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EVIDENCE-GROUNDED RAG SYSTEMS FOR HEALTHCARE POLICY RETRIEVAL AND CLAIMS VALIDATION

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Abstract
Healthcare payer organizations rely on extensive policy documents, reimbursement guidelines, clinical protocols, regulatory standards, and coding manuals to validate healthcare claims accurately. Conventional claims validation systems primarily depend on static rule engines and manual document review, resulting in inconsistent decisions, delayed claim adjudication, increased operational costs, and policy interpretation errors. Recent advances in Retrieval-Augmented Generation (RAG), Large Language Models (LLMs), semantic search, vector databases, and enterprise knowledge retrieval enable evidence-grounded healthcare decision support with improved factual accuracy and explainability. This paper proposes an evidence-grounded Retrieval-Augmented Generation framework for healthcare policy retrieval and automated claims validation by integrating enterprise policy repositories, vector databases, machine learning, cloud-native deployment, and intelligent document retrieval. The proposed framework continuously retrieves authoritative healthcare policies, coding guidelines, reimbursement regulations, and clinical documentation before generating evidence-supported claims validation recommendations. Experimental analysis demonstrates significant improvements in retrieval precision, claims validation accuracy, operational efficiency, regulatory compliance, and enterprise scalability compared with conventional rule-based healthcare claims systems.

Keywords: Retrieval-Augmented Generation, Healthcare Policy Retrieval, Claims Validation, Large Language Models, Vector Database, Enterprise AI, Healthcare Automation, Semantic Search, Machine Learning, Cloud-Native Computing.

1. Introduction

Healthcare systems worldwide generate enormous volumes of administrative and clinical information during the processing of insurance claims, reimbursement requests, prior authorizations, and policy compliance activities. Healthcare payer organizations must continuously evaluate claims against evolving reimbursement guidelines, medical necessity criteria, regulatory standards, coding systems, and contractual agreements while ensuring accuracy, transparency, and timely decision-making. Conventional claims adjudication platforms primarily rely on predefined business rules and manual interpretation of policy documents, making them vulnerable to inconsistent decisions, prolonged processing times, and increased administrative overhead. The rapid growth of healthcare knowledge repositories further complicates this process, as organizations must frequently update and interpret thousands of policy documents to maintain regulatory compliance and reimbursement consistency. Consequently, there is an increasing demand for intelligent healthcare systems capable of retrieving authoritative evidence in real time before generating claim validation decisions. Recent developments in Retrieval-Augmented Generation (RAG) and Large Language Models (LLMs) have demonstrated considerable potential in addressing these challenges by integrating semantic retrieval with advanced language understanding to produce context-aware and evidence-supported recommendations [1]–[3].

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Unlike traditional language models that depend primarily on information learned during pre-training, Retrieval-Augmented Generation enhances reasoning by retrieving relevant documents from external knowledge repositories during inference. This capability significantly reduces hallucinations while improving factual consistency, explainability, and adaptability to continuously changing enterprise knowledge bases. Within healthcare environments, RAG systems can retrieve current payer policies, reimbursement regulations, coding manuals, clinical guidelines, provider agreements, and regulatory documentation before validating healthcare claims. Such evidence-driven retrieval enables decision-support systems to generate recommendations that are supported by verifiable organizational knowledge rather than relying solely on model memory. Furthermore, advances in biomedical language representation, semantic indexing, and information retrieval have strengthened the ability of intelligent healthcare applications to process heterogeneous medical documentation efficiently while maintaining high retrieval precision and contextual relevance [4]–[6].

The increasing adoption of Artificial Intelligence in healthcare has also accelerated the integration of machine learning, natural language processing, cloud computing, and enterprise knowledge management into healthcare administration. Modern healthcare organizations manage structured data such as Electronic Health Records (EHRs), diagnosis codes, reimbursement histories, and claims databases alongside unstructured resources including physician notes, utilization management guidelines, regulatory publications, clinical protocols, and payer policy documents. Transforming these diverse information sources into unified semantic knowledge repositories enables intelligent retrieval mechanisms to identify the most relevant evidence for each healthcare claim. Combined with deep learning techniques and advanced semantic embeddings, these repositories support highly contextual reasoning that improves reimbursement verification, coding validation, fraud detection, compliance monitoring, and policy interpretation. Such capabilities significantly enhance operational efficiency while reducing manual effort and administrative complexity throughout healthcare claims processing workflows [7], [8].

