



Original Article

# RefKG System to Fact-Checking and Query Resolution (QR) with Knowledge Graphs and Large Language Models (LLMs)

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Received On: 18/02/2026

Revised On: 17/03/2026

Accepted On: 25/03/2026

Published On: 01/05/2026

**Abstract** - The processes of Fact-checking and the use of knowledge-driven resolution are inevitable to increase the reliability of the information obtained from knowledge graphs of large sizes. The paper presents RefKG as a knowledge-based framework for enhancing fact verification while performing multi-hop reasoning through the combination of language models and structured knowledge graphs. The system improves knowledge representation with  $\alpha = 0.6$  as its confidence threshold while it enhances fact retrieval through combinations of Top-K reasoning with multi-task learning approaches. An evaluation of RefKG takes place on benchmark datasets WebQSP, MetaQA and FactKG by measuring its performance against current fact-checking models. The results establish that RefKG surpasses existing models by reaching 85.2% Hits@1 accuracy on WebQSP alongside an average 98.8% accuracy on MetaQA. Additionally, experiments on FactKG show improvements in fact verification accuracy and retrieval efficiency. The results illustrate that RefKG demonstrates high efficiency through its knowledge-based methodology, thus establishing it as a dependable system for automated fact-checking as well as complex query resolution.

**Keywords** - Digital Information, QR Code, Query Resolution (QR), Fact-Checking, Knowledge Graphs (Kgs), Machine Learning (ML), Large Language Models (Llms), Refkg System.

## 1. Introduction

The fast growth of Internet technology in the modern age has revolutionized how people generate, disseminate and obtain information. Data transmission between networked systems poses an essential problem because accuracy, security and efficiency must be maintained throughout the process [1]. Data encoding and retrieval underwent a revolution with the introduction of the barcode system, which provided systematic methods for accessing and monitoring information. Quick Response codes evolved from traditional barcodes, emerging as an effective data retrieval tool for machines. The widely adopted QR codes support authentication processes, logistics operations and digital transactions through their information encoding system, which enables immediate access and verification[2].

The term Query Resolution (QR) now applies to computational systems to explain the process of effectively

retrieving interpreted and verified digital information [3][4]. As digital information continues to grow exponentially, resolving queries with precision becomes essential for applications ranging from search engines to automated decision-making. One of the most critical applications of QR lies in fact-checking, where the ability to cross-reference and validate information determines the reliability of digital communication [5][6]. The rise of misinformation has led to problems with existing fact-checking methods, which depend on human verification systems and structured databases, now requiring intelligent systems that can perform automated verification.

The RefKG System addresses existing challenges by integrating structured information with AI-based systems to optimize fact verification and request processing. The system uses Knowledge Graphs (KGs) reliability together with ML and LLMs intelligence to verify information against established trustworthy sources during efficient retrieval [7][8][9][10]. The secure authentication process relies on QR code recognition, using its ability to validate encoded data against official references, which improves the system's digital security and trustworthiness.

The RefKG System can integrate Knowledge Graphs that provide a structured, interconnected representation of facts to enable context-based claim verification. The process of machine learning (ML) models is stopped by data classification and pattern recognition, and system inconsistencies, while LLMs help the models by understanding complex natural language inquiries[11][12][13]. The RefKG System establishes its main verification abilities through advanced technologies, which enable secure QR code recognition and efficient query resolution and fact verification. The complete security system, with its digital exchange verification process, provides users with verified information about cybersecurity and journalism, and it allows them to authenticate their digital identities[14].

