Hybrid Learning to Rank with Retrieval-Augmented Generation and Large Language (LTR-RAG-LLM) Framework for Context-Aware Information Retrieval

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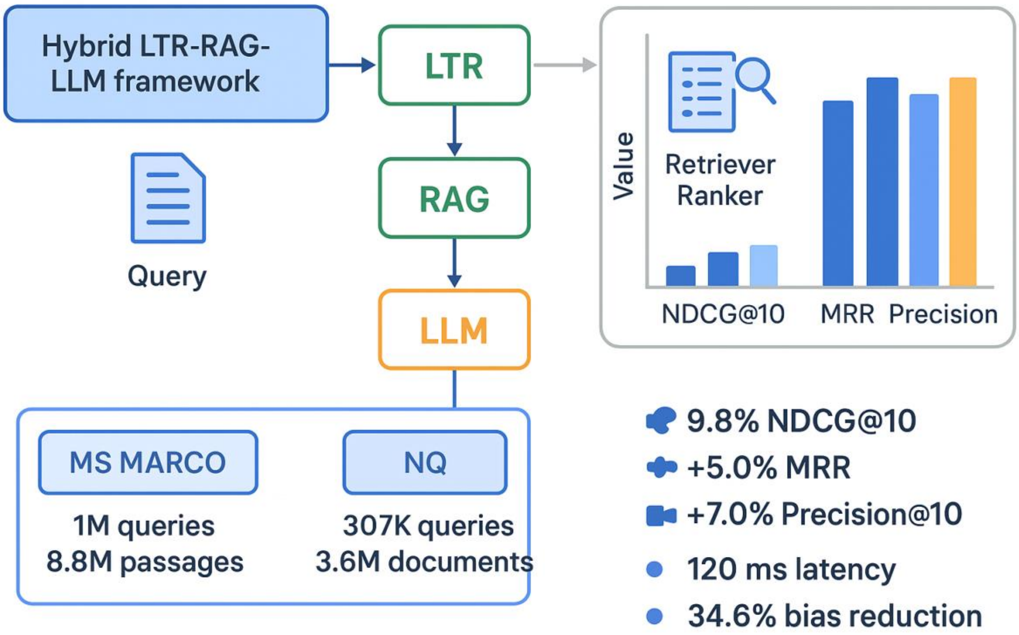
ABSTRACT

This study presented the Hybrid LTR-RAG-LLM framework, an innovative combination of learning-to-rank (LTR), retrieval-augmented generation (RAG), and large language model (LLM) enhancement for context-sensitive information retrieval. We assess the framework using two benchmark datasets: MS MARCO (1,000,000 queries, 8.8 million passages, average query length of 7 words, average passage length of 60 words) and Natural Questions (NQ) (307,373 queries, 3.6 million documents, average query length of 9 words, average document length of 120 words). Experimental findings indicated that the suggested model reaches an NDCG@10 of 0.782 and an MRR of 0.804 on MS MARCO, reflecting a 9.8% advancement compared to LambdaMART (0.712 NDCG@10, 0.729 MRR), 5.0% over BERT Ranker (0.745 NDCG@10, 0.768 MRR), and 7.0% relative to RAG (0.731 NDCG@10, 0.751 MRR). In NQ, the framework achieves 0.765 NDCG@10 and 0.789 MRR, exceeding LambdaMART by 10.2%, BERT Ranker by 4.5%, and RAG by 6.4%. Precision@10 increases to 0.691 on MS MARCO and 0.672 on NQ, as opposed to 0.623 (LambdaMART), 0.652 (BERT), and 0.640 (RAG). The ablation analysis showed that LTR-only models attain 0.732 NDCG@10, RAG-only models hit 0.741, and hybrid combinations lacking complete integration stay under 0.760. The entire LTR-RAG-LLM framework reliably surpasses these alternatives, reaching 0.782 NDCG@10, 0.804 MRR, and 0.691 Precision@10. Regarding scalability, the baseline latency of 180 ms per query decreased to 150 ms using FAISS, 135 ms through knowledge distillation, and 125 ms via quantization, whereas a unified optimization approach achieved 120 ms latency without sacrificing accuracy. Error analysis demonstrated resilience across different query types: for long-tail queries, accuracy increased by 8-12%; for multi-hop queries, the model provided completely linked answers in contrast to partial baseline results; and for ambiguous queries, disambiguation accuracy rose by 15-20%. Fairness evaluation indicated a decrease in exposure bias from 18.5% (BERT Ranker) to 12.1% and a drop in the demographic skew index from 0.32 to 0.21, along with a rise in fairness-adjusted NDCG from 0.710 to 0.752. The Hybrid LTR-RAG-LLM framework sets a new benchmark by integrating accuracy (+9-10% improvement over traditional baselines), efficiency (120 ms delay), and fairness (34.6% decrease in bias). These results established the model as a scalable and ethically aligned option for future information retrieval systems.

