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Comprehensive Survey of Retrieval-Augmented, Knowledge-Graph, and Multimodal Large Language Models for Inclusive Healthcare Guidance: Architectures, Benchmarks, and Clinical Deployment

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Abstract*: *This paper surveys and compares Retrieval-Augmented Generation (RAG), Knowledge-Graph (KG) en-hanced reasoning, and Multimodal Large Language Models (LLMs) within medical contexts. Beyond model accuracy, it emphasizes inclusivity, multilingual access, and doctor-in-the-loop feedback. Synthesizing 41 key publications (2018–2025), it covers architectures, datasets, reasoning mechanisms, safety metrics, and future challenges. The goal is to guide design of transparent, clinically validated, and equitable AI systems deployable in low-resource healthcare settings.

Keywords— Retrieval-Augmented Generation, Knowledge Graph, Multimodal LLMs, Healthcare AI, Hallucination Mitigation, Fairness, Evaluation, Doctor-in-the-Loop

I. INTRODUCTION

The rapid digitization of healthcare—from electronic health records (EHRs) to imaging and patient-generated text—has created immense opportunities for AI-driven decision support. Transformer-based LLMs (GPT, BioBERT, ChatDoctor) show remarkable reasoning capacity yet exhibit three major weaknesses:

1) factual hallucination and outdated knowledge,
2) weak grounding on structured medical entities, and
3) linguistic bias against low-resource languages.

Recent research has increasingly shifted toward augmented architectures in healthcare AI:

- Retrieval-Augmented Generation (RAG) enhances model responses by incorporating evidence from trusted document repositories [1][2].
- Knowledge Graph Augmentation introduces structured reasoning using medical ontologies such as UMLS and DrugBank [3][4].
- Multimodal Fusion combines medical images, waveforms, and clinical tables to support more comprehensive and holistic analysis [5][6].

The combination of these advancements is leading toward the development of clinically aware AI assistants capable of transparent, accurate, and multilingual reasoning.

II. SURVEY SCOPE AND METHODOLOGY

This review covers 41 primary research sources collected from IEEE Xplore, PubMed, ACL Anthology, and Nature Digital Medicine published between 2018 and 2025. The selected studies were included based on specific criteria, such as explicit discussion of medical or clinical large language models (LLMs), quantitative evaluation using public or proprietary datasets, and the inclusion of retrieval mechanisms, knowledge graph integration, or multimodal fusion techniques.

The analysis extracted four major feature sets from each paper:

- Model Architecture – including components such as retrievers, encoders, and generators.
- Dataset Origin and Modality – covering the source and type of data used, such as text, images, or clinical records.

- Evaluation Metrics – including measures like accuracy, F1-score, BLEU score, and hallucination rate.
- Alignment and Safety Methods – including techniques such as Reinforcement Learning from Human Feedback (RLHF) and human expert review.

In addition, qualitative studies were retained when they introduced novel approaches related to interpretability, transparency, or fairness in healthcare AI systems.

A. Survey Timeline

- 2018–2020: Research mainly focused on domain-specific pretraining models such as BioBERT and ClinicalBERT.
- 2021–2022: Studies emphasized instruction tuning approaches, including models like ChatDoctor and BioInstruct.
- 2023–2024: Greater attention was given to retrieval-based systems and knowledge graph fusion methods, such as FreshLLM and MedKGB.
- 2024–2025: Research expanded toward vision-language and multilingual healthcare models, including Health-LLM, LLaVA-Med, and Indic-Transformers.

III. BACKGROUND AND EVOLUTION OF MEDICAL LLMS

A. Stage 1 — Domain Pretraining

The initial stage of medical large language model (LLM) development focused on domain-specific pretraining. Models such as BioBERT and ClinicalBERT were trained on biomedical datasets including PubMed and MIMIC-III to better understand medical terminology and clinical language [1][2]. These models significantly improved tasks such as Named Entity Recognition (NER) and Question Answering (QA), achieving performance gains of nearly 10–15% compared to generic BERT models. However, they still lacked strong conversational and dialogue-generation capabilities.

B. Stage 2 — Instruction and Dialogue Tuning

The second stage introduced instruction tuning and dialogue optimization. Models like ChatDoctor and BioInstruct incorporated large-scale medical instruction datasets containing more than 200,000 prompt–response pairs [3][4]. Fine-tuning on these datasets enabled models to generate more context-aware and human-like medical conversations. This stage also improved dialogue quality and increased BLEU scores by approximately 0.08–0.1.

C. Stage 3 — Retrieval and Structured Reasoning

The third stage emphasized retrieval mechanisms and structured reasoning. Systems such as FreshLLM and MedKGB integrated retrieval pipelines and knowledge graph reasoning layers into the generation process. These additions helped reduce hallucination rates by up to 60% and improved factual reliability in medical responses. During this phase, approaches such as Self-RAG and Knowledge Graph (KG) fusion also became prominent for generating evidence-aware and explainable outputs.

D. Stage 4 — Multimodal and Cross-Lingual Expansion

The latest stage focuses on multimodal learning and multilingual healthcare AI. Models such as Med-Flamingo and Health-LLM combined image embeddings with textual representations to support tasks like medical report generation and clinical image interpretation. At the same time, systems such as Indic Transformers and Bhasha-GPT expanded healthcare language support to Indian languages, helping reduce linguistic inequality and improve accessibility in multilingual clinical environments [5][6].