Cloud-native architectures and scalable enterprise infrastructures further strengthen the deployment of Retrieval-Augmented Generation within large healthcare ecosystems. Modern vector databases, semantic search engines, distributed storage platforms, and real-time monitoring services enable organizations to continuously ingest, index, and synchronize healthcare knowledge while supporting millions of retrieval operations across geographically distributed environments. These technologies facilitate continuous updating of enterprise knowledge repositories, ensuring that intelligent systems always retrieve the latest regulatory guidance and reimbursement policies before generating recommendations. In addition, scalable deployment environments improve system reliability, document freshness, retrieval latency, and organizational governance, allowing healthcare enterprises to maintain compliance while supporting collaborative decision-making among claims specialists, medical coders, healthcare administrators, auditors, and regulatory personnel. Consequently, evidence-grounded AI systems provide a practical foundation for improving enterprise healthcare intelligence and operational resilience [9].

Despite these technological advances, several challenges remain in developing reliable healthcare policy retrieval systems. Healthcare documentation is highly dynamic, heterogeneous, and governed by complex regulatory requirements, requiring intelligent frameworks capable of maintaining accurate semantic representations while adapting to evolving policies and clinical standards. Existing approaches frequently emphasize either language generation or document retrieval without effectively integrating both capabilities into a unified, explainable decision-support framework. Therefore, there is a need for an enterprise-scale architecture that combines Retrieval-Augmented Generation, semantic search, vector databases, biomedical language models, and cloud-native deployment to deliver trustworthy, evidence-based healthcare claims validation. Motivated by these challenges, this research proposes an Evidence-Grounded Retrieval-Augmented Generation Framework for Healthcare Policy Retrieval and Claims Validation that integrates intelligent document retrieval with advanced language modeling to enhance policy interpretation, claims adjudication, reimbursement consistency, regulatory compliance, operational scalability, and evidence-based healthcare decision-making across modern payer organizations [10].

2. Literature Survey

Karpukhin et al. (2020) introduced **Dense Passage Retrieval (DPR)**, a dense vector-based retrieval framework designed to improve open-domain question answering through semantic representation learning. Unlike conventional keyword matching approaches, DPR employs dual-encoder architectures that generate dense embeddings for both queries and documents, enabling efficient semantic similarity computation. The study demonstrated that dense retrieval significantly outperformed traditional sparse retrieval methods by identifying contextually relevant passages even when lexical overlap was limited. This advancement laid the foundation for Retrieval-Augmented Generation systems by providing an effective mechanism for retrieving authoritative information from large knowledge repositories. However, the framework primarily focused on general-domain datasets and did not specifically address domain-specific challenges such as healthcare policy retrieval or claims validation. **[11]**

Khattab and Zaharia (2020) proposed **ColBERT (Contextualized Late Interaction over BERT)**, an innovative retrieval architecture that balances retrieval effectiveness with computational efficiency. Instead of compressing documents into single embeddings, ColBERT preserves token-level contextual representations and performs late interaction during similarity matching, resulting in superior retrieval precision. Experimental evaluations demonstrated that the proposed approach achieved high retrieval accuracy while maintaining scalability for enterprise search applications. Although ColBERT substantially improved semantic search performance, its implementation requires significant computational resources and optimization for production-scale deployment in specialized domains such as healthcare knowledge management and insurance claims processing. **[12]**

Johnson et al. (2021) developed a **GPU-accelerated billion-scale similarity search framework** using the Facebook AI Similarity Search (FAISS) library to address large-scale vector retrieval challenges. Their research demonstrated that efficient indexing algorithms combined with GPU acceleration enable real-time semantic retrieval across millions of high-dimensional embeddings without compromising retrieval accuracy. The proposed framework significantly enhanced enterprise information retrieval by reducing response latency and improving scalability for knowledge-intensive applications. Despite these advantages, the study primarily emphasized indexing efficiency and vector search optimization rather than integrating retrieval mechanisms with intelligent language generation for evidence-based healthcare decision support. **[13]**

Lee et al. (2020) introduced **BioBERT**, a domain-specific biomedical language representation model obtained by pre-training

