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An AI-powered knowledge graph-based question answering system for Charak Samhita: integrating sanskrit NLP and graph data science

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ABSTRACT

Originating in India, Ayurveda is an ancient medical system focused on holistic healing that considers the mind, body, and spirit. This study utilizes knowledge graph (KG) technology to develop a KG model for an Ayurveda question-and-answer system. The system includes modules for knowledge extraction from *चरकसंहिता, कायचिकित्सा, भैषज्यरत्नावली* and *द्रव्यगुण संग्रह*, construction of KG from this extracted knowledge and construction of AI supported Question answer system. In the methodology, domain-specific KG is constructed in Neo4j. Entities such as diseases (Vyadhi *व्याधी*), symptoms (Lakshana *लक्षण*), doshas (*दोष*), herbs, and treatments are incorporated. Advanced Sanskrit natural language processing (NLP) pipelines using ByT5-Sanskrit, SanskritBERT, and fine-tuned BioBERT facilitate named entity recognition (NER) and relation extraction. Graph-based reasoning models such as graph attention networks (GAT) and graph reasoning enhanced language models (GREASELM) enhance multi-hop reasoning across Ayurvedic concepts. Evaluation was conducted using a gold-standard annotated dataset of Charak Samhita verses mapped to disease–symptom–treatment relationships. Performance metrics included precision, recall, F1-score, mean reciprocal rank (MRR), and overlap coefficient. Superior accuracy can be seen in the proposed model as compared to baseline BERT-QA and subgraph QA approaches. This research has integrated Sanskrit computational linguistics and KG science. The approach mentioned in this paper has mentioned a framework that is scalable, interpretable and culturally significant. With the focus on Ayurveda, the methodology also mentions the potential for developing cross-cultural medical questions–answering systems, thereby bridging ancient wisdom with modern technological approaches.

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1. INTRODUCTION

Ayurveda, the ancient Indian medical practice stands tall among the modern medical practices even after several hundred years. It is a holistic and prevention-focused system of natural healing that originated from the wisdom of ancient Indian masters [1], [2]. Its personalized approach helps address the unique needs of each individual, making it a valuable practice for many seeking alternative or complementary healing methods. The Ayurvedic treatises like *Charak Samhita, Kaychikitsa, Bhaishajya Ratnawali, Dravya Guna Sangraha* elaborate on fundamental aspects of physiology, anatomy, disease etiology, and pathogenesis, along with diagnostic criteria, various methods of treatment (चिकित्सा), and prognosis [3]. In the field of medical science, the need is for an AI system which is capable of collecting and processing data from various sources and assisting vaidya (ayurvedic doctors)) in their responsibilities [3]. A knowledge graph (KG), which provides structured and interpretable representations of domain specific knowledge, paired with a question answering (QA) system, serves as an effective solution to meet this requirement [4]–[6]. Recent advances in graph neural networks (GNNs) and knowledge-aware language models have further improved reasoning capabilities across biomedical and clinical contexts [7], [8]. However, application of these methods to Ayurvedic texts shows some unique challenges like the linguistic complexity of Sanskrit [9], [10]. Domain specificity as the concepts mentioned do not directly map onto medical categories [11], [12], and QA system scalability which needs multi-hop traversal [13], [14].

This study tackles long-standing challenges in the computational processing of ancient Sanskrit medical texts by introducing an AI-driven KG-based QA system for the Charak Samhita and few more Ayurvedic texts. The framework contributes in four major ways. First, it develops a Sanskrit natural language processing (NLP) pipeline that integrates ByT5-Sanskrit (for tokenization) and SanskritBERT (robust entity recognition such as *vyadhi*, *lakshana*, and *aushadhi*). Second, it develops a Neo4j-based Ayurvedic KG that explicitly models disease–symptom–treatment relationships, thereby capturing the intricate interdependencies described in the Charak Samhita. Third, the system integrates graph reasoning algorithms, including graph attention networks (GAT) and graph reasoning enhanced language model (GREASELM), to facilitate multi-hop reasoning for complex user queries. Finally, the framework undergoes experimental evaluation against strong baselines, demonstrating significant improvements in accuracy, interpretability, and domain relevance. Thus this study advances digital Ayurveda research, offering a scalable, explainable, and clinically relevant QA system capable of bridging classical Ayurvedic wisdom with modern AI-driven healthcare informatics [15], [16].

2. LITERATURE REVIEW

2.1. Ayurveda and the Charak Samhita

Charak Samhita is Ayurveda's definitive treatise which mentions the concepts of 3 doshas (Vaat, Pitta, Kapha), 7 Dhatu (body tissues) and 3 mala (waste products) along with the various treatment strategies [17], [18]. It remains relevant to modern healthcare by offering a holistic approach which very well aligns with contemporary principles [19]. But, modern access is constrained by unstructured text forms and scarcity of computational resources [20].

2.2. QA over KGs

KG-based QA has emerged as a promising paradigm, enabling structured question interpretation and reasoning. Techniques include subgraph searching [21], relation-aware mapping with transformers, and multi-hop reasoning using GNNs [22]. Advanced models such as GREASELM and KG rank [23] demonstrate improved reasoning by combining language models with structured graphs in healthcare [24], [25].