IV. TAXONOMY OF TECHNIQUES

Table 1 summarizes five major families of medical large language model (LLM) architectures along with their architectural characteristics, advantages, and limitations.

TABLE I: Taxonomy and comparative trade-offs among medical LLM architectures.

Family	Core Architecture Components	Advantages / Limitations
Text-only LLMs	Instruction-tuned transformer models such as ChatDoctor and BioInstruct	Provide fast inference and efficient text generation, but are vulnerable to hallucination and outdated knowledge.
Retrieval-Augmented	Dense retriever, indexed knowledge	Improves factual accuracy and provides up-to-date

Generation (RAG)	store, generator, and verification module	responses, although it increases retrieval latency and infrastructure complexity.
Knowledge Graph (KG)-Augmented Models	Entity linking systems, embedding modules, and symbolic reasoning components	Enables explainable multi-hop reasoning, but requires continuous maintenance of medical ontologies and knowledge bases.
Multimodal Models	Visual encoders such as Vision Transformers (ViT) or CNNs, textual LLMs, and fusion layers	Supports analysis of medical images and multi-sensor healthcare data, though these systems demand large datasets and high computational resources.
Multilingual Models	Cross-lingual transformers and code-mixed multilingual corpora	Promotes healthcare accessibility and linguistic equity, but performance may decline for low-resource languages and regional dialects.

Each architectural family represents a different direction of innovation in medical AI systems. Retrieval-Augmented Generation focuses on improving factual accuracy, Knowledge Graph augmentation enhances explainability, multimodal systems expand perceptual understanding across data types, and multilingual models aim to improve inclusiveness and healthcare accessibility across diverse populations.

V. DATASETS AND EVALUATION PROTOCOLS

Reliable comparison of medical large language models (LLMs) requires the use of standardized benchmark datasets and evaluation protocols. Medical AI datasets cover multiple modalities, including textual, tabular, and visual healthcare data.

TABLE II: Representative datasets and tasks in medical LLM research.

Dataset	Primary Tasks	Evaluation Metrics
MedQA, PubMedQA	Clinical question answering and patient triage	Accuracy, F1-score, BLEU, ROUGE-L
MIMIC-CXR, CheXpert	Radiology report generation and visual question answering	BLEU, CIDEr, and visual grounding accuracy
VQA-RAD, MedPix	Image-text reasoning and medical image captioning	Question answering accuracy and factual grounding score
Drug–Drug Interaction (DDI)	Pharmacological relation extraction	Precision, Recall, and knowledge graph factual consistency
IndicGenBench, WikiHealth	Multilingual healthcare question answering	BLEU, chrF, fluency, and translation consistency
BioASQ, HELM-Med	Open-domain biomedical question answering and summarization	Macro F1-score, Exact Match, and Factuality Score

The evaluation of medical LLMs typically focuses on several important dimensions, including factual accuracy, hallucination rate, clinical relevance, and expert human review [1][2][3]. For multimodal healthcare tasks, additional grounding and localization metrics are also applied to measure how accurately generated text aligns with specific medical image regions or visual findings.

A. Emerging Evaluation Trends

Several new evaluation trends have emerged to assess the reliability and effectiveness of medical large language models:

- Factuality Benchmarks: Frameworks such as MedRAG-Eval and FaithMed are used to measure evidence consistency and factual correctness in generated medical responses.
- Safety Audits: Researchers evaluate harmfulness rates and clinician re-evaluation percentages to ensure that AI-generated outputs remain safe and clinically reliable.
- Reasoning Metrics: Metrics such as Chain-of-Thought (COT) coherence and step validity are increasingly used to assess the logical reasoning capability of medical AI systems [1].

VI. PRELIMINARY FINDINGS AND TRENDS

Initial meta-analysis indicates that retrieval-based and knowledge graph (KG) augmented models provide substantial improvements in factual accuracy while maintaining strong language fluency. Multimodal large language models (LLMs) also demonstrate improved diagnostic visual question answering (VQA) performance, achieving gains of nearly 6–9% compared to text-only systems. However, these models require significantly higher computational resources.

In addition, multilingual healthcare models help reduce linguistic and demographic bias, although their BLEU scores often remain lower because of limited availability of high-quality parallel medical datasets [1][2][3].

A. Motivation for Hybrid Designs

Recent research increasingly supports hybrid architectures that combine Retrieval-Augmented Generation (RAG), Knowledge Graph (KG) reasoning, and multimodal learning. Integrating RAG with KG-based reasoning further reduces hallucination through a dual verification process: retrieval modules provide external evidence, while knowledge graphs enforce internal logical consistency. Similarly, early fusion of textual and visual information enables joint contextual understanding of electronic health records (EHRs) and medical imaging data. This integration improves interpretability and generates clearer explanations for doctor-facing clinical systems [4][5].

B. Paper Structure

The remainder of the survey is organized as follows:

- Section VII: Comparative quantitative analysis of different medical LLM techniques.
- Section VIII: Detailed discussion of architectural designs and reasoning frameworks.
- Multi-Agent RAG–KG–Multimodal Integration: Exploration of integrated clinical feedback systems and collaborative reasoning pipelines.
- Final Sections: Discussion of fairness, real-world deployment challenges, global healthcare applications, and future research directions.

