical notes, medication histories, insurance policy details, provider information, billing records,

and reimbursement requests that serve as inputs for the intelligent validation process.

The data integration layer consolidates heterogeneous healthcare information obtained from multiple clinical systems into a unified analytical environment. Since healthcare organizations often utilize diverse software platforms developed by different vendors, clinical information may exist in inconsistent formats with varying terminology, coding standards, and documentation structures. The integration layer standardizes these heterogeneous datasets by harmonizing patient identifiers, medical terminology, coding systems, timestamps, provider information, and administrative records. Duplicate information is removed, missing values are identified, inconsistent records are corrected where possible, and standardized healthcare terminology is applied throughout the integrated dataset. These preprocessing operations ensure that downstream intelligent agents operate on high-quality and consistent clinical information.

Following data integration, the context understanding layer analyzes the complete clinical context surrounding each submitted insurance claim. Rather than evaluating isolated billing codes or individual physician notes, the framework constructs a comprehensive contextual representation of the patient's healthcare journey. Contextual information includes demographic characteristics, previous medical history, chronic disease conditions, laboratory trends, imaging findings, physician observations, prescribed medications, surgical procedures, hospitalization records, previous insurance claims, reimbursement history, and healthcare provider interactions. This

contextual representation enables intelligent agents to understand relationships among clinical events and supports more accurate interpretation of medical necessity, treatment appropriateness, and reimbursement eligibility.

The core intelligence of the proposed framework consists of multiple specialized Agentic AI components, each responsible for a distinct aspect of the claims validation workflow. The Clinical Documentation Agent reviews physician notes, discharge summaries, laboratory reports, imaging interpretations, and treatment documentation to verify that sufficient clinical evidence supports the submitted claim. Using advanced natural language processing and biomedical language understanding, this agent extracts clinically relevant information, identifies missing documentation, detects inconsistencies between diagnoses and treatments, and summarizes important clinical findings required during subsequent validation stages.

The Medical Coding Validation Agent examines diagnosis codes, procedure codes, billing classifications, and reimbursement categories to ensure compliance with internationally recognized healthcare coding standards such as ICD, CPT, HCPCS, and DRG classifications. The agent verifies whether submitted codes accurately represent documented clinical services and identifies coding inconsistencies, duplicate procedures, unsupported diagnoses, incompatible billing combinations, and incomplete reimbursement submissions. Recommendations for corrected coding are generated whenever discrepancies are identified, thereby reducing administrative rework and minimizing claim rejection rates.

The Insurance Policy Interpretation Agent continuously analyzes payer-specific reimbursement policies, authorization requirements, benefit limitations, coverage exclusions, co-payment structures, deductible requirements, and contractual reimbursement agreements. Unlike traditional rule-based policy engines requiring manual updates, this intelligent agent dynamically interprets evolving insurance guidelines using contextual reasoning and continuously retrieves updated policy information from organizational knowledge repositories. By comparing patient eligibility with submitted clinical services, the agent determines whether requested reimbursements comply with applicable insurance coverage conditions.

4. Results and Discussion

The proposed Agentic AI framework was evaluated using representative clinical claims processing scenarios involving outpatient consultations, inpatient admissions, emergency care, laboratory investigations, diagnostic imaging, surgical procedures, chronic disease management, pharmacy claims, and post-discharge follow-up services. The evaluation included claims containing structured billing records, physician notes, discharge summaries, laboratory reports, diagnostic images, medication histories, insurance policies, prior authorization records, and historical reimbursement information. Each claim was processed through the proposed multi-agent architecture, where specialized intelligent agents collaboratively performed clinical documentation review, medical coding validation, insurance policy interpretation, medical necessity assessment, fraud detection, reimbursement estimation, and

explainable decision generation. The evaluation focused on determining whether collaborative Agentic AI could improve claims validation accuracy, reduce processing time, minimize administrative errors, and support consistent reimbursement decisions compared with traditional rule-based and manually supervised workflows.

During normal claims processing, the framework demonstrated stable coordination among specialized AI agents responsible for different validation tasks. The Clinical Documentation Agent successfully extracted relevant diagnoses, treatment procedures, physician observations, laboratory findings, and medication details from both structured and unstructured clinical records. Simultaneously, the Medical Coding Validation Agent verified the consistency between clinical documentation and submitted diagnosis and procedure codes, while the Insurance Policy Interpretation Agent confirmed coverage eligibility according to payer-specific reimbursement guidelines. The collaborative interaction among these agents enabled the framework to identify complete and compliant claims efficiently without requiring extensive manual intervention. Claims containing appropriate documentation and valid coding were processed rapidly, resulting in timely reimbursement recommendations and reduced administrative workload.

The proposed framework was further evaluated using claims containing incomplete or inconsistent clinical documentation. In several representative scenarios, physician notes omitted important clinical observations, laboratory reports were unavailable, or treatment summaries lacked sufficient evidence to justify submitted

procedures. Conventional claims processing systems generally flagged such claims for manual review without providing detailed explanations regarding the missing information. In contrast, the proposed Agentic AI framework automatically identified documentation deficiencies, determined the specific clinical evidence required for validation, and generated structured recommendations describing the missing records necessary to support reimbursement approval. This capability reduced unnecessary claim rejections while assisting healthcare providers in correcting documentation before claim resubmission.

Medical coding consistency represented another important aspect of the evaluation. The Medical Coding Validation Agent successfully identified discrepancies between documented clinical services and submitted billing codes, including incorrect diagnosis classifications, unsupported procedure codes, duplicate billing entries, incompatible coding combinations, and incomplete reimbursement submissions. Instead of immediately rejecting affected claims, the framework generated coding correction recommendations together with explanations describing the identified inconsistencies. Healthcare coders were therefore able to review suggested modifications and update claim submissions before reimbursement processing, significantly improving coding quality while reducing administrative rework.

5. CONCLUSION

The proposed Agentic AI framework demonstrates the potential to transform clinical claims validation by replacing fragmented, rule-based workflows with a collaborative, autonomous, and context-

aware decision-support architecture. By integrating specialized AI agents for clinical documentation analysis, medical coding validation, insurance policy interpretation, fraud detection, medical necessity assessment, and reimbursement estimation, the framework provides a comprehensive solution for managing the increasing complexity of modern healthcare claims. The collaborative reasoning capability enables accurate interpretation of heterogeneous clinical information while maintaining transparency through explainable recommendations, thereby improving the reliability and consistency of reimbursement decisions.

The evaluation indicates that the proposed framework significantly enhances operational efficiency by reducing manual intervention, minimizing coding inconsistencies, accelerating claims processing, and identifying documentation deficiencies before reimbursement decisions are finalized. The integration of contextual reasoning with real-time policy interpretation enables the system to adapt to evolving healthcare regulations and payer-specific requirements while reducing unnecessary claim denials and administrative costs. Furthermore, the inclusion of intelligent fraud detection and evidence-based validation strengthens regulatory compliance, improves financial integrity, and supports informed decision-making for healthcare providers, insurers, and administrative personnel.

Overall, the proposed architecture establishes a scalable and trustworthy foundation for next-generation intelligent healthcare administration. Its modular multi-agent design facilitates seamless integration with

Electronic Health Records, insurance platforms, and clinical decision-support systems, making it suitable for deployment across diverse healthcare environments. As Agentic AI technologies continue to evolve, future enhancements may incorporate continual learning, federated intelligence, multimodal clinical reasoning, and advanced interoperability standards to further improve adaptability, security, and personalized decision support. These advancements position the proposed framework as a promising solution for achieving efficient, transparent, and intelligent clinical claims management in future digital healthcare ecosystems.

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