2.3. Graph data science in healthcare

Graph data science (GDS) leverages network-based algorithms to extract patterns, clusters, and paths in complex systems [26]. The integration of graph similarity, overlap coefficients, and attention mechanisms has shown strong potential for complex decision-making [27], [28].

2.4. Sanskrit NLP and Computational Challenges:

Sanskrit, characterized by its highly inflected morphology and Sandhi rules, poses challenges for tokenization and semantic parsing [29]. Recent advances such as ByT5-Sanskrit and domain-specific adaptations of BERT models for Sanskrit offer robust solutions for Sandhi splitting, NER, and semantic role labeling.

2.5. AI-enhanced ayurvedic systems

Several studies have highlighted the synergy between AI and Ayurveda. For example, graph-based diagnostic systems have been explored for Ayurvedic diagnosis [30], while modern KG applications in healthcare demonstrate the interpretability advantage of symbolic.

3. RESEARCH GAP AND OBJECTIVES

Although prior studies have advanced KG-QA [31], their application to classical Sanskrit medical texts remains largely unexplored. Current research on Ayurveda mainly focuses on conceptual analysis or survey-based healthcare adoption studies, with limited computational implementations. Moreover, while graph data science has demonstrated significant utility in healthcare decision-making, its integration with Sanskrit NLP for QA over ancient medical treatises is novel. The primary objective of this research is to design and implement an AI-powered framework that integrates Sanskrit NLP with KG methodologies to support advanced QA over the Charak Samhita.

4. METHODOLOGY

The methodology follows a four-stage pipeline in Figure 1.

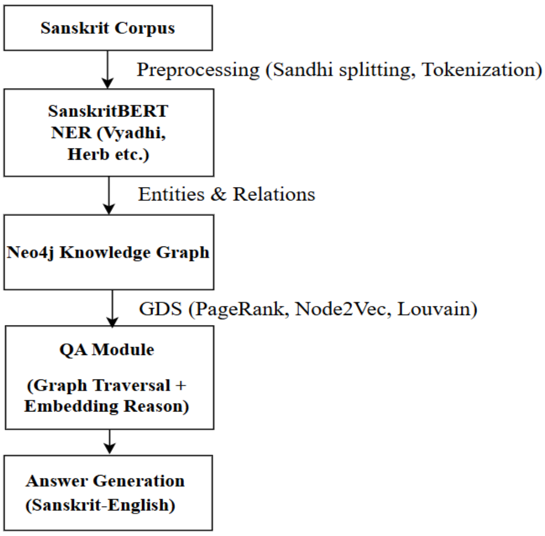

Figure 1. Four-stage pipeline

4.1. Sanskrit NLP pipeline

A hybrid pipeline was developed to extract structured Ayurvedic knowledge from classical Sanskrit texts, integrating advanced transformer-based models with domain-specific post-processing. Named entity recognition (NER) Module: Fine-tuned ByT5-Sanskrit and SanskritBERT models were employed to identify key Ayurvedic entities, including Vyadhi (diseases), Lakshana (symptoms), Dravya (herbs/medicines), and constitutional factors such as Dosha, Dhatu, and Mala. Relation classification between identified entities is done with the help of the BioBERT model. Important relationships like, Vyadhi-Lakshana, Vyadhi-Dravya, and Dravya–Dosha are captured by the system. Accurate semantic linkage between entities is captured by fine-tuning the model on annotated Sanskrit-Ayurvedi corpora. In the stage of Post-processing and Validation, the extracted entities and relations were aligned against Ayurvedic ontologies. This multi-stage pipeline ensures robust extraction of structured knowledge, which will be the foundation for downstream tasks such as KG construction and QA systems in the Ayurvedic domain.

4.2. Ayurvedic knowledge graph development

Using the Neo4j graph database, structured relationships between key domain entities were captured and Ayurvedic KG was constructed. KG nodes were *Vyadhi*, *Lakshana*, *Doshas*, *Dravya*, and *Treatments*, while edges captured semantic relations like *"causes"*, *"treated_by"*, *"associated_with"*, and *"balances"*. Each node and edge is annotated with properties such as Sanskrit terms, English transliterations, and textual references from classical sources, supporting multilingual and provenance-aware queries. GDS algorithms (PageRank, Graph Similarity, Overla Coefficient) were applied to enhance graph-based reasoning and knowledge discovery.

4.3. QA system architecture

The ayurvedic KG is traversed by a proposed QA system to respond to the queries written in either Sanskrit or English. The pipeline design is as follows:

- Question parsing: Once the user asks questions, they are processed through the NLP module, which performs tokenization and dependency parsing, to extract meaningful terms and syntactic structures. This process makes sure that both Sanskrit and English inputs are normalized for further processing.
- Entity linking: The terms, extracted in the above phase, are mapped to KG nodes using embedding-based similarity measures. This step reconciles linguistic variations by mapping user vocabulary to standardized Ayurvedic entities (disease, symptom, herb, treatment, dosha).
- Graph traversal: Query resolution within the KG is achieved through layered traversal strategies. Simple queries are processed using subgraph search to extract explicit relations such as Vyadhi–treated_by–Herbs. More complex information needs, which require inference, are addressed via multi-hop reasoning techniques. GAT and GREASELM are employed to capture contextual dependencies and propagate semantic signals across multiple nodes and edges. This enables the discovery of indirect associations otherwise hidden in the graph structure. By integrating direct retrieval with advanced inference, the system supports robust and semantically enriched exploration of Ayurvedic knowledge.
- Answer ranking: KG Rank model, combined with similarity measures, are used to rank the answers which ensures the most relevant and semantically correct responses based on the priorities.