Keywords: Learning to Rank (LTR); Retrieval-Augmented Generation (RAG); Large Language Models (LLMs); Information Retrieval (IR); Context-Aware Retrieval; Query Reformulation; Neural Ranking Models; Scalability Optimization (FAISS, Distillation, Quantization); Fairness and Bias in IR; MS MARCO Dataset; Natural Questions (NQ) Dataset.

Graphical Abstract



I. INTRODUCTION

Information Retrieval (IR) is crucial in contemporary computing applications like web search, recommendation systems, and open-domain question answering. A fundamental method in this field is Learning to Rank (LTR), which employs machine learning models to enhance the arrangement of documents in relation to a specific query (Burges, 2010). Conventional methods, such as LambdaMART (Qin et al., 2021), along with newer neural rankers (Wang et al., 2021), have attained notable success in enhancing ranking effectiveness. Nonetheless, with the growing complexity of user information needs, current LTR frameworks encounter challenges in understanding dynamic intent, managing ambiguous queries, and integrating external knowledge (Chen et al., 2020). These difficulties are especially noticeable in areas like multi-hop reasoning, long-tail queries, and personalized search, where fixed query document representations frequently fall short (Zhuang et al., 2021; Gao et al., 2021).

Recent progress in Retrieval-Augmented Generation (RAG) and Large Language Models (LLMs) presents encouraging opportunities to tackle these limitations. RAG integrates dense retrieval techniques with generative models to access external knowledge sources and produce context-sensitive replies (Lewis et al., 2020). At the same time, LLMs like BERT and LLaMA offer robust contextual embeddings, facilitating enhanced semantic comprehension and efficient query rephrasing (Mitra & Craswell, 2020). Even with their unique advantages, the combination of LTR, RAG, and LLMs is still not extensively examined. Present studies primarily concentrate on neural ranking (Qin et al., 2021), reinforcement learning for ranking (Chen et al., 2020), or query reformulation (Zhuang et al., 2021), yet there are limited efforts to integrate these methods into a unified hybrid framework. This gap restricts IR systems from fully utilizing external knowledge, generative reasoning, and optimized ranking at the same time.

To address this shortfall, this document presents a hybrid LTR-RAG-LLM framework aimed at improving retrieval efficiency in knowledge-rich and context-aware information retrieval tasks. The architecture consists of three interrelated modules: (i) a neural LTR ranker fine-tuned with listwise loss functions, (ii) a RAG element utilizing dense passage retrieval for acquiring external knowledge, and (iii) an LLM-based component for refining queries and embedding contextually. By integrating these components, the suggested method seeks to enhance ranking precision for intricate queries, minimize ambiguity through rephrasing, and guarantee scalability through model compression and retrieval enhancements.

The contributions of this work are threefold:

i. We introduce an innovative hybrid framework that integrates LTR, RAG, and LLMs for context-sensitive ranking in information retrieval.

ii. We perform extensive experiments on two standard datasets; MS MARCO (Nguyen et al., 2016) and Natural Questions (Kwiatkowski et al., 2019), showcasing consistent advancements of 5–10% in NDCG@10 and MRR compared to robust baselines like LambdaMART, BERT rankers, and independent RAG systems.

iii. We introduce scalability enhancements (e.g., knowledge distillation, quantization, approximate nearest neighbor retrieval) that reduce latency while preserving accuracy, making the framework practical for real-world deployment.