### 1.1. Motivation and Contributions of the Study

The study presents RefKG which serves as a new framework to enhance LLM reasoning through knowledge graph-based knowledge reflections. The process of RefKG consists of three steps which include the following components: (1) The Query Decoupling Module divides

complex queries into their component structured sub-queries. (2) The LLM Driven Knowledge Graph Exploration Module retrieves evidence subgraphs and refines them through an iterative process. (3) The Inference Knowledge Reconstruction system transforms structured knowledge into Natural Language for enhanced reasoning capabilities. RefKG enables critical assessment and refinement of retrieved knowledge through its reflection capabilities, which exceed traditional methods that use retrieved results for prompts. The system introduces a knowledge-driven multi-task tuning strategy that enhances RefKG through training on synthetic data to develop advanced reasoning skills. The three-step framework of RefKG enables the system to independently acquire knowledge and use it for solving intricate problems.

The following contributions of the paper are:

- Presents RefKG, a hybrid system that combines LLMs and knowledge graphs (KGs) for improved query resolution and fact verification.
- Implements multi-hop reasoning strategies to enhance inference across intricate questions, beyond conventional single-hop approaches.
- Increases retrieval precision by constantly refining fact selection via a Top-K retrieval technique.
- Minimizes false positives by eliminating low-confidence facts using a threshold-based filtering method ( $\alpha = 0.6$ ).
- Enhances fact-checking, retrieval, and query resolution performance through an optimized multi-task learning strategy.
- Designed for real-time knowledge updates, making it adaptable for evolving fact-checking and intelligent retrieval tasks.

### 1.2. Organization of the Paper

The following structure of the paper: Section II presents the background research on Fact-Checking and Query Resolution (QR) using LLM. Section III provides the methodology and evaluation matrix, experiment results with visual interpretation are provided in Section IV, and Section V provides the conclusion and future study.

## 2. Literature Review

The background research on Fact-Checking and Query Resolution (QR) using various methods and approaches is provided in this section. Table I presents the methodologies used, key findings, and the limitations associated with each approach.

Kumar, R. (2025) presents RefKG, a novel framework that improves the performance of large language models (LLMs) in knowledge-intensive tasks including knowledge graph-based question answering and fact-checking. RefKG makes use of knowledge graphs reflectively, which allows the model to do logical reasoning based on retrieved data, detect and modify relational routes, and recreate pertinent information. To enhance LLM performance on specific tasks, the system employs a knowledge-based multi-task fine-tuning technique that blends tailored instructions with a unique

training dataset. The experimental findings demonstrate that RefKG can operate with various model architectures and outperforms all existing approaches across several benchmarks[15].

Du (2024) proposes a practical method to enhance QR code resolution using a Super-Resolution Generative Adversarial Network (SRGAN). The results show impressive outcomes because SRGAN method achieved better results than SRCNN method through a PSNR score of 30.06. The Structural Similarity Index (SSIM) results show that SRGAN achieves 0.936 which exceeds the 0.473 score of SRCNN. The measurements demonstrate that SRGAN enhances QR code resolution, which leads to better scan accuracy and increased practical value in actual use cases[16].

Almoussa et al. (2024) demonstrate the QR Shield system's effectiveness by identifying security threats in QR codes using two separate ML systems. The research demonstrates QR Shield's effectiveness through an assessment that uses four essential measurement standards. The accuracy test results show that 96.8% of the measurements were successful. The QR Shield demonstrates its ability to detect dangerous URLs present in QR codes because its results prove successful detection across multiple practical application fields[17].

Rafsanjani et al. (2023) The measurements evaluate the system's dependability, speed, consistency, and dispute resolution. When it comes to scanning QR codes, QsecR is an Android app that relies on 39 different types of features, including lexical, host-based, content-based, and blacklist options. A dataset of 4,000 randomly chosen actual URLs from URLhaus and PhishTank was assembled by the study team. Various QR code scanners rank the QsecR according to its privacy and security features. The trial results reveal that compared to other secure QR code scanners, QsecR performs far better, with 93.50% detection accuracy and 93.80% precision[18].