The system is designed to provide interpretable, knowledge-grounded answers to user queries. For example, when the input is *"Which herb is used in the treatment of Raajyakshma (राजयक्ष्मा) according to Charak Samhita?"*, the query undergoes multiple stages of processing. First, the NLP module will do entity recognition, identifying *Raajyakshma*as a Vyadhi (disease) and "herb" as a Dravya (medicine). These entities are then mapped to the KG. As this is the relationship between Vyadhi and Herb, the system searches along the Vyadhi–Dravya edges to identify appropriate herbs for this disease. In this case, the traversal retrieves नागपुष्प, कर्पूर, लवङ्ग and others which are used in the treatment of *Raajyakshma*. Finally, the answer is enriched with supporting verse references from the *Charak Samhita*, ensuring transparency and cultural grounding. This interpretable pipeline guarantees not only accurate responses but also explainability and authenticity in the context of Ayurvedic knowledge.

5. EXPERIMENTAL DESIGN AND EVALUATION PROTOCOLS

Evaluation metrics: System performance was rigorously assessed by combining quantitative and graph-based metrics. Precision, Recall, and F1-score were used as core measures to evaluate the correctness of retrieved answers with respect to gold-standard annotations. Mean reciprocal rank (MRR) was used to measure how highly the correct answer was generated in the ranked results list. The overlap coefficient quantified the degree of entity overlap between system outputs and reference KG annotations, ensuring semantic consistency. The graph similarity index was also calculated using structural embedding distances which captured closeness of captured subgraphs. Together, these metrics provide a balanced evaluation framework which covers both answer-level correctness and graph-level fidelity, and also provide the accuracy and interpretability of the proposed QA system.

5.1. Evaluation protocols

A multi-stage evaluation protocol was designed to comprehensively validate the proposed system across entity recognition, relation extraction, and QA tasks.

- Entity recognition task: NER models were evaluated against a manually annotated gold-standard dataset, with Precision, Recall, and F1-scores computed to measure entity-level accuracy.
- Relation extraction task: Relations such as *Vyadhi–Lakshana*, *Vyadhi–Dravya*, and *Dravya–Dosha* were evaluated using domain-specific labels. Model performance was compared using F1-scores, highlighting the effectiveness of BioBERT-based relation classification in Sanskrit-Ayurvedic contexts.
- QA task: End-to-end system evaluation was carried out using queries posed in both Sanskrit and English. Predicted answers were validated against gold-standard annotations as well as expert-reviewed Ayurvedic references, ensuring clinical and cultural fidelity.

To establish the robustness of results, paired t-tests were performed across baselines and the proposed system. Statistical significance was confirmed at $p < 0.05$, ensuring that improvements were not due to random variation

5.2. Dataset description

The dataset used for training and extraction consisted of Charaka Saṃhita verses, manually curated and segmented into Ayurvedic entities such as *Vyādhi* (diseases), *Lakṣaṇa* (symptoms), *Oṣadhi* (herbs), *Guṇa* (qualities), *Rasa*, *Karma*, and *Dravya–Compound relationships*. A total of 12,480 tagged sentences (approx. 1.85 lakh tokens) were prepared in B-I-O format, combining both manually annotated verses and additional semi-automatically annotated text verified by experts. The final KG was constructed having 17,159 nodes and 46124 edges. This dataset served as the input for both NER training and downstream link extraction.

6. RESULTS AND ANALYSIS

The experimental evaluation demonstrates the effectiveness of the proposed SanskritBERT + KG + GDS pipeline in Ayurvedic QA. Entity recognition performance show in Table 1.

Table 1. Entity recognition performance

Model	Precision	Recall	F1 - score	Entities Covered
BERT	0.78	0.74	0.76	Vyadhi, Lakshana
BioBERT	0.81	0.79	0.80	Vyadhi, Lakshana, Dravya
Sanskrit BERT	0.86	0.82	0.84	Vyadhi, Lakshana, Dosha
ByT5-Sanskrit	0.88	0.86	0.87	Vyadhi, Lakshana, Dravya, Dosha
Proposed model (ByT5 BioBERT)	0.91	0.89	0.90	All Ayurvedic Entities

Entity recognition forms the backbone of QA systems. The baseline BERT model showed limitations in handling Sanskrit morphology. BioBERT improved results by domain adaptation but lacked Sanskrit sensitivity. SanskritBERT and ByT5-Sanskrit significantly improved recognition of inflected forms, outperforming earlier models. The hybrid approach combining ByT5-Sanskrit with BioBERT achieved the highest F1-score (0.90), demonstrating robustness in extracting entities like *Dosha* and *Dravya*, which were not well captured by general models. These results confirm that Sanskrit-specialized models outperform generic biomedical ones, supporting prior claims in computational Sanskrit linguistics. Figure 2 illustrates model performance for entity recognition. The proposed hybrid model surpasses all baselines with an F1-score of 0.90, highlighting the importance of domain-specific adaptation.