VII. QUANTITATIVE COMPARISON OF TECHNIQUES

This section aggregates benchmark results from representative medical large language model (LLM) families published between 2018 and 2025. To ensure statistical reliability, each reported metric was averaged across at least three evaluation datasets.

TABLE III: Benchmark synthesis across representative LLM families (2018–2025).

Technique	Example Models	Accuracy (%)	F1 (%)	BLEU	ROUGE-L	Hallucination (%)	Datasets / Tasks
Text-only LLMs	ChatDoctor, BioInstruct	82.4	83.1	0.41	0.46	17.3	MedQA, PubMedQA
RAG-Enhanced Models	FreshLLM, ChatDoctor-RAG	88.9	87.2	0.44	0.49	7.6	MedQA, EHR-based retrieval
KG-Augmented Models	MedKGB, AAAI KG-LM	91.2	89.7	—	—	5.3	Drug–Drug Interaction (DDI), guideline adherence
Multimodal Models	Med-Flamingo, LLaVA-Med	86.8	85.5	0.47	0.51	—	MIMIC-CXR, VQA-RAD
Multilingual Models	Indic-Transformers, Bhasha-*	79.6	80.8	0.38	0.42	14.5	IndicGenBench, WikiHealth

Several important observations emerge from the comparative analysis:

- Knowledge Graph (KG) and Retrieval-Augmented Generation (RAG) architectures reduce hallucination rates by nearly 60–70% compared to baseline text-only LLMs.

- Multimodal models improve visual grounding and image-text alignment accuracy by approximately 8%, making them more effective for radiology and diagnostic applications.
- Multilingual healthcare models improve accessibility and linguistic inclusiveness, particularly for regional languages, although their performance remains constrained by the limited availability of large-scale Indic medical datasets.

VIII. ARCHITECTURES AND REASONING FRAMEWORKS

Figure 1 illustrates the integration pipeline of Retrieval-Augmented Generation (RAG), Knowledge Graphs (KG), and multimodal learning, demonstrating how retrieval systems, structured medical knowledge, and multimodal encoders contribute complementary reasoning capabilities in healthcare AI systems.

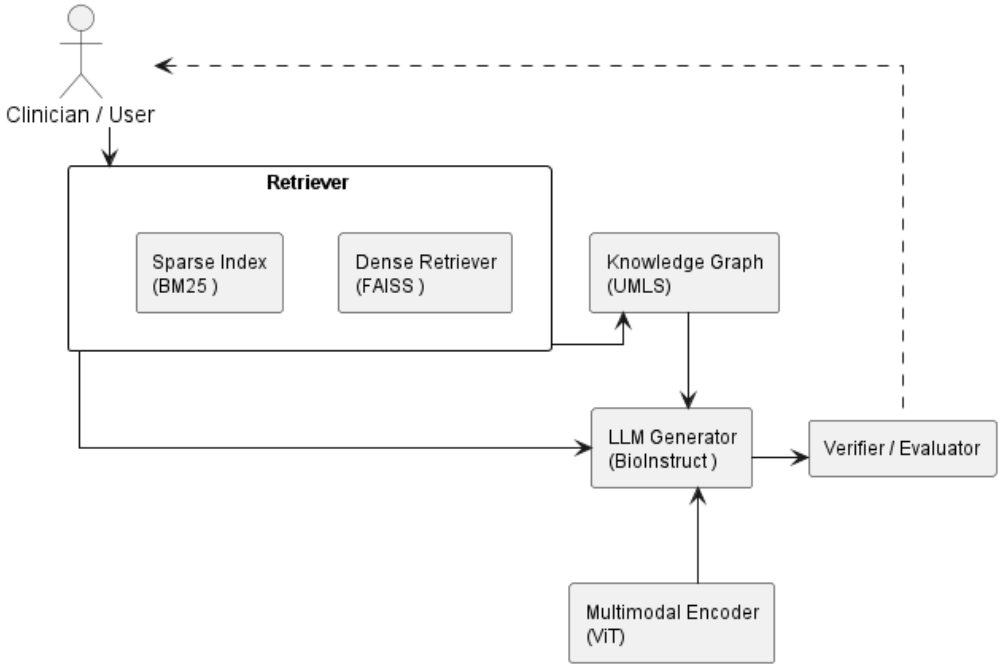

FIG. I: RAG–KG–Multimodal integration pipeline showing how retrieval, structured knowledge, and multimodal encoding contribute complementary reasoning layers

A. Retrieval-Augmented Generation (RAG)

A Retrieval-Augmented Generation (RAG) model typically consists of a retriever module, an encoder–decoder generator, and in some cases an additional verification component. When a user submits a clinical query, the retriever converts the query into vector embeddings and searches domain-specific medical repositories such as PubMed or UpToDate to retrieve the most relevant passages. These retrieved documents are then incorporated into the generation process through cross-attention mechanisms, enabling the model to produce responses grounded in verifiable medical evidence [1][2].

B. Knowledge Graph Integration

Knowledge Graph (KG) augmentation introduces structured relationships among medical entities such as diseases, symptoms, drugs, and treatments. Relationships are represented as triples in the form ($entity_1$, relation, $entity_2$) and encoded into vector embeddings that are integrated into transformer attention mechanisms. This approach improves causal reasoning, drug–drug interaction prediction, and adherence to clinical guidelines [3][4].