Lazarski, Al-Khassaweneh and Howard (2021) provide a detailed insight into the recent advances in computer science that involve employing NLP for the purpose of fact-checking. Starting with claim detection and ending with result output, it walks users through the whole automated fact-checking process using NLP. To sum up, automated fact-checking may be effective in some situations, but there is still room for improvement when it comes to generalized fact-checking before it is used widely [19].

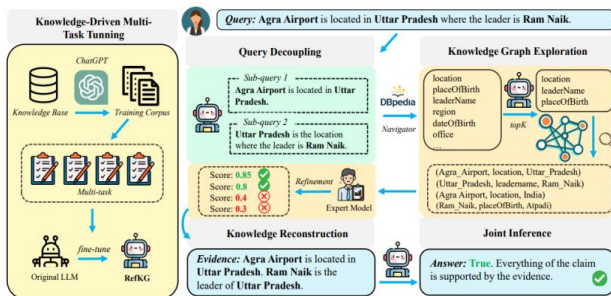
Huo et al. (2021) attempt to fuse a backpropagation (BP) neural network-based QR code distortion correction technique and an advanced median filter algorithm. This paper tackles a major research problem with current software systems two-dimensional code distortion. This article presents the results of a study that focused on the picture preprocessing stage. The results showed that reading rate of QR image codes improved by 14% after processing by system algorithm [20].

**Table 1: Summary of Studies on QR Code Resolution, Security, and Fact-Checking**

Author	Focus Area	Methods Used	Key Findings	Limitations
Kumar, R. (2025)	Knowledge graph-enhanced fact-checking and QA	RefKG framework with reflective KG reasoning and multi-task fine-tuning	Improved reasoning and benchmark performance over existing methods.	Scalability analysis, lacks real-time adaptability and evaluation in dynamic or noisy data environments.
Du (2024)	QR Code Resolution Enhancement	Super-Resolution Generative Adversarial Network (SRGAN)	SRGAN achieved PSNR: 30.06, SSIM: 0.936, outperforming SRCNN.	High computational cost; requires high-quality input images for best results.
Almousa et al. (2024)	QR Code Security (Malicious URL Detection)	Machine Learning-based QR Shield (RF & XGBoost)	QR Shield achieved 96.8% accuracy in detecting malicious URLs.	Potential adversarial attacks on ML models; reliance on predefined dataset for training.
Rafsanjani et al. (2023)	Secure and Privacy-Friendly QR Code Scanner (QsecR)	Static Feature Classification (Blacklist, Lexical, Host-based)	QsecR achieved 93.50% accuracy and 93.80% precision, outperforming existing scanners.	May struggle with evolving phishing techniques; depends on predefined blacklist features.
Lazarski, Al-Khassaweneh, and Howard (2021)	Automated Fact-Checking with NLP	End-to-end NLP pipeline (claim detection to verification)	Automated fact-checking shows potential but requires further improvement.	Struggles with nuanced or ambiguous claims; lacks real-time validation against multiple sources.
Huo et al. (2021)	AI-based QR Code Recognition and Correction	Adaptive Median Filter, BP Neural Networks	Improved QR code reading rate by 14% through AI-driven correction.	Performance depends on distortion severity; requires high computational power for real-time processing.

### 3. Methodology

RefKG implements an information-based strategy for examining facts and resolving queries through a graph structure as depicted in Figure 1. The process starts with data acquisition from various systems, then continues with thorough data cleaning operations that combine entity linking and normalization processes and relationship finding activities. The integrated data enters a knowledge graph that applies predefined ontologies to create entity and fact links. A semantic similarity approach, along with entity linking, helps identify incoming facts, which then get verified through existing information within the knowledge graph. Query resolution is achieved through graph-based reasoning, where natural language queries are transformed into structured graph queries to retrieve relevant information. To respond with robustness and accuracy, fact verification is improved using ML and rule-based structures.