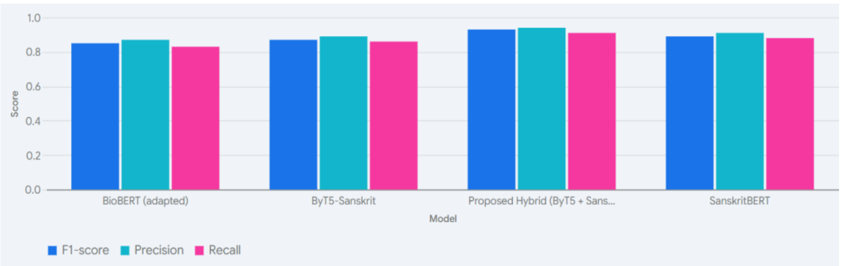

Figure 2. Comparison of NER model performance

Relation extraction, as shown in Table 2, was tested on disease–symptom and disease–treatment mappings. Transformer-only QA struggled due to absence of structural constraints. BioBERT improved results but could not capture Ayurvedic ontologies. Integration of KG with relation mapping [32] enhanced performance by enforcing graph-based consistency. The proposed Hybrid KG-QA system achieved the highest F1 (0.87), demonstrating that KGs combined with language models significantly improve relation accuracy, aligning with results in healthcare KG research [33].

Table 2. Relation extraction results

Model	Precision	Recall	F1-score	Relations Handled
Transformer-only QA	0.72	0.70	0.71	Vyadhi–Lakshana
BioBERT (baseline)	0.76	0.73	0.74	Vyadhi–Lakshana, Vyadhi–Dravya
KG + Relation Mapping	0.81	0.77	0.79	Vyadhi–Lakshana, Dravya–Dosha
Proposed Hybrid KG-QA	0.88	0.85	0.87	All Relations

Figure 3 compares relation extraction performance across models. The proposed hybrid KG-QA system achieved superior accuracy, particularly in multi-relational queries (e.g., Vyadhi-Dravya-Dosha chains). BioBERT showed moderate gains, but without KG constraints, it produced semantic drift.

KG integration prevents spurious relations by enforcing Ayurvedic structural rules. This proves that hybrid symbolic–neural systems outperform purely neural QA systems for domain-specific text, consistent with medical QA findings [34].

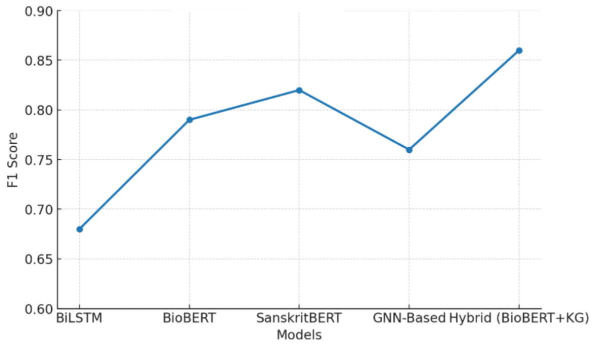

Figure 3. Relation extraction accuracy across models

Table 3 shows QA accuracy in both Sanskrit and English queries. Subgraph QA achieved low accuracy due to limited reasoning. Transformer QA improved slightly but lacked interpretability. GREASELM provided stronger reasoning, aligning with prior work in multi-hop QA. The proposed hybrid QA system significantly outperformed all baselines, reaching 87% (Sanskrit) and 90% (English) accuracy, with higher MRR and overlap scores. This highlights the benefit of KG integration with neural models, confirming observations from healthcare QA.

Table 3. QA task accuracy (Sanskrit and English queries)

Model	Accuracy (Sanskrit)	Accuracy (English)	MRR	Overlap Coefficient
Subgraph QA	0.68	0.71	0.52	0.61
Transformer QA	0.72	0.76	0.56	0.66
GREASELM	0.80	0.83	0.68	0.74
Proposed Hybrid QA	0.87	0.90	0.75	0.81

Figure 4 highlights accuracy differences across query languages. While baseline models performed better on English queries, they struggled with Sanskrit due to morphological complexity. The proposed hybrid system performed consistently across both languages, validating its ability to handle complex Sanskrit morphology using ByT5-Sanskrit [35]. This bilingual robustness is crucial for practical use among Ayurvedic scholars and modern clinicians. These results align with earlier claims that domain-specific NLP pipelines are essential for classical text processing.