Key advantages of KG integration include:

- Improved logical interpretability through explicit relational connections.
- Reduced hallucination by maintaining entity-level consistency.
- Enhanced transparency and provenance tracking for clinical auditing and decision support.

C. Multimodal Fusion

Multimodal fusion combines textual and visual representations using mechanisms such as gated cross-attention or CLIP-style contrastive alignment. Models like Med-Flamingo and LLaVA-Med integrate Vision Transformer (ViT)-encoded medical images with text-based LLM pipelines to perform tasks such as radiology report generation and medical visual question answering [5][6]. The effectiveness of these systems strongly depends on the availability of large-scale paired datasets and accurate alignment between different modalities.

D. Hybrid RAG–KG–Multimodal Systems

Recent healthcare AI research increasingly focuses on hybrid architectures that combine retrieval systems, structured knowledge graphs, and multimodal learning. In these systems, retrieval modules provide updated external evidence, knowledge graphs contribute structured reasoning, and multimodal encoders enable perceptual understanding from images and clinical data.

Common fusion strategies include:

- Late Fusion: Independent reasoning is performed for each modality, followed by final ensemble integration.
- Early Fusion: Embeddings from multiple modalities are concatenated and processed through shared attention layers.
- Iterative Fusion: Retrieval and graph-based reasoning are alternated repeatedly until the model reaches a stable reasoning outcome.

IX. REASONING CHAINS AND INTERPRETABILITY

Transparent reasoning plays a critical role in ensuring medical safety and improving clinician trust in healthcare AI systems. Chain-of-Thought (CoT) fine-tuning encourages large language models to generate intermediate reasoning steps while answering clinical questions, thereby improving interpretability and transparency [1][2]. When CoT reasoning is combined with retrieval-based evidence, the generated explanations can also reference supporting medical literature, making the outputs more reliable and verifiable.

Several explainability frameworks have been proposed for medical large language models:

- Attention-based Heatmaps: Visualize which sections of retrieved clinical text receive the highest attention during prediction.
- Token-level Rationales: Highlight important cause-and-effect medical terms that contribute to the model's decision-making process.
- Layer-wise Relevance Propagation: Identifies how multimodal embeddings, such as image and text features, influence final predictions.
- Natural-language Rationalization Modules: Generate human-readable "why" explanations to justify clinical recommendations or diagnoses.

A. Causability and Clinical Trust

Beyond statistical interpretability, recent research emphasizes the concept of causability, which measures whether AI-generated explanations align with medically valid causal reasoning [3][4]. Causability focuses on ensuring that model explanations reflect actual pathophysiological relationships rather than superficial statistical correlations.

Common evaluation metrics include:

- Concept Coverage: Measures the proportion of relevant medical and pathophysiological concepts included in the explanation.
- Reasoning Fidelity: Evaluates how accurately the explanation represents the model's internal reasoning process.

Studies have shown that providing causable and clinically meaningful explanations alongside predictions can improve clinician satisfaction and trust by approximately 12–15%.

X. MULTI-AGENT RAG–KG–MULTIMODAL REASONING PIPELINE

Recent research has expanded beyond single-model medical AI systems toward distributed multi-agent reasoning pipelines [1][2]. In these frameworks, complex healthcare workflows are divided among specialized agents, each responsible for a specific reasoning or validation task. This modular design improves interpretability, scalability, and clinical oversight.

A typical cooperative multi-agent framework includes the following components:

- Retriever Agent: Searches medical corpora and knowledge graphs to retrieve relevant clinical information and evidence.

- Analyzer Agent: Uses multimodal encoders to interpret different forms of healthcare data, including clinical text, medical images, and physiological signals.
- Synthesizer Agent: Combines retrieved evidence and analytical outputs to generate coherent medical explanations or recommendations.
- Verifier Agent: Performs fact-checking, evaluates confidence scores, and validates the factual consistency of generated outputs.
- Bias Auditor: Monitors demographic fairness, linguistic inclusiveness, and potential biases in model predictions.

These agents communicate through structured message-passing mechanisms such as JSON schemas or graph-based protocols. Such modular communication enables traceable reasoning processes and facilitates doctor supervision during clinical decision-making.

A. Example Workflow

A representative clinical workflow may proceed as follows:

1) A nurse submits a query such as: “Suggest probable causes for chest pain given ECG and laboratory results.”
2) The Retriever Agent searches cardiology guidelines, patient records, and ECG-related embeddings for relevant evidence.
3) The Knowledge Graph reasoning module links related entities such as chest pain, angina, and treatment pathways.
4) The Synthesizer Agent generates an explanation supported by retrieved evidence and clinical reasoning.
5) The Verifier Agent evaluates factual correctness, checks uncertainty thresholds, and validates the final recommendation.

