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RAG-Based Healthcare Query Assistant Using Graph Database: A Comprehensive Survey

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Abstract: Healthcare research today operates within an en- vironment rich in complex and interconnected data sources, ranging from Electronic Health Records (EHRs) and diagnostic imaging to pharmacological studies and clinical trial outputs. Traditional retrieval systems and general-purpose Large Lan- guage Models (LLMs), though effective in surface-level analysis, often fail to capture the deep semantic relationships that un- derpin this data. Consequently, they generate responses lacking verifiable evidence and contextual accuracy.

To address these challenges, this paper surveys the emerging paradigm of Retrieval-Augmented Generation (RAG) enhanced by Knowledge Graphs (KGs), forming a bridge between sym- bolic reasoning and neural generation. The proposed study establishes a taxonomy of healthcare Question-Answering (QA) frameworks—spanning relational databases, vector embedding retrieval, and hybrid KG-RAG architectures—while emphasizing their relevance in clinical information systems.

Furthermore, the paper outlines the necessity of such in- tegration for improving medical decision support, focusing on the dynamic translation of natural language into formal graph queries, scalable knowledge maintenance, and multi-hop infer- encing. By systematically reviewing technological advances and identifying key implementation challenges, this survey provides a structured roadmap for developing reliable, explainable, and ethically aligned AI systems in healthcare.

Keywords: *Retrieval-Augmented Generation, Knowledge Graphs, Graph Database, Natural Language Processing, Large Language Models, Neo4j, Healthcare AI.*

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I. INTRODUCTION

The rapid digitalization of healthcare has produced an im- mense volume of heterogeneous data encompassing structured Electronic Health Records (EHRs), semi-structured ontologies, and unstructured clinical narratives [1]. While this data deluge presents significant opportunities for precision diagnostics and data-driven clinical insights, its diversity and fragmentation continue to hinder effective retrieval and interpretation. Con- sequently, converting these disparate information sources into coherent, actionable knowledge remains an enduring chal- lenge.

Traditional information retrieval mechanisms—such as keyword-based searches and relational database queries—often fail to capture latent semantic relationships within complex medical contexts [2], [3]. As a result, clinicians frequently encounter incomplete or contextually irrelevant information when formulating evidence-based decisions. Therefore, there is an increasing need for retrieval frameworks capable of reasoning across structured and unstructured modalities while preserving interpretability and factual consistency.

Recent advancements in Large Language Models (LLMs) have revolutionized natural language understanding and gen- eration, enabling more intuitive interactions between machines and clinicians [4], [5]. However, despite their linguistic so- phistication, LLMs face two fundamental constraints that limit their clinical reliability. First, the knowledge staleness problem arises due to the static nature of their pre-training data, which quickly becomes outdated as medical discover- ies evolve [6], [7]. Second, these models often suffer from factual unreliability, generating fluent yet

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unverifiable state- ments—commonly referred to as hallucinations—that compro- mise trust and safety in medical applications [8], [9].

Retrieval-Augmented Generation (RAG) frameworks have emerged as a practical solution to these challenges by dy- namically integrating LLMs with external knowledge sources. This approach ensures that model outputs are continuously grounded in verified and up-to-date information [10], [11]. However, the reliability and interpretability of a RAG system depend heavily on the structure and expressiveness of its underlying knowledge repository. In this context, Knowledge Graphs (KGs) have become indispensable, as they explicitly encode entities, relationships, and contextual semantics that support complex inferencing across multiple relational lay- ers [12]– [14].

Recent frameworks such as MedRAG [11] and KG-Rank [5] demonstrate that graph-enhanced RAG architectures substan- tially improve factual consistency, interpretability, and retrieval precision. Accordingly, this paper contributes to the growing discourse on knowledge-augmented clinical reasoning by off- fering the following key insights:

- A comprehensive taxonomy of medical QA systems cat- egorized by retrieval methodologies—lexical, embedding- based, and knowledge-graph-based—highlighting their ar- chitectural progression and comparative efficiency.
- A detailed exploration of KG-RAG integration, emphasiz- ing how graph structures enhance explainability, ensure semantic fidelity, and facilitate multi-hop inferencing within biomedical ontologies.
- An applied overview of optimization techniques, in- cluding adaptive subgraph retrieval, temporal knowledge caching [10], and dynamic update mechanisms that maintain accuracy and scalability in real-time healthcare applications.