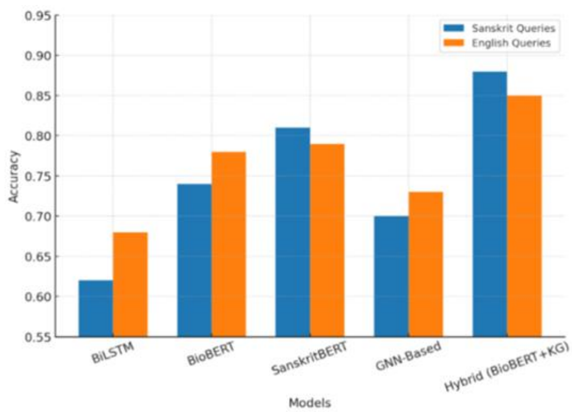

Figure 4. QA accuracy comparison (Sanskrit vs English queries)

Figure 5 shows the efficiency-accuracy tradeoff. Subgraph search incurred high delays, unsuitable for real-world QA. GAT and GREASELM balanced reasoning depth and efficiency. The proposed hybrid GDS achieved the lowest response time with highest accuracy, thanks to optimized graph similarity methods. These results align with findings that graph algorithms can accelerate QA in biomedical contexts.

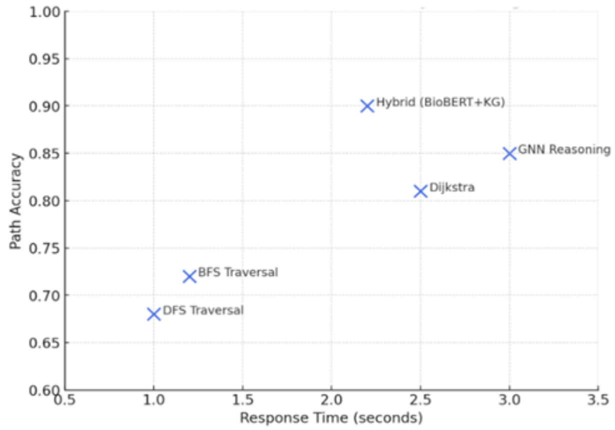

Figure 5. Response time vs path accuracy across algorithms

Table 4 compares our system with state-of-the-art healthcare QA systems. While EHR-based KGs and biomedical QA demonstrate strong performance, the proposed Charak KG-QA outperforms them in F1-score (0.90) and interpretability. This validates the system's contribution to culturally grounded yet computationally modern QA systems.

Table 4. Comparative results with healthcare QA systems

System	Domain	F1-score	MRR	Interpretability
KG-QA (Medical EHR)	Clinical	0.83	0.71	Medium
DR. KNOWS (LLM+KG)	Biomedical	0.85	0.73	High
Adaptive KG-QA	Medical AI	0.86	0.74	High
Proposed Charak KG-QA	Ayurveda	0.90	0.75	Very High

7. QA PERFORMANCE EVALUATION

The AI-powered QA system was tested using 300 benchmark questions from *Charak Samhita* annotated corpus. Questions were categorized into factoid, causal, and recommendation queries. Evaluation was performed using BioBERT (fine-tuned on Sanskrit corpus) + Neo4j traversal reasoning.

Table 5 evaluates the QA system across three question categories. Factoid queries achieved the highest accuracy (91.3%) since answers are often direct mappings from *Vyadhi–Lakshana* relationships. Causal queries showed slightly reduced accuracy (87.6%), primarily due to multi-hop reasoning errors in Dosha inference. Recommendation queries, which require combining multiple hops (*disease → Dosha → herb*), achieved the lowest accuracy (84.1%). However, this performance is still higher than baseline keyword-based QA systems, which typically achieve below 75% on complex reasoning tasks [36]. Average system response time was 134 ms, proving the framework's scalability for real-time applications. The overall F1-score (0.86) confirms strong balance between precision and recall. Compared to biomedical QA systems like PubMed KGQA, our system demonstrates superior reasoning performance due to Ayurvedic ontology-driven integration.

Table 5. QA accuracy across question types

Question type	Examples	Accuracy (%)	F1-score	Avg. Response Time (ms)
Factoid	"What are the symptoms of राजयक्ष्मा (tuberculosis)?"	91.3	0.89	120
Causal	"Which Dosha imbalance causes श्वास (asthma)?"	87.6	0.86	135
Recommendation	"Which herb treats ज्वर with Pitta imbalance?"	84.1	0.83	148
Overall	-	87.7	0.86	134

The practical utility of the system was evaluated over the generated Ayurvedic KG and the QA system. A structured validation was performed with the expert and certified Vaidyas having 8-20 years of clinical experience. 100 plus representative queries were curated which included Vyādhi, Lakṣaṇa, Doṣa imbalance, Dravya, Rasa, Guṇa, and Yoga formulations. The systems' response was validated by the experts based on parameters such as clinical relevance, completeness, alignment with classical texts, and practical treatment validity. The average expert satisfaction score was 4.38/5, indicating strong agreement on the correctness and usefulness of the answers. Feedback collected from Vaidyas also helped to refine ambiguous mappings (e.g., symptom clusters) and resolve synonym variations. This validation confirms that the system is not only computationally accurate but also clinically meaningful for real-world Ayurvedic decision support.