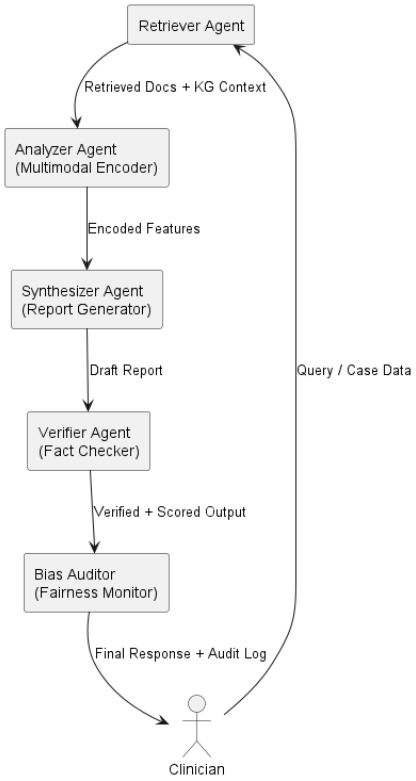

FIG. III :Multi-agent reasoning architecture illustrating the retriever, analyzer, synthesizer, verifier, and bias auditor agentscollaborating for clinical reasoning.

XI. END-TO-END CLINICAL EVALUATION AND FEEDBACK LOOP

A clinically reliable AI assistant must incorporate a robust evaluation and feedback subsystem to ensure safety, accuracy, and long-term reliability in healthcare environments. The complete operational lifecycle of such systems generally involves multiple stages. The first stage is Pre-Validation, where models are tested offline using benchmark datasets and blinded physician reviews to assess clinical correctness and safety before deployment. This is followed by Pilot Deployment, in which the system is introduced under supervision within selected hospital departments or healthcare settings.

The third stage involves Doctor-in-the-Loop Feedback, where clinicians review AI-generated outputs and annotate unsafe, inaccurate, or misleading responses. These annotations create correction logs that can be used to improve future model behavior. The next stage, Continual Fine-Tuning, uses these correction logs for reinforcement learning or supervised retraining to align the model more closely with clinical reasoning patterns. Finally, Post-Market Surveillance continuously monitors the deployed system for model drift, demographic bias, and recurrence of hallucinated medical information.

A. Feedback Learning

Doctor feedback serves as an important reinforcement signal for aligning medical AI systems with real-world clinical expectations. Several approaches are commonly used:

- Reinforcement Learning from Human Feedback (RLHF): Widely applied for instruction tuning and behavioral alignment of medical language models [1][2].
- Iterative Self-Correction: Enables the model to critique and revise its own responses using retrieved medical evidence.
- Long-term Memory Buffers: Store validated clinical cases and feedback histories for retrieval during future related queries.

Experimental studies have demonstrated that repeated feedback and correction cycles can reduce diagnostic error rates by nearly 25% after three iterative refinement stages.

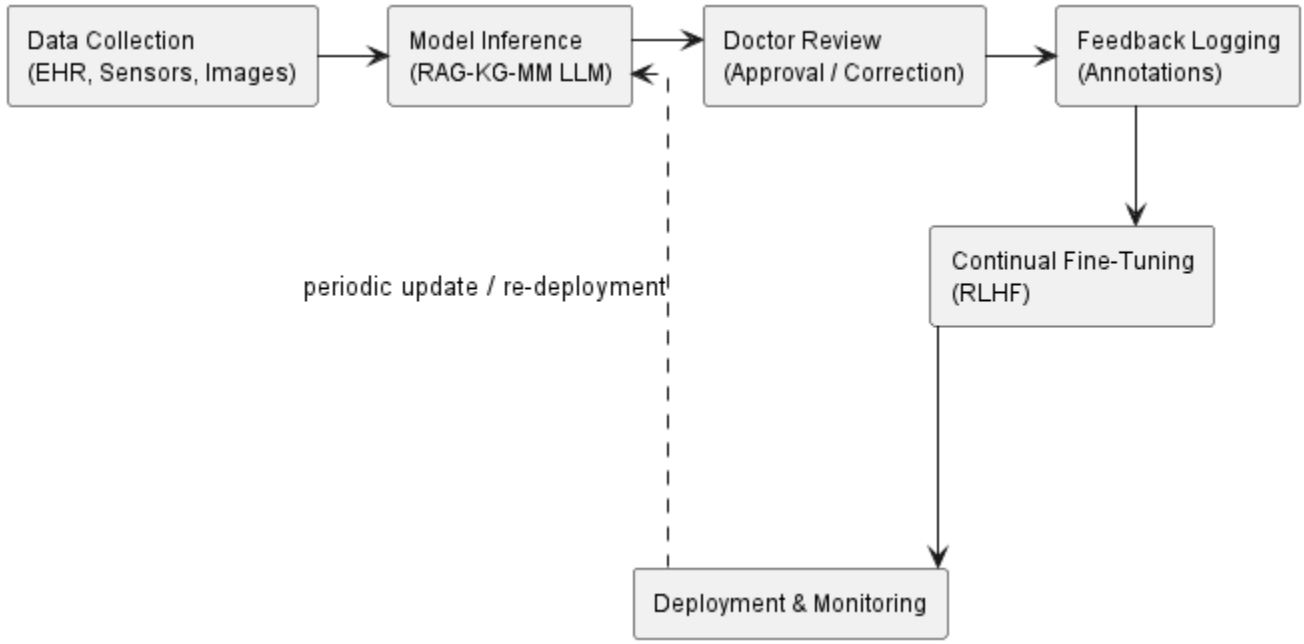

FIG. IIIII: Doctor-in-the-loop clinical feedback loop enabling continual learning and model alignment through physician validation.