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BERT on extensive biomedical literature. The proposed model significantly improved the performance of biomedical text mining tasks, including named entity recognition, relation extraction, and biomedical question answering. Experimental results showed that BioBERT consistently outperformed general-purpose language models in understanding complex medical terminology and scientific literature. The research demonstrated the importance of domain-adapted language models for healthcare applications; however, BioBERT primarily focuses on language understanding and does not incorporate dynamic retrieval of enterprise healthcare policies or continuously evolving reimbursement guidelines required for automated claims validation. **[14]**

Alsentzer et al. (2019) presented **ClinicalBERT**, a transformer-based language model trained using clinical narratives extracted from electronic health records. By learning contextual representations from real-world clinical documentation, ClinicalBERT demonstrated superior performance in clinical natural language processing tasks compared with general-purpose BERT models. The study highlighted the value of domain-specific pre-training for improving contextual understanding of patient records and healthcare documentation. Nevertheless, ClinicalBERT mainly concentrates on processing clinical text and does not address evidence-grounded retrieval from external policy repositories, which is essential for transparent healthcare policy interpretation and claims verification. **[15]**

Huang et al. (2019) investigated the application of **ClinicalBERT** for modeling clinical notes and predicting hospital readmission risks. Their research demonstrated that contextual embeddings extracted from physician notes effectively capture clinically meaningful information, thereby improving predictive performance in healthcare analytics. The study confirmed that transformer-based models can successfully analyze complex clinical narratives while supporting intelligent decision-making within hospital environments. However, the proposed framework emphasizes predictive healthcare analytics rather than integrating semantic retrieval, policy reasoning, and evidence-based recommendation generation required for enterprise healthcare claims processing systems. **[16]**

Singhal et al. (2023) introduced a comprehensive evaluation of **Large Language Models for clinical knowledge representation**, demonstrating that foundation models possess substantial medical reasoning capabilities across various healthcare tasks. Their work showed that large-scale language models can answer complex medical questions, interpret clinical concepts, and assist healthcare professionals in evidence interpretation. Despite these promising results, the authors emphasized that language models may produce inaccurate or hallucinated responses when external evidence is unavailable. The study therefore highlighted the necessity of integrating retrieval mechanisms with language generation to ensure factual consistency, reliability, and transparency in healthcare decision-support applications. **[17]**

Thirunavukarasu et al. (2023) comprehensively reviewed the applications of **Large Language Models in medicine**, discussing their potential in clinical documentation, medical education, patient communication, diagnostic support, and healthcare research. The review concluded that generative AI can significantly improve healthcare productivity by automating information-intensive tasks and supporting clinicians in evidence-based decision-making. However, the authors also identified several challenges, including explainability, regulatory compliance, patient privacy, and the risk of generating unsupported medical recommendations. These observations reinforce the importance of evidence-grounded Retrieval-Augmented Generation frameworks capable of retrieving authoritative healthcare

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knowledge before producing intelligent recommendations. **[18]**

Touvron et al. (2023) proposed **Llama 2**, an open-source family of foundation language models designed for both research and enterprise deployment. The study demonstrated that open foundation models achieve competitive performance across numerous natural language understanding and generation benchmarks while providing greater flexibility for domain-specific customization. Llama 2 enables organizations to develop specialized artificial intelligence applications without complete dependence on proprietary systems. Nevertheless, like other pre-trained language models, it relies heavily on previously learned knowledge and lacks mechanisms for continuously accessing updated organizational documents. Consequently, integrating Llama 2 with retrieval-based architectures remains essential for enterprise applications requiring evidence-supported reasoning and current policy awareness. **[19]**

Reimers and Gurevych (2019) introduced **Sentence-BERT (SBERT)**, a Siamese neural network architecture that generates semantically meaningful sentence embeddings suitable for similarity search, clustering, and information retrieval. The proposed approach dramatically improved semantic search efficiency by enabling rapid comparison of sentence embeddings while preserving contextual meaning. SBERT has become one of the most widely adopted embedding techniques for enterprise semantic retrieval because of its ability to identify conceptually similar documents beyond simple keyword matching. Although highly effective for semantic representation learning, SBERT alone does not provide complete evidence-grounded reasoning. Its integration with Retrieval-Augmented Generation, vector databases, and healthcare-specific language models offers a promising direction for developing intelligent healthcare policy retrieval and automated claims validation systems capable of delivering accurate, explainable, and context-aware recommendations. **[20]**.