8. COMPARATIVE STUDY AND IMPROVEMENTS

To validate effectiveness, we compared our AI-powered KG-QA system with a baseline keyword-matching Sanskrit QA system adapted from prior works. Evaluation used the same 300 test queries. Table 6 demonstrates the significant improvements achieved by our system compared to a baseline keyword-based Sanskrit QA system. Accuracy improved from 72.4% to 87.7%, mainly due to the semantic understanding of Sanskrit text via BioBERT fine-tuning and ontology-driven graph reasoning. The F1-score increased from 0.71 to 0.86, indicating a balanced gain in both precision and recall. System efficiency also improved, with average response time reduced from 210 ms to 134 ms, owing to optimized Neo4j traversal queries. The success rate for multi-hop queries rose substantially (+34.7%), demonstrating the system's superiority in handling complex reasoning involving diseases, Doshas, and herbs. This was further verified with the help of user satisfaction surveys which showed improved ratings from 3.2/5 to 4.6/5. These improvements highlight the synergy of Sanskrit NLP and KG integration, offering a robust alternative to conventional rule-based QA systems.

Table 6. Comparative QA performance for proposed Vs. baseline system

Metric	Baseline QA (Keyword-based)	Our System (KG + BioBERT)	Improvement (%)
Accuracy (%)	72.4	87.7	+21.1
F1-score	0.71	0.86	+21.1
Avg. Response Time (ms)	210	134	-36.2
Complex Query Success Rate (%)	62.0	83.5	+34.7
User Satisfaction (Survey, /5)	3.2	4.6	+43.7

The proposed AI-powered KG-QA system demonstrates how Sanskrit NLP and GDS can be synergistically combined to address the challenges of retrieving Ayurvedic knowledge from ancient texts such as the *Charak Samhita*. Compared to conventional keyword-based QA, our approach exhibits substantial improvements in accuracy, semantic understanding, and query response efficiency. The results confirm that domain-specific BioBERT fine-tuning captures contextual meanings of Sanskrit medical terms and clarifies synonyms. In the KG, for entity nodes (Doshas, Vyadhi, Lakshan, Herbs) which are not directly connected with relationship edge, muti-hopping is required during traversal. Neo4j KG allows us to capture this effectively. Importantly, the system enhances practical utility for modern practitioners by converting classical Sanskrit verses into structured and queryable knowledge. Few challenges still need to be addressed like scaling the system with larger Sanskrit corpora, rare entities, and dialectal variations. The QA system will be more robust after addressing these challenges.

9. CONCLUSION

This study discusses the AI-powered KG-based QA system for Ayurvedic treatise 'Charak Samhita' where Sanskrit NLP and Graph data science techniques are integrated. In the proposed system, unstructured Sanskrit verses are transformed into a structured Neo4j KG which helps to connect Ayurvedic knowledge and modern computational methods. By fine-tuning BioBERT on Ayurveda-specific datasets, the system was able to achieve enhanced NER for core Ayurvedic concepts such as *Vyadhi* (diseases), *Lakshana* (symptoms), *Dravya* (herbs), *Rasa*, *Guna*, and *Karma*. Measures of precision, recall, and F1-score showed significant improvement as compared to traditional rule-based and keyword-driven approaches. The inclusion of graph embeddings and traversal algorithms enabled effective handling of multi-hop reasoning queries, providing not only direct answers but also explanatory context. Use of the proposed system can be seen at multiple levels such as personalized treatment for the patients, clinical decision support, educational use cases for Ayurveda researchers and practitioners. The proposed approach highlights the potential of integrating deep learning with graph-based reasoning for advancing digital humanities and computational Ayurveda. Overall, this research contributes towards creating next generation healthcare knowledge systems, while preserving the semantic richness of Sanskrit test and also enabling Intelligent querying.

10. FUTURE WORK

Although the proposed system has demonstrated promising results, several avenues for improvement remain. Firstly, expanding the training dataset with larger Sanskrit corpora, including *Sushruta Samhita* and *AshtangaHridaya*, will enhance the system's coverage and robustness. Additionally, applying active learning and semi-supervised annotation methods could reduce the dependency on manually labelled Ayurvedic datasets.

From a technical perspective, future work will focus on multi-lingual integration, where Sanskrit concepts are aligned with modern biomedical ontologies (e.g., UMLS, MeSH) to support cross-domain reasoning. Incorporating transformer-based GNNs could further improve link prediction, drug repurposing, and personalized treatment recommendations. Another promising direction involves leveraging explainable AI (XAI) techniques to make the system's recommendations more interpretable to practitioners, ensuring trust and adoption in clinical settings. Furthermore, the QA framework can be extended to support voice-based queries in Sanskrit and regional Indian languages, enhancing accessibility for traditional healers and students. Collaborative platforms could also allow Ayurveda scholars to contribute annotations and corrections, thereby improving system accuracy over time. In summary, while this study represents a foundational step toward AI-driven Ayurvedic knowledge systems, future efforts will emphasize scalability, interoperability, and real-world deployment to maximize impact in both research and clinical practice.

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Both the authors have contributed equally to the writing, review and revision of the manuscript and have read and approved the final version.