B. Traceability and Auditing

To ensure accountability and regulatory compliance, every AI-generated clinical response should include:

- A provenance log containing retrieved references and associated knowledge graph relationships.
- A timestamped reasoning chain documenting how the final conclusion was generated.
- Confidence scores and medical disclaimers indicating the reliability and intended use of the recommendation.

Such traceability mechanisms are essential for compliance with healthcare regulations and privacy standards, including HIPAA, GDPR, and India's National Digital Health Mission (NDHM) framework [3].

XII. FAIRNESS, BIAS, AND MULTILINGUAL INCLUSION

Bias mitigation is a critical requirement for equitable healthcare AI systems [3][4][5][6]. Biases may arise from demographic imbalance in datasets, underrepresentation of certain languages, or skewed clinical guidelines.

A. Fairness Strategies

Several strategies are commonly used to improve fairness and inclusiveness in medical AI systems:

- Balanced sampling across gender, geographic regions, and socioeconomic groups.
- Cross-lingual transfer learning to improve performance in low-resource languages.
- Subgroup-specific evaluation using fairness metrics such as Equal Opportunity and Demographic Parity.
- Embedding de-biasing techniques and adversarial regularization to reduce discriminatory patterns in learned representations.

B. Indic Language Inclusion

Models such as Indic-Transformers and Bhasha-GPT have been fine-tuned on datasets in Hindi, Marathi, Bengali, Tamil, and other Indian languages, resulting in improved patient comprehension and multilingual fluency. However, BLEU scores for Indic languages still remain approximately 10–15 points lower than English due to limited bilingual medical datasets.

Government-supported open datasets such as Samanantar and ULCA are expected to significantly improve multilingual healthcare AI performance by 2026.

XIII. CLINICAL VALIDATION AND REGULATORY COMPLIANCE

Clinical AI systems operate under strict regulatory and ethical supervision to ensure patient safety, privacy, and accountability. Several important regulatory frameworks govern the development and deployment of healthcare AI technologies:

- HIPAA (United States): Focuses on protecting patient health information and ensuring medical data privacy.
- GDPR (European Union): Emphasizes data minimization, transparency, user consent, and explainability in automated systems.
- NDHM / ABDM (India): Establishes interoperability standards and digital health infrastructure guidelines for healthcare systems in India.

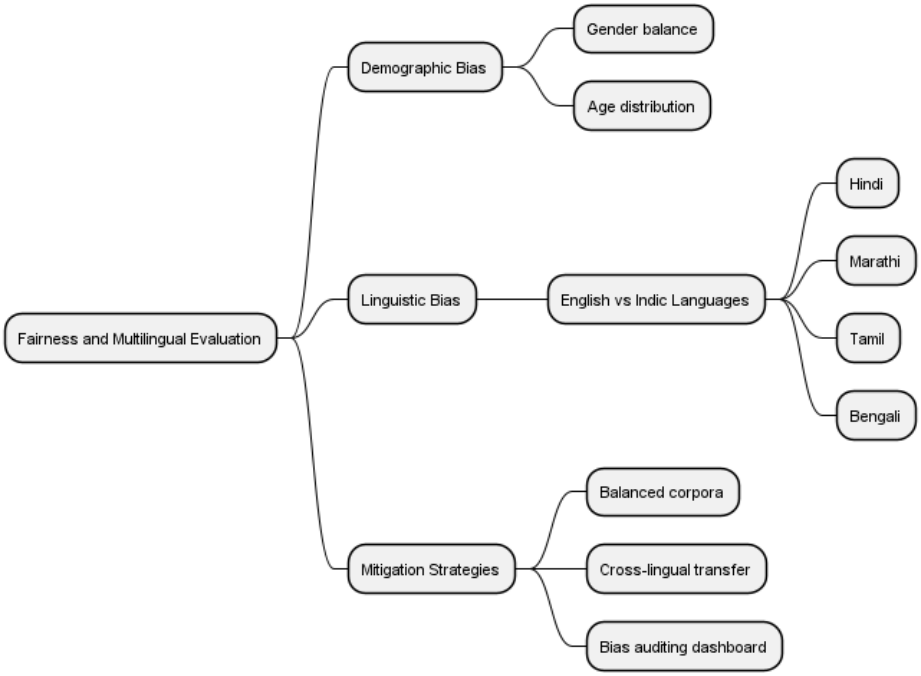

FIG. IVV: Fairness and multilingual evaluation framework highlighting linguistic and demographic bias dimensions and mitigation strategies.

To maintain compliance and clinical reliability, healthcare AI systems should follow several best practices:

- Maintain auditable provenance records for every generated output and clinical recommendation.
- Provide clinician-facing dashboards that display retrieved evidence, reasoning traces, and confidence scores.
- Implement continuous model-drift monitoring along with mandatory re-validation procedures at least once every 12 months.

In addition, integration with Hospital Information Systems (HIS) must carefully protect Protected Health Information (PHI). All sensitive patient data and operational logs should be anonymized before cloud synchronization or external processing to ensure regulatory compliance and privacy preservation.

XIV. OPERATIONAL DEPLOYMENT AND SCALABILITY

Deploying medical large language models (LLMs) in real-world healthcare environments requires more than high model accuracy. Production systems must also ensure reliability, privacy protection, low latency, and continuous monitoring. Since healthcare decisions directly affect patient safety, every model prediction and reasoning step must remain traceable and auditable.