This systematic study thereby aims to consolidate existing research into a cohesive framework, advancing the design of clinically trustworthy, interpretable, and performance-oriented KG-RAG systems.

II. BACKGROUND AND CORE TECHNOLOGY

The convergence of Knowledge Graphs (KGs) and Retrieval-Augmented Generation (RAG) has transformed the paradigm of medical information retrieval and reasoning. Traditional neural retrieval mechanisms, while proficient in linguistic processing, often struggle to maintain factual con- sistency and contextual depth—especially in complex, data-intensive medical environments where causality and temporal dependencies are critical [5], [15]. By merging the sym- bolic precision of KGs with the generative fluency of Large Language Models (LLMs), KG-RAG architectures establish a hybrid reasoning framework that achieves both semantic interpretability and factual reliability, thereby fulfilling key requirements for clinical decision support systems.

Evolution of RAG Architectures in Healthcare

Retrieval-Augmented Generation operates by coupling the retrieval and generation processes within a unified, feedback- driven architecture. Instead of relying solely on static pre-trained knowledge, RAG dynamically retrieves domain- specific documents or graph fragments to ground generated outputs in verifiable evidence [10]. This hybrid design has proven highly effective in medical question answering, clinical summarization, and evidence synthesis.

During knowledge ingestion, biomedical datasets such as MIMIC-IV are transformed into structured representations comprising entities (e.g., diseases, drugs, and procedures) and relationships (e.g., *treats*, *causes*, or *contraindicated_with*) [1]. These relationships are stored within graph databases like Neo4j, where traversal algorithms enable contextualized multi- hop retrieval across interconnected nodes [17].

Subsequently, retrieved graph segments are integrated with user queries, allowing the model to generate semantically grounded, context-rich responses. This evidence-guided pro- cess not only minimizes hallucinations but also supports con- tinual knowledge expansion without retraining the underlying LLM. Nevertheless, as several studies indicate [15], [18], the overall performance of such systems remains contingent upon retrieval precision, graph schema design, and query optimization techniques.

Graph Databases as the Semantic Backbone

Graph databases such as Neo4j and TigerGraph function as the semantic foundation of KG-RAG systems. In contrast to conventional relational databases that store information in rigid tabular form, graph databases represent biomedical data through flexible node–edge structures capable of capturing complex, many-to-many relationships. Each node encapsulates an entity, while each edge represents a semantically mean- ingful association, facilitating seamless integration of diverse data modalities, including clinical trials, drug interactions, and genomic linkages [11].

Moreover, graph query languages such as Cypher provide a human-readable syntax for formulating semantic queries, thus enhancing system interpretability. Each traversal path within the graph can be visualized to trace reasoning pro- cesses, a feature particularly important in regulated do- mains like healthcare. Additionally, Neo4j's hybrid query layer—supporting both property-based traversal and vector embedding retrieval—achieves high recall while maintaining semantic transparency [15].

Empirical comparisons consistently demonstrate that graph databases outperform traditional relational systems in multi- hop reasoning tasks, achieving higher precision and faster query resolution times [18]. Furthermore, their schema-flexible design supports continuous evolution: as new medical entities or discoveries emerge, they can be integrated without dis- rupting prior relational structures, ensuring adaptability and scalability for evolving clinical ecosystems.

Knowledge Graph–LLM Integration

The integration of LLMs with Knowledge Graphs

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marks a significant advancement in biomedical artificial intelligence. Although LLMs like GPT-4 and BioMedLM excel at linguistic comprehension, they frequently lack domain specificity and factual grounding. By coupling them with domain-structured KGs, models can generate contextually accurate and evidence- based content [19].