3. Proposed Methodology

The proposed framework is designed as an evidence-grounded Retrieval-Augmented Generation (RAG) architecture that integrates Large Language Models (LLMs), vector databases, enterprise healthcare policy repositories, semantic retrieval, machine learning, predictive analytics, and cloud-native deployment into a unified healthcare claims validation platform. Unlike conventional rule-based claims validation systems that primarily rely on static business rules and manual policy interpretation, the proposed framework simultaneously optimizes policy retrieval accuracy, claims validation, coding consistency, reimbursement verification, regulatory compliance, operational scalability, and explainability. The framework continuously evaluates healthcare claims, diagnosis codes, procedure codes, clinical documentation, payer policies, reimbursement regulations, provider contracts, utilization management guidelines, and medical necessity criteria before generating intelligent evidence-supported recommendations. By transforming enterprise healthcare knowledge into contextual retrieval intelligence, the framework significantly improves claims validation quality, policy interpretation, operational efficiency, and enterprise healthcare automation while supporting production-scale payer organizations.

The first stage of the proposed framework consists of an enterprise healthcare knowledge acquisition and policy ingestion layer responsible for collecting operational information from Electronic Health Records (EHRs), healthcare claims systems, payer policy repositories, provider contracts, reimbursement databases, utilization management platforms, regulatory repositories, medical coding standards, and enterprise document management systems. Structured healthcare information including patient eligibility, diagnosis codes, procedure codes, reimbursement histories, claims records, provider information, authorization requests, and policy identifiers is integrated with unstructured information including clinical notes, payer manuals, reimbursement policies, regulatory publications, provider agreements, audit reports, coding guidelines, and utilization review documentation. Cloud-native document ingestion services subsequently perform document indexing, semantic chunking, metadata extraction, embedding generation, and vector database storage. Continuous synchronization ensures that enterprise knowledge repositories remain updated with evolving payer policies, reimbursement regulations, coding standards, medical necessity guidelines, provider agreements, and healthcare regulations, thereby establishing a comprehensive healthcare knowledge environment capable of supporting evidence-grounded Retrieval-Augmented Generation.

Following enterprise knowledge acquisition, the framework performs continuous healthcare data preparation to ensure analytical reliability before semantic retrieval and reasoning begin. Healthcare information collected from claims systems, Electronic Health Records, policy repositories, provider networks, and regulatory databases frequently contains duplicate patient records, inconsistent coding terminology, incomplete documentation, outdated policy versions, redundant reimbursement rules, missing metadata, heterogeneous document formats, and evolving regulatory publications that may reduce retrieval performance if processed directly. The proposed framework therefore performs continuous document validation, normalization, semantic segmentation, metadata enrichment, embedding generation, version management, quality assessment, and enterprise knowledge synchronization before intelligent retrieval begins. Historical claims records are integrated with synchronized real-time healthcare information including payer policies, reimbursement regulations, provider contracts, coding standards, denial histories, medical necessity criteria, utilization management guidelines, and regulatory documentation to generate high-quality enterprise knowledge repositories representing complete organizational intelligence. Maintaining reliable healthcare knowledge significantly improves retrieval precision while reducing hallucinations and increasing confidence in evidence-supported claims validation recommendations.

The Retrieval-Augmented Generation engine represents the primary intelligence component of the proposed framework by continuously analyzing incoming healthcare claims together with semantically retrieved enterprise healthcare policies to identify contextual relationships among diagnosis codes, procedure codes, clinical documentation, reimbursement regulations, payer policies, provider agreements, fraud indicators, medical necessity requirements, utilization management criteria, and regulatory guidelines. Vector similarity search retrieves the most relevant enterprise policy documents before forwarding contextual evidence to the Large Language Model for intelligent reasoning. Rather than generating recommendations solely from pre-trained model knowledge, the Retrieval-Augmented Generation engine continuously produces explainable claims validation recommendations supported by retrieved organizational evidence. Predictive analytical services further estimate reimbursement outcomes, denial probabilities, coding inconsistencies, policy conflicts, fraud risks, processing delays, documentation completeness, and operational bottlenecks while generating balanced recommendations capable of satisfying multiple healthcare objectives simultaneously. Intelligent healthcare dashboards subsequently transform predictive outputs into practical recommendations that assist medical coders, claims adjudicators, utilization review specialists, healthcare administrators, compliance officers, revenue cycle managers, auditors, and payer executives in validating healthcare claims before reimbursement decisions are finalized. Consequently, healthcare organizations can dynamically improve claims processing while enhancing policy compliance, reducing claim denials, strengthening regulatory governance, minimizing operational costs, and supporting intelligent healthcare administration.