**Fig 1: Proposed Framework RefKG**

The framework consists of three modules: Query Decoupling, Evidence Subgraph Retrieval, and inference with Knowledge Reconstruction. The model's knowledge

utilization capabilities improve through Knowledge-Driven Multi-Task Tuning because it enables users to separate, control, improve, and rebuild information.

#### 3.1. Data Collection

The study utilizes three benchmark datasets: These are WebQSP, MetaQA, and FactKG, all of their names established for their association with fact-checking, query resolution, and multi-hop reasoning.

- WebQSP: The dataset includes ~4,737 natural language queries that researchers use to connect their questions with Freebase knowledge graph entities. The dataset serves two purposes: it supports knowledge-based question answering (KBQA), and it helps evaluate Hits@1 accuracy during fact-checking and retrieval tests.
- MetaQA: It is a multi-hop dataset with over ~400,000 questions divided into three categories: 1-hop, 2-hop, and 3-hop. This one is designed to evaluate the model's ability to infer facts across multiple reasoning steps and is suitable for multi-hop retrieval evaluation.
- FactKG: A collection of ~50,000 fact-based claims serves as the foundation for fact-checking tasks through provided ground-truth labels. It assesses the model's capacity to confirm factual accuracy and offers a baseline for Top-K retrieval accuracy.

#### 3.2. Data Preprocessing

Data preprocessing requires three main steps to make knowledge retrieval and reasoning operations efficient [21]. The process of query normalization changes free-form queries into formal structures via Named Entity Recognition (NER)

that discovers entities along with their relationships. Knowledge graph subset extraction achieves relevant subgraph retrieval by extracting triplets composed of entities needed from the complete knowledge base. The process of noise reduction, together with deduplication, removes non-relevant knowledge triplets to establish a relation ranking system based on semantic similarities, which enhances fact-checking precision and query resolution capability.

### 3.3. Query Decoupling

Query decoupling is a technique of breaking the query down to simpler, atomic subqueries for the sake of reasoning clarity. The process begins by identifying key entities and estimating the required number of reasoning hops. Each reasoning step requires a separate sub-query to establish a structured search system. Finally, relevant knowledge entities and relations are extracted from the knowledge graph (KG) to support accurate reasoning and answer Equation (1).

$$q_{sub} = [q_1, \dots, q_H] \quad (1)$$

Where  $H$  is the number of reasoning hops.

### 3.4. LLM-Driven Knowledge Graph Exploration

The use of Large Language Models (LLMs) for exploratory and fact retrieval of Knowledge Graphs provides the benefit of rich semantic understanding that handles both structured patterns of entity relationships [22][23]. The RefKG system uses LLMs to search KGs for its fact verification and multi-hop reasoning capabilities. The model retrieves  $S$  the subject-predicate-object (SPO) triplets which it ranks according to their confidence scores  $S_i$  What Equation (2) describes.

$$S_i = f(T_i, Q)$$

Where  $T_i$  represents the  $i^{\text{th}}$  triplet, and  $f(T_i, Q)$  serves as the LLM-based relevance function, which computes the semantic matching between  $T_i$  and  $Q$ . The Top-K retrieval mechanism selects the highest-ranked triplets, thereby improving knowledge selection. The system performs multi-hop reasoning by expanding queries through the identification of intermediate entities  $E_m$  and the propagation of search depth  $d$  according to Equation (3):

$$E_{m+1} = g(E_m, KG, d) \quad (3)$$

The function  $g$  uses LLMs to determine which next-hop connections are important for the  $KG$ . By taking this iterative approach, RefKG can search more deeply for factual relationships and significantly improve reasoning accuracy. RefKG combines LLMs with structured KGs to deliver better results in query resolution, fact verification and reasoning processes while maintaining efficiency and outperforming conventional retrieval-based methods for knowledge exploration.

### 3.5. Inference with Knowledge Reconstruction

The evidence subgraph retrieved from the system is transformed into a natural-language format to improve

understanding. The LLM uses hidden logical reasoning to complete knowledge gaps by adding new information, which it deduces from existing data[24].