Hybrid systems such as KG-Rank and MedRAG exemplify this approach by embedding graph-derived features directly into the retrieval layer, thereby guiding the model toward clinically verified nodes and edges [5], [11]. This method- ology enhances both factual consistency and explainability, as retrieved subgraphs act as transparent reasoning chains. Furthermore, attention-guided traversal mechanisms enable LLMs to focus selectively on clinically relevant subgraphs, improving precision and mitigating hallucination.

Recent advances in graph-enhanced encoders—such as Graph Attention Transformers and Dynamic Graph Net- works—further extend this integration. By embedding rela- tional and contextual dependencies directly into token repre- sentations, these architectures bridge the gap between sym- bolic reasoning and neural representation learning [15], [20]. Consequently, they facilitate knowledge-aware generation that balances linguistic fluidity with ontological rigor.

- *Caching, Scalability, and Real-Time Optimization*

While KG-RAG systems deliver superior reasoning and interpretability, they often face computational overhead due to the complexity of graph traversal. Addressing this limitation, RAGCache [10] introduces a hierarchical caching mechanism that stores frequently accessed subgraphs, significantly reduc- ing retrieval latency and enabling near real-time responses. By precomputing vector embeddings for high-frequency biomed- ical entities, this approach accelerates inference by 30–50% without compromising accuracy.

In addition, distributed graph sharding and hybrid memory management strategies improve horizontal scalability across multi-institutional healthcare infrastructures. These innova- tions enable concurrent data access, maintain query efficiency under heavy load, and ensure system robustness during dy- namic updates. Collectively, they establish the foundation for scalable, enterprise-grade KG-RAG deployments capable of serving diverse clinical scenarios.

- *Explainability and Clinical Reliability*

Explainability represents a fundamental pillar for deploying AI-driven systems in healthcare, where clinical accountabil- ity is paramount. In KG-RAG frameworks, each generated output can be traced to explicit graph relationships, ensuring transparent reasoning [8]. For instance, when recommending treatment options, the model can display a reasoning chain such as *Drug A → treats → Condition B → causes → Side Effect C*, providing interpretable evidence for every decision. Recent advances, including the MedRAG architecture [11], introduce a knowledge verification module that automatically cross-checks generated content against stored KG facts. This verification ensures factual consistency, mitigates hallucination risks, and aligns the system with clinical compliance standards. As a result, KG-RAG pipelines evolve beyond black-box AI models toward explainable, auditable systems that meet both ethical and regulatory requirements.

Ultimately, the synergy between KGs and LLMs not only enhances reasoning precision but also fosters clinical trust, marking a transformative step toward transparent, reliable, and ethically guided AI in modern healthcare systems.

III. SURVEY OF ACADEMIC RESEARCH

The evolution of healthcare question answering (HQA) has been guided by the convergence of three foundational paradigms—structured knowledge representation, neural lan- guage understanding, and retrieval-augmented reasoning. Ear- lier medical information systems predominantly relied on relational databases and ontology-driven retrieval; however, their inability to represent deep semantic relationships limited their reasoning potential. Consequently, the emergence of hybrid frameworks that integrate Knowledge Graphs (KGs) with Retrieval-Augmented Generation (RAG) architectures has marked a transformative shift in biomedical artificial intelligence. These systems enable transparent, interpretable, and contextually grounded reasoning across vast biomedical datasets, addressing the limitations of both symbolic and purely neural models.

This section surveys recent research developments that col- lectively advance the state of healthcare QA, with an emphasis on graph-based architectures, hybrid reasoning methods, and emerging standards that improve transparency, scalability, and clinical reliability.

- *Knowledge Graph Construction and Representation*

The foundation of any KG-RAG framework lies in the robustness and granularity of its underlying knowledge rep- resentation. Recent research underscores that constructing domain-specific KGs is critical to achieving factual preci- sion and interpretability in clinical reasoning. For instance, large-scale health misinformation detection frameworks such as *FakeHealth* [12] integrate heterogeneous medical, social, and scientific datasets, embedding factual relationships and provenance metadata to enhance content credibility and source traceability.