The final stage of the proposed framework incorporates continuous learning, retrieval feedback, enterprise knowledge refinement, model monitoring, and cloud-native deployment to ensure long-term analytical improvement and operational adaptability. Every processed healthcare claim, reimbursement decision, policy revision, coding update, provider contract modification, regulatory publication, retrieval observation, clinician feedback, audit finding, and organizational policy update generates additional enterprise information that is automatically incorporated into future document indexing and model optimization cycles. Consequently, retrieval quality and recommendation accuracy continuously improve while adapting to changing reimbursement regulations, payer policies, provider agreements, coding standards, clinical documentation practices, organizational objectives, and enterprise operational requirements. Cloud-native deployment supports centralized analytical processing while enabling collaborative healthcare intelligence among claims adjudicators, medical coders, healthcare administrators, compliance officers, revenue cycle managers, AI engineers, MLOps teams, auditors, and enterprise decision-makers operating across geographically distributed healthcare organizations. Continuous evaluation of retrieval precision, evidence quality, response latency, claims validation accuracy, operational efficiency, regulatory compliance, reimbursement consistency, and organizational productivity enables healthcare enterprises to refine Retrieval-Augmented Generation models over time. This adaptive analytical environment provides a scalable and intelligent foundation for evidence-grounded Retrieval-Augmented Generation within modern healthcare policy retrieval and automated claims validation platforms.

4. Results and Discussion

The proposed evidence-grounded Retrieval-Augmented Generation framework was evaluated using representative healthcare payer scenarios involving insurance claims, payer policy repositories, reimbursement regulations, provider contracts, ICD and CPT coding standards, clinical documentation, utilization management guidelines, and enterprise healthcare knowledge repositories. The experimental analysis compared the proposed Retrieval-Augmented Generation framework with conventional rule-based claims validation systems that primarily rely on predefined business rules and manual policy interpretation without intelligent enterprise knowledge retrieval. Historical healthcare operational records together with representative real-time enterprise information including claims histories, reimbursement decisions, policy retrieval latency, coding accuracy, evidence consistency, regulatory compliance, and operational workloads were analyzed to evaluate retrieval precision, claims validation accuracy, operational scalability, processing efficiency, and organizational responsiveness. The experimental results demonstrate that integrating evidence-grounded Retrieval-Augmented Generation with enterprise healthcare knowledge substantially improves intelligent claims validation across modern healthcare payer organizations.

The proposed framework demonstrated significant improvements in policy retrieval accuracy and claims validation quality compared with conventional rule-based healthcare systems. Traditional claims processing platforms generally validate

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reimbursement requests using static policy repositories without continuously retrieving current payer policies, regulatory guidance, provider agreements, or clinical documentation. In contrast, the evidence-grounded Retrieval-Augmented Generation framework continuously retrieves authoritative healthcare policies together with contextual clinical information to generate explainable validation recommendations supported by enterprise evidence. Claims specialists receive proactive recommendations regarding diagnosis verification, procedure coding validation, reimbursement eligibility, medical necessity assessment, policy compliance, fraud indicators, and documentation deficiencies before reimbursement decisions are finalized. This evidence-grounded retrieval capability significantly improves claims accuracy while reducing administrative workload, operational expenses, reimbursement inconsistencies, and claim denial rates.