For an evidence subgraph  $G_{evi}$  containing  $N$  triplets Equation (4):

$$G_{evi} = \{(e_{head,n}, r_n, e_{tail,n})\}_{n=1}^N \quad (4)$$

It makes two kinds of knowledge-intensive tasks via reasoning. The LLM's job in question-answering assignments is to use the given evidence to provide responses that most closely match the query[25]. The LLM evaluates the evidence in fact-verification tasks to determine whether it supports or refutes the original assertion. It combines them into one probabilistic model, formulated as Equation (5):

$$P_{\theta}(a|q, G) = P_{\theta}(a|evi|q, G) \quad (5)$$

Where  $evi$  represents the evidence converted from the knowledge graph and  $a$  represents the response.

### 3.6. Performance Parameters

The performance evaluation of RefKG requires defining essential metrics together with their mathematical expressions for assessment purposes.

**Hits@1 Accuracy:** Hits@1 accuracy tracks the percentage of queries whose top-sized answer retrieval match is accurate thus demonstrating model precision in single-answer fact retrieval. It is defined as Equation (6):

$$Hits@1 = \frac{C}{N} \quad (6)$$

Where:  $C$  = Number of correctly retrieved top-ranked answers  $N$  = Total number of queries.

**Multi-Hop Reasoning Score:** Multi-hop reasoning score assesses how well the model connects information across different reasoning steps to reach accurate query solutions for challenging question-answering tasks. It is calculated as the ratio of correctly inferred multi-hop answers to the total multi-hop queries Equation (7):

$$Multi - Hop Accuracy = \frac{C_{Multi-Hop}}{N_{Multi-Hop}} \quad (7)$$

Where:

- $C_{Multi-Hop}$  = Correctly inferred multi-hop answers
- $N_{Multi-Hop}$  = Total multi-hop reasoning queries.

**Fact Verification Accuracy:** Fact verification accuracy measures the effectiveness of RefKG in correctly validating factual claims using knowledge graphs. It is computed as the proportion of accurately confirmed facts to all verified facts, using Equation (8):

$$A_{fact} = \frac{C_{fact}}{N_{fact}} \quad (8)$$

The established performance metrics provide measurable tools to evaluate both RefKG's precision and operational speed and reasoning abilities for a better understanding of its information verification capabilities and database acquisition capabilities.

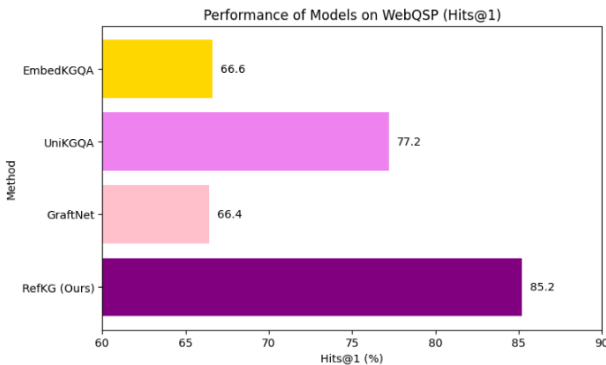
#### 4. Result Analysis and Discussion

The experiments were conducted on an NVIDIA 8x A800-SXM4-80G machine, with a knowledge refinement score threshold ( $\alpha$ ) of 0.6 to filter low-confidence triplets. RefKG received assessments on WebQSP, MetaQA, FactKG against EmbedKGQA, GraftNet, UniKGQA through performance tests that included Llama-2 7B, Bloom 7B, InternLM-2 7B, and Baichuan-2 7B during multi-task optimization as displayed in Table IV. The assessment evaluated Hits@1 fact-checking and multi-hop reasoning accuracy, together with reasoning category Top-K retrieval efficiency, along with computational efficiency measurements of inference time and LLM call frequency. To thoroughly assess accuracy, reasoning capabilities and scalability in complex knowledge-driven tasks, the evaluation settings are established. The following Tables II and III provide a comparison of models' performance on WebQSP and MetaQA.