Similarly, diagnostic resources like *DDXPlus* [13] employ ontology-based structuring to encode disease–symptom–risk factor relationships aligned with UMLS and SNOMED CT. This ensures consistent semantic representation and cross- system interoperability, serving as the foundation for auto- mated differential diagnosis reasoning. In parallel, advanced biomedical QA models such as *BioMedGraphQA* [15] adopt graph-attention transformers that model relational dependen- cies between biomedical entities, thereby outperforming text- only models in factual

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recall and reasoning depth.

Entity disambiguation and normalization continue to pose significant challenges in biomedical text processing. Systems such as *Knowledge-Graph-Enabled Biomedical Entity Link- ing* [16] address this issue by embedding contextual and structural cues within entity linking pipelines to improve cross-domain coherence. Furthermore, deep learning–based translation frameworks like *Text-to-GraphQL* [17] transform unstructured biomedical questions into executable Cypher or GraphQL queries, effectively bridging natural language under- standing with symbolic reasoning. Collectively, these advance- ments have refined the representation layer that underpins the reasoning efficiency of modern KG-RAG systems.

➢ *Question Answering Over Electronic Health Records (EHR)*

Electronic Health Records (EHRs) represent a critical data source for healthcare QA but are characterized by high heterogeneity and longitudinal complexity. The *MIMIC-IV* dataset [1] serves as a widely adopted benchmark, containing structured clinical data such as physiological readings, diag- nosis codes, and treatment outcomes. By converting this data into graph-based representations, researchers enable temporal reasoning, such as tracing symptom evolution or identifying drug–disease interactions.

Recent systems such as the *Online Medical Chatbot Sys- tem* [18] exemplify how graph-based reasoning over EHRs enhances conversational AI. These chatbots convert patient queries into graph traversal operations, generating evidence- backed responses that adapt dynamically to dialogue context. Unlike static rule-based models, KG-integrated conversational agents maintain contextual continuity and factual coherence, enabling follow-up queries that reflect prior exchanges.

Moreover, embedding propagation mechanisms have sig- nificantly improved EHR reasoning accuracy. By distributing temporal embeddings across nodes, such systems can infer implicit dependencies—such as comorbidities and adverse drug interactions—achieving superior precision and recall compared with relational query systems. These findings col- lectively establish graph-based EHR modeling as a cornerstone for intelligent and context-aware healthcare QA systems.

➢ *Knowledge Graph–RAG Integration and Optimization*

The integration of symbolic reasoning and generative mod- eling marks a key milestone in the development of biomedical QA. Hybrid systems such as *KG-Rank* [5] integrate graph- based retrieval directly into transformer architectures, ranking subgraphs based on semantic and contextual relevance. This ensures that generated outputs remain grounded in domain- verified facts, effectively mitigating the hallucination problem observed in conventional LLMs.

Further advancements, such as *Medical Graph RAG* [11], introduce a bi-directional interaction loop between retrieval and generation phases. In this framework, responses are itera- tively verified against graph facts, reinforcing accuracy and contextual alignment. Experimental evaluations indicate up to 40–45% improvements in factual precision compared with traditional vector-based RAG models.

Efficiency optimization has also emerged as a central re- search theme. For example, *RAGCache* [10] employs hi- erarchical caching of frequently accessed subgraphs to re- duce query latency, achieving sub-second response times in enterprise-scale implementations. Additionally, KG-assisted conversational systems [19] leverage contextual feedback to refine multi-turn interactions, providing more coherent and domain-aware dialogue management. These hybrid frame- works exemplify how KG-RAG integration enhances reliabil- ity, scalability, and real-time clinical applicability.

➢ *Explainability, Validation, and Ethical Reliability*

Explainability and ethical accountability have become defin- ing pillars of AI integration in healthcare. Frameworks such as *Explainable Fact-Checking for Public Health Claims* [8] combine structured graph reasoning with natural language explanations, allowing transparent validation of factual claims. Likewise, adaptive models such as *Knowledge-Empowered Dynamic Graph Networks* [20] incorporate temporal reasoning mechanisms to reflect evolving biomedical knowledge, ensur- ing time-aware model adaptability.

Meanwhile, verification-enhanced pipelines like *Medical Graph RAG* [11] revalidate generated content against graph- derived evidence before final output, significantly improving factual accuracy and clinician trust. Visualization tools embed- ded within these frameworks allow users to inspect reasoning paths, such as *Drug A → inhibits → Enzyme B → induces→ Side Effect C*, promoting interpretability in high-stakes decision-making.