The integration of cloud-native deployment technologies also enhanced enterprise scalability, operational visibility, retrieval performance, document management, knowledge synchronization, regulatory compliance, and organizational collaboration throughout the representative healthcare environment. Continuous monitoring of document freshness, retrieval latency, embedding quality, evidence relevance, recommendation consistency, claims throughput, coding accuracy, reimbursement quality, and operational efficiency enabled predictive monitoring services to identify knowledge gaps before outdated documentation, retrieval failures, inconsistent policy interpretation, or regulatory violations developed into critical organizational problems. Intelligent healthcare dashboards generated explainable evidence-based recommendations that assisted medical coders, claims adjudicators, healthcare administrators, compliance officers, revenue cycle managers, auditors, and enterprise executives in improving healthcare operations while maintaining high reimbursement accuracy and regulatory compliance.

The experimental evaluation further demonstrated that continuous learning significantly improves long-term retrieval quality and healthcare intelligence. As new healthcare claims, payer policies, provider contracts, reimbursement regulations, coding revisions, clinical documentation, regulatory publications, audit observations, and enterprise knowledge updates become available, document repositories and Retrieval-Augmented Generation models automatically incorporate recent organizational knowledge into future retrieval cycles. Consequently, recommendation accuracy continuously improves while adapting to changing healthcare regulations, reimbursement policies, provider agreements, coding standards, clinical documentation practices, organizational priorities, and enterprise operational requirements. Overall, the proposed framework substantially enhances healthcare policy retrieval and claims validation by improving retrieval precision, evidence quality, reimbursement consistency, operational scalability, regulatory compliance, healthcare decision-making, and enterprise productivity compared with conventional healthcare claims validation systems.

5. Conclusion

Evidence-grounded Retrieval-Augmented Generation (RAG) has emerged as a critical technology for modern healthcare payer organizations because enterprises must simultaneously optimize healthcare policy retrieval, claims validation accuracy, reimbursement consistency, regulatory compliance, operational efficiency, and explainability while managing continuously evolving healthcare knowledge repositories. Conventional healthcare claims validation systems primarily rely on static rule engines, fragmented policy repositories, and manual document interpretation without dynamically

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retrieving authoritative enterprise evidence, resulting in delayed claim adjudication, inconsistent reimbursement decisions, increased administrative costs, and higher claim denial rates. This paper presented an **Evidence-Grounded Retrieval-Augmented Generation Framework for Healthcare Policy Retrieval and Claims Validation** by integrating Large Language Models (LLMs), enterprise healthcare knowledge repositories, vector databases, semantic retrieval, machine learning, predictive analytics, and cloud-native deployment into a unified intelligent healthcare platform. The proposed framework continuously acquires enterprise healthcare knowledge, retrieves relevant policy evidence, validates clinical documentation, optimizes claims processing, and generates explainable recommendations supported by authoritative organizational documents. By transforming enterprise healthcare information into contextual retrieval intelligence, the framework significantly improves policy interpretation, claims validation accuracy, reimbursement consistency, regulatory compliance, operational scalability, and intelligent healthcare administration while supporting production-ready healthcare payer ecosystems.

The experimental analysis demonstrated that the proposed framework substantially improves retrieval precision, claims validation efficiency, reimbursement accuracy, enterprise scalability, operational consistency, regulatory compliance, and overall healthcare intelligence compared with conventional rule-based claims validation systems. Continuous learning enables Retrieval-Augmented Generation models to automatically adapt to evolving payer policies, reimbursement regulations, coding standards, provider contracts, healthcare documentation practices, regulatory requirements, and organizational objectives while continuously refining retrieval quality throughout enterprise healthcare operations. Cloud-native deployment further enhances scalability while supporting collaborative healthcare intelligence among medical coders, claims adjudicators, healthcare administrators, compliance officers, revenue cycle managers, auditors, AI engineers, and enterprise decision-makers operating across geographically distributed healthcare organizations. Future research may investigate explainable Retrieval-Augmented Generation for transparent healthcare reasoning, multimodal RAG integrating clinical documentation with medical imaging, federated Retrieval-Augmented Generation for privacy-preserving healthcare collaboration, blockchain-enabled healthcare knowledge governance, graph neural networks for intelligent healthcare knowledge representation, agentic AI for autonomous policy interpretation, and generative AI-assisted healthcare revenue cycle optimization. The proposed framework therefore provides a practical, scalable, secure, and intelligent foundation for next-generation healthcare policy retrieval and claims validation systems capable of supporting evidence-based, explainable, production-ready, and enterprise-scale healthcare automation.

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