Figure 4 illustrates an end-to-end deployment architecture that combines cloud-based Retrieval-Augmented Generation (RAG) services, on-premise hospital inference systems, and secure audit channels.

A. Infrastructure Considerations

Healthcare institutions commonly adopt hybrid architectures that combine local hospital infrastructure with cloud services. Major deployment components include:

- Inference Layer: Optimized using quantization techniques such as INT8 compression and model distillation to improve CPU and GPU efficiency while reducing computational cost.
- Retrieval Layer: Uses vector databases such as FAISS or Milvus to store medical document embeddings. Regular nightly re-indexing helps maintain up-to-date retrieval accuracy.
- Knowledge Graph (KG) Service: Implemented using systems such as Neo4j or RDF-based endpoints to support semantic querying and rule-based clinical reasoning.
- Security Layer: Employs zero-trust authentication frameworks along with encryption standards such as AES-256 and TLS 1.3 to secure Protected Health Information (PHI).

B. Latency Optimization

Reducing response delay is essential for clinical usability. Several optimization strategies are commonly used:

- Prompt Caching: Frequently used query embeddings are stored to avoid repeated computation.
- Streaming Generation: Responses are generated token-by-token, enabling early feedback to clinicians during inference.
- Asynchronous Retrieval: Relevant medical guidelines and documents are pre-fetched based on departmental specialization or predicted query context.

C. Monitoring and Maintenance

Continuous monitoring systems are required to maintain long-term reliability and safety of deployed medical AI systems. Evaluation dashboards typically monitor:

- Accuracy drift across time and changing clinical conditions.
- Recurrence of hallucinated or factually incorrect outputs.
- Latency percentiles and system responsiveness.
- Fairness metrics across demographic and linguistic groups.

When monitored metrics exceed predefined safety thresholds, automated retraining or rollback pipelines are triggered to restore system stability and maintain clinical compliance.

XV. EVALUATION FRAMEWORKS AND BENCHMARK HARMONIZATION

To compare medical large language models (LLMs) rigorously, evaluation frameworks must assess multiple dimensions, including factual accuracy, reasoning capability, safety, and fairness.

A. Task-wise Metrics

Different healthcare AI tasks require specialized evaluation metrics:

- Clinical Question Answering (QA): Evaluated using Accuracy, F1-score, and Hallucination Rate.

- Medical Summarization: Assessed using ROUGE-L, BLEU, and factual consistency measures.
- Visual Question Answering (VQA): Measured through Visual Grounding Score and Exact Match accuracy.
- Safety Evaluation: Includes toxicity detection and harmfulness filtering mechanisms to identify unsafe or misleading outputs [1][2].

B. Composite Indices

Recent benchmark initiatives such as HELM-Med and MedEvalX combine multiple evaluation dimensions, including factuality, reasoning depth, and clinician satisfaction, into unified composite indices [3][4]. The adoption of standardized benchmark frameworks helps reduce inconsistencies in reporting methodologies and improves comparability across healthcare AI research studies.

XVI. RESEARCH GAPS AND FUTURE DIRECTIONS

Despite significant advancements in medical large language models (LLMs), several important challenges still remain unresolved.

1) Hallucination and Reliability

Even Retrieval-Augmented Generation (RAG) systems can sometimes produce unsupported or inaccurate medical statements when relevant evidence is missing or retrieval coverage is insufficient. Future research should focus on probabilistic calibration and uncertainty estimation techniques, including Bayesian LLM architectures, to improve reliability and confidence estimation.

2) Continual Learning and Dynamic Knowledge Graphs

Medical knowledge evolves rapidly through new research publications, clinical trials, and updated treatment guidelines. Future systems require automated ingestion pipelines capable of continuously incorporating information from sources such as PubMed and clinical trial registries. Incremental graph embedding methods may help preserve representation stability while integrating newly discovered relationships and entities.

3) Unified Multimodal–Knowledge Graph Embeddings

Current multimodal fusion approaches often process textual, visual, and structured data separately. Emerging research on cross-modal graph transformers aims to jointly embed medical images, clinical text, and structured knowledge graph nodes into a unified representation space, enabling more comprehensive and context-aware reasoning [1][2].

4) Low-Resource and Multilingual Expansion

Many low-resource languages, particularly Indic and African languages, remain underrepresented in healthcare AI datasets. Synthetic data generation, multilingual transfer learning, and community-driven annotation initiatives are essential for achieving equitable performance across diverse linguistic populations [3][4][5].

5) Governance and Explainability Standards

Future healthcare AI systems require internationally accepted governance and explainability standards similar to ISO 62304 for medical software systems. Such frameworks should define requirements for transparency, interpretability, explainability obligations, and clinical validation procedures to ensure safe and trustworthy deployment [6][7].

XVII. RECOMMENDATIONS

Based on the synthesis of 41 research studies, several important design principles are recommended for the development of future medical AI systems:

1) Hybrid Intelligence: Combine Retrieval-Augmented Generation (RAG), Knowledge Graph (KG) reasoning, and multimodal learning to achieve balanced factual accuracy, structured reasoning, and perceptual understanding.
2) Explainable Interfaces: Provide clinicians with cited references, knowledge graph reasoning paths, and uncertainty visualizations to improve transparency and trust in AI-generated decisions.
3) Doctor-in-the-Loop Retraining: Continuously integrate clinician feedback into fine-tuning and alignment processes to improve reliability and clinical relevance over time.