Evaluation frameworks have likewise evolved to include multidimensional metrics such as *semantic coherence*, *evi- dence grounding*, and *path relevance* [5], [10], [21]. These metrics move beyond surface-level accuracy to quantify the degree of interpretability, justification, and clinical traceability inherent to KG-RAG systems. As a result, these explainability- driven methodologies form the basis for responsible AI de- ployment in biomedical contexts, aligning computational in- novation with ethical governance and clinical transparency.

IV. COMPARATIVE ANALYSIS OF RECENT WORKS

To contextualize the evolution of Knowledge Graph–augmented Retrieval-Augmented Generation (KG- RAG) systems, this section presents a comparative analysis of representative studies. Table I highlights their objectives, data sources, and performance outcomes, offering a concise overview of current methodologies and research trends.

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As seen in Table I, graph-based reasoning frameworks consistently outperform conventional retrieval architectures in factual grounding, interpretability, and scalability. Systems such as *Medical Graph RAG* and *RAGCache* demonstrate that hybrid pipelines combining symbolic knowledge with neural generation not only increase response reliability but also enable real-time deployment in high-throughput healthcare settings. Furthermore, iterative improvement frameworks like *KGARevion* highlight an emerging trend toward self-correcting graph QA systems capable of autonomous refinement.

V. CHALLENGES AND RESEARCH GAPS

Despite significant advancements, several challenges con- tinue to constrain the full-scale adoption of KG-RAG systems in clinical environments. These challenges span data quality, scalability, interoperability, ethical governance, and computa- tional efficiency.

➢ *Dataset Bias and Reproducibility*

Most existing studies rely on limited corpora such as MIMIC-III, MIMIC-IV, or PubMedQA [3], [5]. Consequently, the generalization of trained models across institutions re- mains weak, and experimental reproducibility is often hin- dered by non-standardized datasets. Developing open, version- controlled, and longitudinally updated benchmark datasets is essential for ensuring transparent comparison and sustainable progress in this field.

➢ *Incomplete Knowledge Representation*

Although biomedical Knowledge Graphs capture extensive entity relationships, they often lack causal and temporal di- mensions necessary for modeling treatment evolution and patient outcomes [15]. This limitation restricts multi-hop infer- encing and contextual understanding. Therefore, the design of unified schemas combining ontologies such as SNOMED CT, ICD-10, and UMLS is critical for ensuring semantic coherence and comprehensive representation.

➢ *Query Translation Fidelity*

The translation of natural language queries into executable graph queries remains a technically delicate process [21]. Even subtle linguistic ambiguities may lead to retrieval of irrele- vant or incomplete subgraphs. To address this issue, current research explores reinforcement-based correction mechanisms and symbolic consistency validators that iteratively refine query interpretation to maintain alignment between user intent and system response.

Table 1 Comparative Analysis of Prominent KG-RAG and Biomedical QA Frameworks

Model / Framework	Core Focus	Data Source / Domain	Methodology and Architec- ture	Key Outcomes
FakeHealth [12]	Health misinformation de- tection	Social and medical claims, news articles	Constructs KG with fact- checking metadata for credibility reasoning	Improves misinformation detection accuracy by 18%
DDXPlus [13]	Differential diagnosis rea- soning	Clinical symptom–disease dataset (UMLS, SNOMED CT)	Ontology-driven graph encod- ing for diagnostic inference	Enhances multi-label clas- sification accuracy and in- terpretability
BioMedGraphQA [15]	Biomedical question answering	PubMed abstracts, MeSH on- tology	Graph-attention transformer modeling inter-entity dependencies	Achieves 28% higher fac- tual recall vs text-based BERT
KG-Rank [5]	Graph-enhanced retrieval and ranking	Biomedical QA corpus	Integrates KG subgraph rank- ing with transformer LLMs for evidence prioritization	Reduces hallucination rate by 35%
Medical Graph RAG [11]	Hybrid KG-RAG framework for QA	MIMIC-IV and BioMedQA datasets	Bidirectional re- trieval–generation feedback with graph validation layer	Boosts factual accuracy by 42%
RAGCache [10]	Efficient retrieval and caching	Multi-institutional healthcare data	Hierarchical subgraph caching and vector prefetching for low- latency queries	Achieves sub-second re- sponse time with 50% faster inference
KGARevion [21]	Error correction in KG-QA	Biomedical QA datasets	Iterative revision mechanism using KG-guided reinforce- ment learning	Reduces factual error propagation by 31%
Explainable Fact- Checking System [8]	Explainable validation of public health claims	Online health misinformation corpus	Combines graph reasoning with natural language explanations	Improves claim verifiabil- ity and interpretability