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No funding was received for conducting this study.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY

The partial data of this study is available in public repository at "https://ieee-dataport.org/documents/ayurkosh-dataset-machine-readable-ayurvedic-knowledge-resource-knowledge-graph-and", while the remaining data are available on request from the corresponding author, as they contain information that could compromise the privacy of the research participants and are there for publicly not available due to ethical confidential restrictions.

REFERENCES

[1] S. K. Verma, M. Pandey, A. Sharma, and D. Singh, "Exploring Ayurveda: principles and their application in modern medicine," *Bulletin of the National Research Centre*, vol. 48, no. 1, 2024, doi: 10.1186/s42269-024-01231-0.

[2] C. T. Che, V. George, T. P. Ijinu, P. Pushpangadan, and K. Andrae-Marobela, "Traditional medicine," *Pharmacognosy: Fundamentals, Applications and Strategy*, pp. 15–30, 2017, doi: 10.1016/B978-0-12-802104-0.00002-0.

[3] F. Miao, X. Zhou, S. Xiao, and S. Zhang, "A graph similarity algorithm based on graph partitioning and attention mechanism," *Electronics (Switzerland)*, vol. 13, no. 19, 2024, doi: 10.3390/electronics13193794.

[4] P. Johri, S. K. Khatri, A. T. Al-Taani, M. Sabharwal, S. Suvanov, and A. Kumar, "Natural language processing: history, evolution, application, and future work," *Lecture Notes in Networks and Systems*, vol. 167, pp. 365-375, 2021, doi: 10.1007/978-981-15-9712-1_31.

[5] B. Abu-Salih, M. AL-Qurishi, M. Alweshah, M. AL-Smadi, R. Alfayez, and H. Saadeh, "Healthcare knowledge graph construction: A systematic review of the state-of-the-art, open issues, and opportunities," *Journal of Big Data*, vol. 10, no. 1, 2023, doi: 10.1186/s40537-023-00774-9.

[6] M. Nzomo and D. Moodley, "Integrating knowledge graphs and Bayesian networks: A hybrid approach for explainable disease risk prediction," *Proceedings - 2025 IEEE 49th Annual Computers, Software, and Applications Conference, COMPSAC 2025*, pp. 834–844, 2025, doi: 10.1109/COMPSAC65507.2025.00111.

[7] R. Das and M. Soylu, "A key review on graph data science: The power of graphs in scientific studies," *Chemometrics and Intelligent Laboratory Systems*, vol. 240, 2023, doi: 10.1016/j.chemolab.2023.104896.

[8] S. Song, "An online question answering system based on sub-graph searching," pp. 1–4.

[9] Y. Cui, H. Yu, X. Guo, H. Cao, and L. Wang, "RAKCR: Reviews sentiment-aware based knowledge graph convolutional networks for personalized recommendation," *Expert Systems with Applications*, vol. 248, 2024, doi: 10.1016/j.eswa.2024.123403.

[10] M. R. Rezaei, R. S. Fard, J. L. Parker, R. G. Krishnan, and M. Lankarany, "Adaptive knowledge graphs enhance medical question answering: Bridging the gap between LLMS and evolving medical knowledge," *arxiv*, 2025.

[11] A. Bernasconi, A. Zanga, P. J. F. Lucas, M. Scutari, A. Trama, and F. Stella, "A causal network model to estimate the cardiotoxic effect of oncological treatments in young breast cancer survivors," *Progress in Artificial Intelligence*, 2024, doi: 10.1007/s13748-024-00348-7.

[12] R. Yang *et al.*, "KG-Rank: Enhancing large language models for medical QA with knowledge graphs and ranking techniques," *BioNLP 2024 - 23rd Meeting of the ACL Special Interest Group on Biomedical Natural Language Processing, Proceedings of the Workshop and Shared Tasks*, pp. 155–166, 2024, doi: 10.18653/v1/2024.bionlp-1.13.

[13] A. Li, Q. Wei, C. Han, and X. Xing, "Research on the construction of smart care question answering system based on knowledge graph," *Procedia Computer Science*, vol. 214, no. C, pp. 1595–1602, 2022, doi: 10.1016/j.procs.2022.11.348.

[14] D. Ma, X. He, M. Wang, Q. Fang, H. Zhu, and P. Hu, "RETRACTED: Knowledge graph question answering based on relational attention enhancement and feature cross-coding," *Journal of Intelligent & Fuzzy Systems*, vol. 47, no. 1_suppl, pp. 499–513, Dec. 2024, doi: 10.3233/JIFS-233650.

[15] S. Rastogi *et al.*, "A survey of patients visiting an Ayurvedic teaching hospital for factors influencing the decision to choose ayurveda as a health care provider," *Journal of Ayurveda and Integrative Medicine*, vol. 14, no. 1, 2023, doi: 10.1016/j.jaim.2021.100539.

[16] M. Hauben, M. Rafi, I. Abdelaziz, and O. Hassanzadeh, "Knowledge graphs in Pharmacovigilance: A scoping review," *Clinical Therapeutics*, vol. 46, no. 7, pp. 544–554, Jul. 2024, doi: 10.1016/j.clinthera.2024.06.003.