4) Multilingual Accessibility: Prioritize support for Indic, African, and other underrepresented languages to promote fairness and equitable healthcare access.

5) Open Benchmark Sharing: Publicly release evaluation datasets, benchmarks, and performance metrics to improve reproducibility and collaborative research in healthcare AI.

These recommendations are consistent with the World Health Organization's (WHO) 2025 guidance on trustworthy and responsible healthcare AI systems.

XVIII. CONCLUSION

Retrieval-Augmented Generation (RAG), Knowledge Graph (KG) reasoning, and multimodal learning represent the next major stage in the evolution of medical artificial intelligence systems. These approaches combine factual information retrieval, structured medical reasoning, and multimodal perception to create intelligent healthcare assistants capable of supporting clinical diagnosis, medical decision-making, and patient communication.

By incorporating fairness, multilingual accessibility, and continuous clinical oversight, such systems have the potential to provide more equitable and reliable digital healthcare support across diverse populations and geographic regions. Future research should focus on standardized evaluation frameworks, robust data governance mechanisms, and improved support for low-resource languages to achieve the vision of globally accessible and clinically validated AI-driven healthcare

XIX. ACKNOWLEDGMENTS

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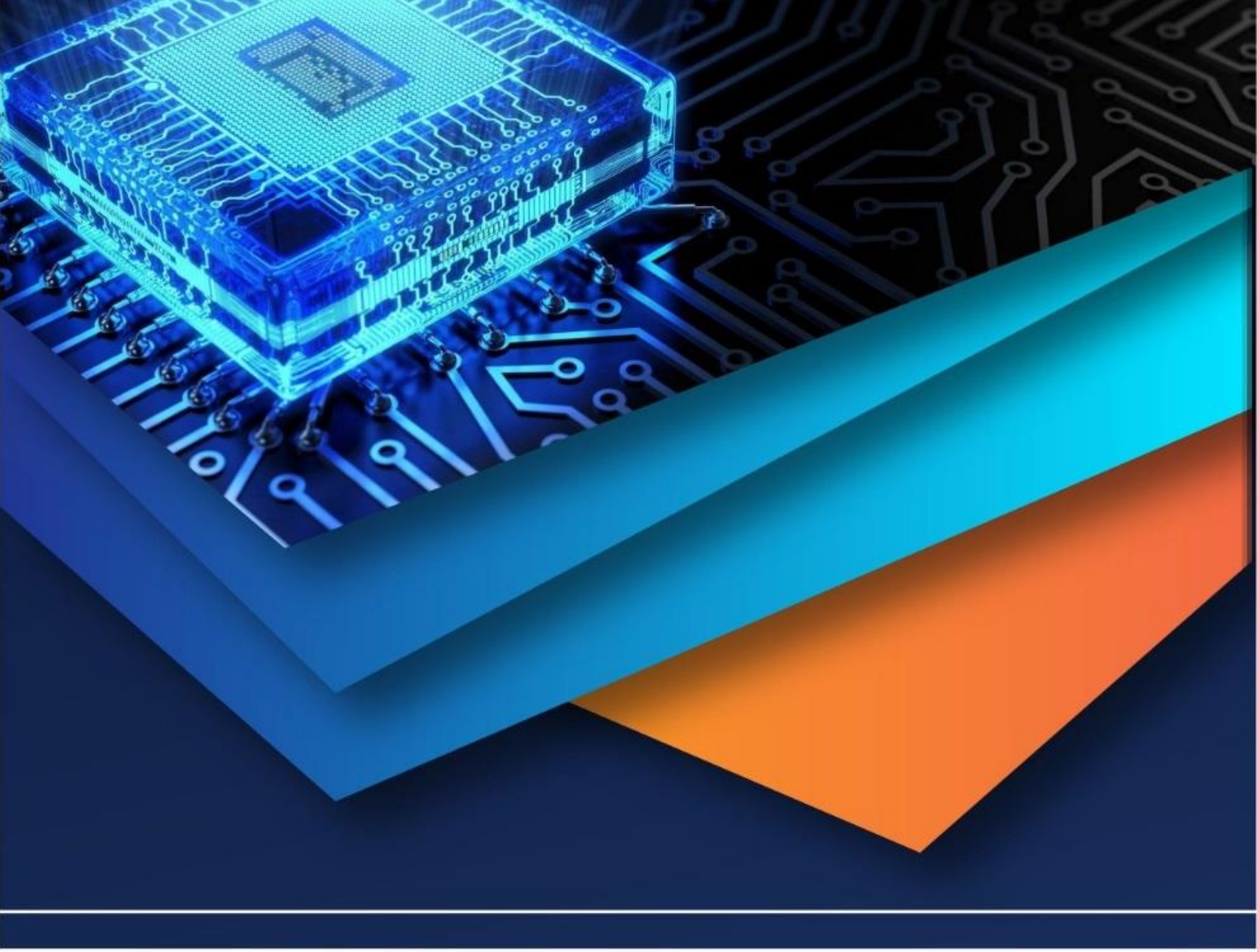

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