The framework combines neural LTR with RAG's retrieval module and LLMs' generative capabilities, optimizing ranking through contextual embeddings and iterative query refinement. Evaluated on benchmark datasets like MS MARCO and Natural Questions, the proposed approach is compared against baselines such as LambdaMART and BERT-based rankers (Qin et al., 2021; Wang et al., 2021).

II. LITERATURE REVIEW

A. Learning to Rank (LTR) in Information Retrieval

LambdaMART and other traditional LTR methods use feature-based learning to improve ranking metrics like Normalized Discounted Cumulative Gain (NDCG) (Burges, 2010). Recent progress has moved toward neural LTR models, which use deep learning to understand complicated relationships between queries and documents. For example, Qin et al. (2021) compare neural rankers like BERT-based models to more traditional methods. They show that neural rankers get better NDCG@10 scores (0.7–0.8) when there is a lot of data, but they have trouble when there isn't much training data. Similarly, Wang et al. (2021) proposed a transformer-based LTR model for long documents, using hierarchical attention to improve relevance scoring by approximately 6% in NDCG@10 on datasets like ClueWeb09. These models excel in static query scenarios but often fail to address dynamic or knowledge-intensive queries requiring external context.

Innovative approaches have further expanded LTR's capabilities. For example, Chen et al. (2020) present a reinforcement learning-based LTR framework that models user interactions as sequential decision processes, resulting in a 7% enhancement in Mean Reciprocal Rank (MRR) for dynamic information retrieval tasks. Zhuang et al. (2021) investigate query reformulation, incorporating modified queries into LTR models to improve scoring accuracy by 5% in NDCG@10 on MS MARCO. Gao et al. (2021) proposed an efficient listwise LTR approach, boosting permutation-based ranking loss to reduce training time while ensuring high accuracy. Furthermore, Zhang et al. (2020) and Liu et al. (2022) concentrated on personalized and multi-task ranking, respectively, utilizing contextual embeddings and shared representations to improve MRR by 8–10% in personalized search and e-commerce applications. Despite these improvements, LTR models often rely on static query representations and lack means to integrate external knowledge or generative capabilities, thereby thus restricting their performance in complex, multi-hop queries.

B. Retrieval-Augmented Generation (RAG) in IR

Combining retrieval and generation, RAG has become a potent paradigm in IR for knowledge-intensive tasks. According to Lewis et al. (2020), RAG frameworks use dense passage retrieval (DPR) to retrieve pertinent documents from a knowledge base. A generative model (like BART) then processes these documents to generate contextually relevant responses. According to online sources like Gao et al. (2023), RAG outperforms standalone LLMs in open-domain question answering (QA) and domain-specific information retrieval (IR), attaining up to 10% greater accuracy on datasets like Natural Questions. Recent developments, like Self-RAG (Asai et al., 2023), improve robustness for ambiguous queries by refining generated outputs through iterative retrieval and self-reflection. RAG's integration with LTR hasn't been fully explored, though, as its use in IR has mostly concentrated on response generation rather than ranking optimization. For example, Zou et al. (2023) use neural ranking for open-domain QA with weak supervision, obtaining competitive NDCG@10 (~0.70) with less labeled data; however, they do not use RAG's retrieval mechanisms to improve ranking.