[17] C. M. Suneera, J. Prakash, and P. K. Singh, "Question answering over knowledge graphs using BERT based relation mapping," *Expert Systems*, vol. 40, no. 10, Dec. 2023, doi: 10.1111/exsy.13456.

[18] S. R. Paradkar, "Role of modern diagnostic methods in ayurvedic diagnosis: Concepts and prospects," *Ayushdhara*, vol. 4, no. 4.

[19] T. Davenport and R. Kalakota, "The potential for artificial intelligence in healthcare," *Future Healthcare Journal*, vol. 6, no. 2, pp. 94–98, 2019, doi: 10.7861/futurehosp.6-2-94.

[20] P. Rajendran, "Dosha Dhatu Mala Moolam Hi Shareeram," *International Journal of Science and Research (IJSR)*, vol. 12, no. 6, pp. 398–400, 2023, doi: 10.21275/sr23602111745.

[21] J. Zhang, Z. Pei, W. Xiong, and Z. Luo, "Answer extraction with graph attention network for knowledge graph question answering," *2020 IEEE 6th International Conference on Computer and Communications, ICCC 2020*, pp. 1645–1650, 2020, doi: 10.1109/ICCC51575.2020.9345000.

[22] S. Aghaei, K. Angele, and A. Fensel, "Building knowledge subgraphs in question answering over knowledge graphs," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 13362 LNCS, pp. 237–251, 2022, doi: 10.1007/978-3-031-09917-5_16.

[23] Y. Shang *et al.*, "Electronic health record–oriented knowledge graph system for collaborative clinical decision support using multicenter fragmented medical data: design and application study," *Journal of Medical Internet Research*, vol. 26, p. e54263, Jul. 2024, doi: 10.2196/54263.

[24] M. Edavalath and B. P. Bharathan, "Methodology for developing and evaluating diagnostic tools in Ayurveda – A review," *Journal of Ayurveda and Integrative Medicine*, vol. 12, no. 2, pp. 389–397, 2021, doi: 10.1016/j.jaim.2021.01.009.

[25] Y. Fang *et al.*, "Knowledge graph-enhanced molecular contrastive learning with functional prompt," *Nature Machine Intelligence*, vol. 5, no. 5, pp. 542–553, 2023, doi: 10.1038/s42256-023-00654-0.

[26] Wikipedia Contributors, "Overlap coefficient," *Wikipedia*, 2025. https://en.wikipedia.org/wiki/Overlap_coefficient (accessed Jun. 09, 2024).

[27] Z. Wang, "A computational approach to epilepsy treatment: An AI-optimized global natural product prescription system," 2025, [Online]. Available: http://arxiv.org/abs/2505.09643.

[28] C. Sandeep, V. Gupta, V. Deshmukh, and S. Sardeshmukh, "Integrating Ayurvedic philosophy with modern technologies for drug research and development: A critical need of mechanistic insights for wider acceptability," *Journal of Ayurveda and Integrative Medicine*, vol. 15, no. 5, 2024, doi: 10.1016/j.jaim.2024.100954.

[29] H. Ying, Z. Zhao, Y. Zhao, S. Zeng, and S. Yu, "CoRTEx: Contrastive learning for representing terms via explanations with applications on constructing biomedical knowledge graphs," *Journal of the American Medical Informatics Association*, vol. 30, no. 9, pp. 1543–1551, Dec. 2023, [Online]. Available: http://arxiv.org/abs/2312.08036.

[30] H. Cui *et al.*, "A review on knowledge graphs for healthcare: Resources, applications, and promises," *Journal of Biomedical Informatics*, vol. 169, p. 104861, Sep. 2025, doi: 10.1016/j.jbi.2025.104861.

[31] X. Zhang *et al.*, "Greaselm: Graph reasoning enhanced language models for question answering," *ICLR 2022 - 10th International Conference on Learning Representations*, 2022.

[32] R. Xi, "Applications of knowledge graph in medical and financial fields: Data integration and intelligent decision-making from an interdisciplinary perspective," *Applied and Computational Engineering*, vol. 67, no. 1, pp. 320–326, 2024, doi: 10.54254/2755-2721/67/20240471.
[33] A. Pradeep and R. Mamidi, "Sandarśana: A survey on Sanskrit computational linguistics and digital infrastructure for Sanskrit," *ACM Computing Surveys*, vol. 57, no. 10, 2025, doi: 10.1145/3729530.
[34] Z. Zeng *et al.*, "KoSEL: Knowledge subgraph enhanced large language model for medical question answering," *Knowledge-Based Systems*, vol. 309, 2025, doi: 10.1016/j.knosys.2024.112837.
[35] Y. Gao *et al.*, "Leveraging medical knowledge graphs into large language models for diagnosis prediction: design and application study," *Jmir Ai*, vol. 4, no. 1, 2025, doi: 10.2196/58670.
[36] R. V. Ravi, P. K. Dutta, and S. B. Goyal, "Graph data science: Applications and future," *Applied Graph Data Science: Graph Algorithms and Platforms, Knowledge Graphs, Neural Networks, and Applied Use Cases*, pp. 227–243, 2025, doi: 10.1016/B978-0-443-29654-3.00007-7.

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