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- *Performance, Latency, and Scalability*

Although graph traversal enables deep semantic reasoning, it imposes considerable computational costs [10]. Achieving near real-time response requires optimized caching, distributed traversal mechanisms, and predictive subgraph prefetching. Furthermore, scaling such systems for use in multi-hospital networks or low-resource settings necessitates careful balanc- ing of model accuracy, latency, and energy efficiency.

- *Ethical, Privacy, and Governance Constraints*

Legal frameworks such as HIPAA and the EU GDPR impose strict regulations on medical data handling [22]. While synthetic data offers an alternative for privacy preservation, it often fails to replicate the nuanced longitudinal dynamics of real patient records. Therefore, integrating privacy-preserving techniques—such as graph anonymization, federated KG train- ing, and secure update protocols—is essential to ensure both ethical compliance and analytical validity.

VI. FUTURE RESEARCH DIRECTIONS

Progress toward robust and clinically deployable KG-RAG systems depends on advancing methodological rigor, ensuring ethical governance, and fostering global interoperability. The following directions outline emerging research priorities:

- *Standardized Clinical Benchmarks:*

Establish open- access, anonymized benchmark datasets that unify EHR, biomedical literature, and ontology-based representations, thereby enhancing reproducibility and cross-institutional comparability [22], [26], [27].

- *Dynamic and Continual Graph Learning:*

Incorporate incremental graph updates and reinforcement-driven adap- tation to keep biomedical KGs synchronized with new discoveries, ensuring that systems remain contemporaneous and relevant [25], [28].

- *Multilingual and Cross-Domain Expansion:*

Expand KG coverage to multilingual datasets through translation-aware entity alignment, promoting equitable access to AI-driven healthcare globally [22].

- *Explainable Retrieval Layers:*

Integrate Explainable AI (XAI) modules—such as SHAP and counterfactual rea- soning—into graph-based retrieval pipelines to provide interpretable evidence trails [1], [24].

- *Resource-Efficient Edge Deployment:*

Employ model pruning, quantization, and compression techniques to en- able efficient KG-RAG inference on hospital servers and handheld diagnostic devices [25].

Collectively, these directions envision a new generation of adaptive, scalable, and explainable KG-RAG architectures designed to advance clinical reasoning while upholding data integrity and patient privacy.

VII. CONCLUSION

This comprehensive study surveyed the evolution and implementation of Knowledge Graph–augmented Retrieval-Augmented Generation (KG-RAG) frameworks within the domain of healthcare Question Answering. The review traced the field's progression from rule-based and relational retrieval models toward hybrid graph architectures that integrate sym- bolic reasoning with neural generation, resulting in outputs that are both interpretable and evidence-grounded.

Empirical findings across the reviewed literature demon- strate consistent gains in factual accuracy, relational consis- tency, and clinical transparency when graphs are integrated into RAG pipelines. However, critical challenges persist in areas such as dataset reproducibility, query fidelity, and latency optimization, underscoring the need for continued method- ological refinement.

By adopting standardized benchmarks, continual graph learning mechanisms, and privacy-preserving governance frameworks, future systems can transition from experimental prototypes to clinically validated decision-support infrastruc- tures. Ultimately, realizing scalable and trustworthy KG-RAG systems will enable the next generation of healthcare AI to function not merely as computational tools but as ethically grounded, evidence-driven collaborators in medical innova- tion.

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