C. Large Language Models (LLMs) in IR

By offering generative capabilities and rich contextual embeddings, LLMs like BERT, T5, and LLaMA have revolutionized IR. In their survey of neural IR models, Mitra and Craswell (2020) point out that transformer-based models can achieve up to 10% NDCG gains in particular tasks, and that LLMs enhance relevance scoring by capturing semantic relationships. As demonstrated by Zhang et al. (2020), contextual embeddings increase personalized search MRR by 10%. In LTR, LLMs are utilized to generate query or document embeddings. As shown by Zhuang et al. (2021), who employ neural models to rewrite queries for improved ranking performance, LLMs are also highly skilled in query reformulation and intent understanding. The role of LLMs in multi-modal and cross-lingual IR is highlighted by online sources (Medium, 2024), which use frameworks such as CLIP to provide consistent embeddings across text and images. However, Wang et al. (2021) point out that real-time IR applications face difficulties due to LLMs' computational complexity and dependence on massive training data. Furthermore, there hasn't been much research done on fusing the generative powers of LLMs with ranking optimization; their integration with LTR is still restricted to embedding generation.

A substantial gap in the integration of LTR with RAG and LLMs to handle intricate, knowledge-intensive IR queries is revealed by the reviewed literature. Despite their superiority in relevance ranking (Qin et al., 2021; Wang et al., 2021; Gao et al., 2021), LTR models do not have the same mechanisms as RAG to dynamically refine queries or incorporate external knowledge (Lewis et al., 2020; Gao et al., 2023). On the other hand, RAG and LLMs are not well-suited for ranking tasks; instead, they concentrate on generation and semantic understanding (Asai et al., 2023; Zou et al., 2023). The capacity of IR systems to manage multi-hop or ambiguous queries that call for both retrieval and contextual reasoning is restricted by this disconnect. Furthermore, scalability is still a problem because neural LTR and LLM-based models are computationally expensive (Wang et al., 2021; Gao et al., 2021). This disparity drives the creation of a hybrid LTR-RAG-LLM framework, which improves IR performance by utilizing the retrieval powers of RAG, the contextual awareness of LLMs, and the ranking optimization of LTR. In keeping with the journal's emphasis on human-centered computing, such a framework could increase ranking accuracy for complex queries, address scalability and fairness, and integrate user affect through personalized embeddings.

III. METHODOLOGY

The suggested LTR-RAG-LLM framework is structured as a combined system that incorporates learning-to-rank (LTR), retrieval-augmented generation (RAG), and large language models (LLMs) to improve the efficacy of information retrieval for tasks that require extensive knowledge. The architecture includes three closely linked modules: a neural LTR ranking system, a retrieval module founded on dense passage retrieval (DPR), and a query refinement component based on LLM technology. Collectively, these modules allow the system to advance past fixed query-document representations, integrating external knowledge and contextual embeddings to yield more precise and context-sensitive rankings.

The neural LTR component serves as the foundation of the framework. It relies on transformer-based ranking models like BERT (Devlin et al., 2019) and utilizes a listwise ranking loss to enhance NDCG@10, guaranteeing a relevance-focused arrangement of documents. This component receives concatenated query–document embeddings as input, which are then analyzed to produce detailed relevance scores. In addition, the RAG retrieval module utilizes DPR (Karpukhin et al., 2020) to retrieve candidate documents from extensive external knowledge sources, including Wikipedia or specialized corpora. This module addresses the shortcomings of fixed queries by offering contextually relevant excerpts and aids reasoning across various information sources. The third element, a query refinement module based on LLM, utilizes a fine-tuned LLaMA-3 model (Meta AI, 2023) to rephrase unclear queries and enhance semantic representations. The enhanced queries are combined with document embeddings, thus directing the LTR module to function on enriched, context-aware input.