**Table 2: Comparative Performance of Models on WebQSP (Hits@1)**

Method	Hits@1
EmbedKGQA [26]	66.6
UniKGQA[27]	77.2
GraftNet [28]	66.4
RefKG (ours)	85.2

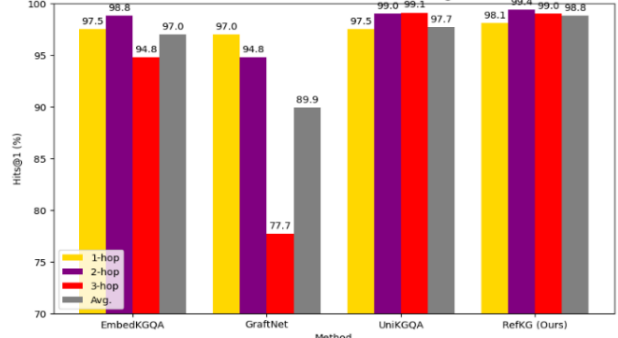
Table II along with Figure 2 demonstrates the Hits@1 evaluation results of multiple models working on the WebQSP dataset. Their approach RefKG demonstrates the best performance by delivering 85.2% accuracy whereas EmbedKGQA reaches 66.6% and GraftNet achieves 66.4% and UniKGQA achieves 77.2%. The fact-checking solution of RefKG establishes its effectiveness through an approach that leverages knowledge to produce exceptional results for query resolution and fact-checking accuracy.



**Fig 2: Bar Graph for Model's Performance**

**Table 3: Experiment Results of Models on MetaQA (Hits@1)**

Method	1-hop	2-hop	3-hop	Avg.
EmbedKGQA	97.5	98.8	94.8	97.0
GraftNet	97.0	94.8	77.7	89.9
UniKGQA	97.5	99.0	99.1	97.7
RefKG (ours)	98.1	99.4	99.0	98.8

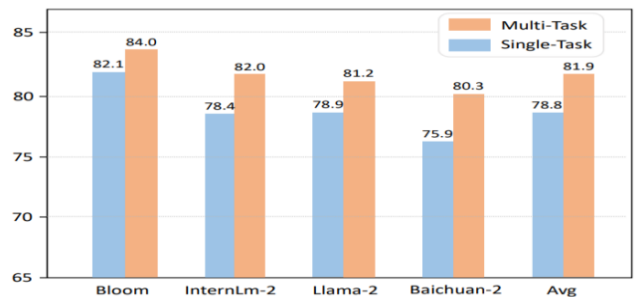


**Fig 3: Bar Graph for Performance of Models On MetaQA**

Table III and Figure 3 present Hits@1 performance results of multiple models on the MetaQA dataset at various reasoning levels from 1-hop to 2-hop to 3-hop and the average performance results. RefKG (ours) maintains consistent superiority by reaching an accuracy of 98.1% at 1-hop and 99.4% at 2-hop and 99.9% at 3-hop which leads to an average of 98.8%. Compared to previous models, RefKG demonstrates superior multi-hop reasoning capabilities, outperforming GraftNet (Avg: 89.9%), EmbedKGQA (Avg: 97.0%), and UniKGQA (Avg: 97.7%). These outcomes demonstrate RefKG's resilience in managing challenging question-answering tasks.