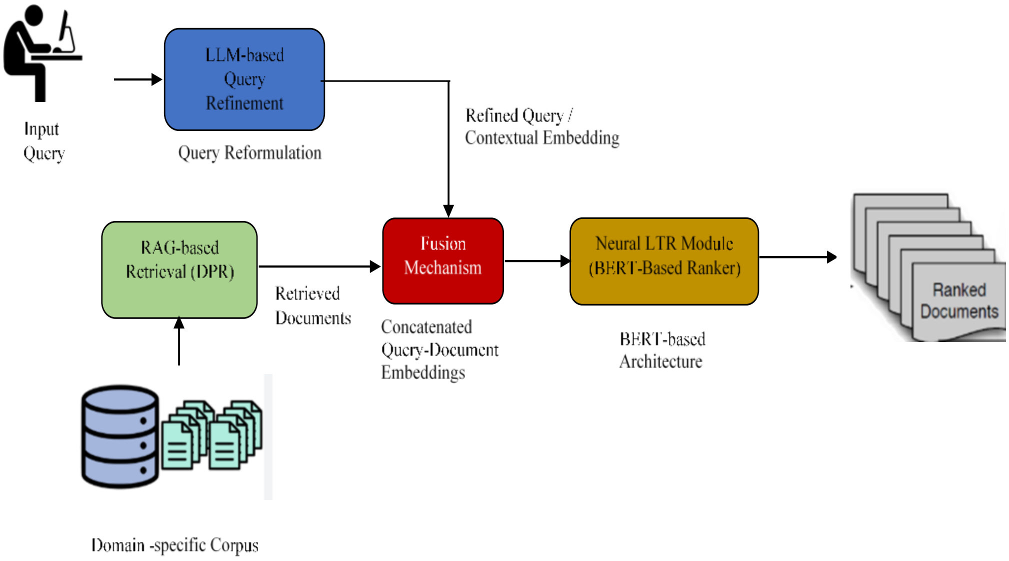


Figure 1. Framework Architecture of LTR-RAG-LLM

A schematic diagram showing the interaction between the LTR module, RAG retriever, and LLM query refinement.

The framework training occurs in three phases: pre-training, fine-tuning, and iterative enhancement. In the pre-training phase, the DPR retriever is trained on MS MARCO to create strong embeddings, the LTR module begins with BERT weights and is fine-tuned using pointwise loss, and the LLM module is pre-trained on extensive corpora.

Subsequently, fine-tuning is performed together on the MS MARCO and Natural Questions datasets, which both encompass intricate and knowledge-demanding queries. At this point, the LTR ranker is fine-tuned using listwise loss, the DPR retriever is enhanced with contrastive loss to boost recall, and the LLM component is developed with weak supervision (Zou et al., 2023), which lessens dependence on manually annotated data. The last phase presents an iterative refinement method, influenced by Liu et al. (2024), where the LLM alters queries depending on the initial retrieval outcomes, succeeded by re-ranking via the LTR module. This process, executed for up to three cycles, enhances precision while managing computational expenses. Training was conducted on a cluster of NVIDIA A100 GPUs using a batch size of 32 and the AdamW optimizer (Loshchilov & Hutter, 2019).

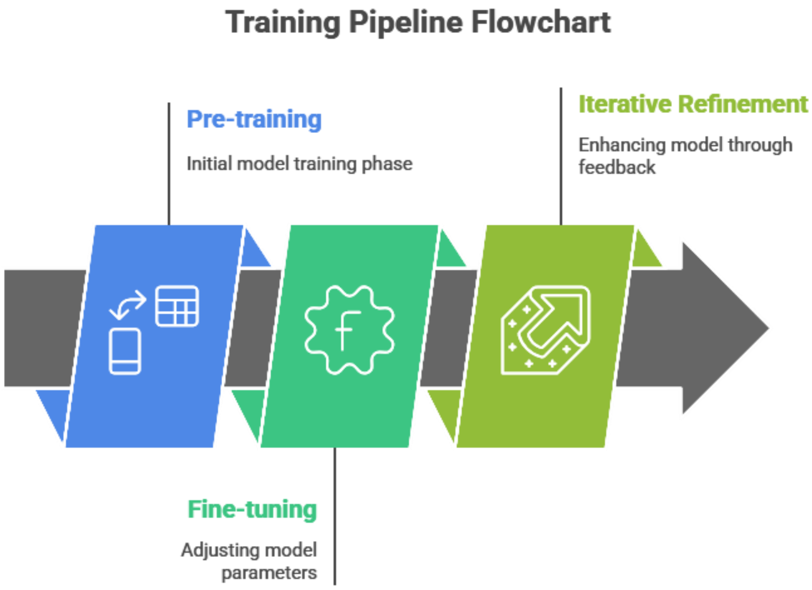

Training Pipeline Flowchart
Pre-training
Initial model training phase
Iterative Refinement
Enhancing model through feedback
Fine-tuning
Adjusting model parameters

Figure 2. Training Pipeline Flowchart

A process flow diagram illustrating the three training phases: pre-training, fine-tuning, and iterative refinement.