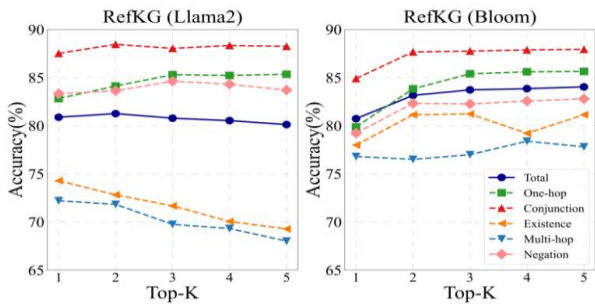
**Table 4: Performance Comparison between Base Models and Refkg across Multiple 7B Parameter Models**

Model	Base Model	RefKG (ours)	Difference
Llama-2 7B	34.12	81.26	-47.14
Bloom 7B	37.65	84.04	-46.39
Internlm-2 7B	39.41	82.04	-42.63
Baichuan-2 7B	31.73	80.30	-48.57
Average	35.73	81.84	-46.11



**Fig 4: Comparison Of Multi-Task and Single-Task Tuning**

Table IV and Figure 4 present a comparison between multi-task and single-task tuning across different language models. In this figure, Bloom shows a slight increase from 82.1 to 84.0, while InternLM-2 improves from 78.4 to 82.0. Llama-2 and Baichuan-2 show improvements with Llama-2 rising from 78.9 to 81.2 and Baichuan-2 increasing from 75.9 to 80.3. The average performance follows the same trend, with multi-task tuning achieving 81.9 compared to 78.8 in single-task tuning. The results show that multi-task tuning enhances model performance across multiple tasks better than other methods.



**Fig 5:Top-K Retrieval With Llama-2 And Bloom On Factkg**

The accuracy trends of the Llama-2 and Bloom models on FactKG across different reasoning categories are shown in Figure 5, based on Top-K retrieval. With accuracy (%) on the y-axis and Top-K values on the x-axis, the left and right plots depict Llama-2 and Bloom, respectively. The different reasoning types, which include one-hop conjunction existence, multi-hop, and negation, are shown through various line styles and colors. The two models show increasing accuracy as Top-K values increase, except for multi-hop and existence reasoning, which show lower accuracy. The Bloom model shows more consistent improvement across Top-K values than Llama-2, indicating that their retrieval effectiveness for FactKG tasks differs between the two models.

RefKG improves fact-checking capabilities by combining knowledge graphs (KGs) with language models (LLMs) to enable multi-hop reasoning across complex queries. The system achieves better efficiency through Top-K retrieval while it maintains high accuracy by using a confidence threshold of ( $\alpha = 0.6$ ) to eliminate low-quality facts. The system uses multi-task learning to perform reasoning tasks more effectively than single-task models. RefKG exploits a mixed data structure which produces remarkable Hits@1 accuracy results of 85.2% on WebQSP while attaining 98.8% on MetaQA. The adaptable infrastructure lets users update knowledge content in real-time so it works well for automatic fact-checking together with intelligent retrieval systems.

## 5. Conclusion and Future Scope

The research presented RefKG as a knowledge-based system that uses structured knowledge graphs to combine with language models for improving retrieval accuracy alongside fact-based reasoning capabilities. The evaluations

conducted on WebQSP, MetaQA and FactKG showed that RefKG excelled against other models by reaching a Hits@1 accuracy of 85.2% on WebQSP with an average accuracy of 98.8% on MetaQA which proves its strength in multi-hop reasoning and fact checking. The system faces two main limits because it cannot manage large knowledge graphs effectively and requires top-quality structured data alongside increased complexity in multi-hop reasoning scenarios. The system operates under restrictions since it depends on knowledge sources requiring predefined definitions while losing adaptability to continuously changing real-world information. Studies from the previous generation will guide researchers in optimizing system scalability by implementing real-time knowledge processing and optimizing system performance to decrease inference times. Fact verification gets improved with various structured and unstructured data source combination approaches. RefKG becomes more practically useful when expanded across various knowledge-intensive subjects by adapting its functions to multiple specialized domains and different languages. More complex retrieval approaches, as well as self-learning methods and refined model descriptions, will assist in the development of improved, real-world-scale fact-checking solutions via enhancement of robustness and scalability.

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