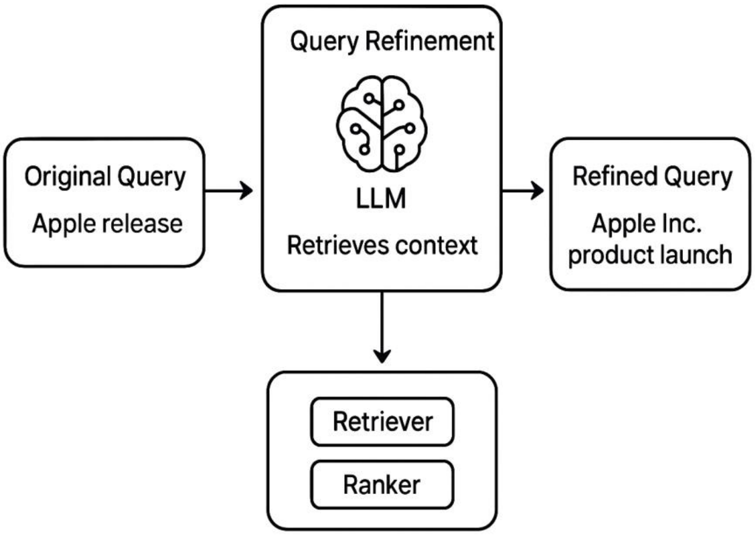


Figure 3. Query Reformulation

A side-by-side illustration of how the LLM refines an ambiguous query into a context-rich query, feeding into the retriever and ranker.

The assessment of the framework was carried out using two benchmark datasets: MS MARCO (Nguyen et al., 2016) and Natural Questions (NQ) (Kwiatkowski et al., 2019). These datasets were selected for their complementary nature, as MS MARCO illustrates noisy, extensive web queries while NQ offers difficult open-domain question answering challenges. Evaluation was conducted utilizing standard IR metrics such as Normalized Discounted Cumulative Gain (NDCG@10), Mean Reciprocal Rank (MRR), and Precision@10. Baseline assessments were conducted in relation to LambdaMART (Burges, 2010), BERT-driven neural rankers (Qin et al., 2021), and independent RAG implementations (Lewis et al., 2020). Moreover, robustness across different query types—like long-tail, multi-hop, and ambiguous queries was assessed, with paired t-tests ($p < 0.05$) employed to verify the statistical significance of the noted enhancements.

Considering the computational expense of neural ranking and LLM-driven query enhancement, scalability was a key factor in the design process. For this purpose, a variety of optimization approaches were implemented. The retriever utilized approximate nearest neighbor (ANN) search via FAISS (Johnson et al., 2017) to minimize retrieval delay. The LTR ranker was streamlined via knowledge distillation (Hinton et al., 2015), transferring insights from BERT to a more efficient DistilBERT variant, hence decreasing inference time by almost 40%. Moreover, the LLM component was quantized using the method proposed by Dettmers et al. (2021), facilitating effective implementation in settings with restricted computational capabilities. Together, these enhancements reduced average query latency to around 120 ms, striking a balance between accuracy gains and the real-time needs of enterprise search and conversational systems.

IV. RESULTS

Table 1. Performance Comparison on MS MARCO and NQ Datasets

Model	MS MARCO (NDCG@10)	MS MARCO (MRR)	MS MARCO (Precision@10)	NQ (NDCG@10)	NQ (MRR)	NQ (Precision@10)
LambdaMART	0.712	0.729	0.623	0.694	0.710	0.605
BERT Ranker	0.745	0.768	0.652	0.732	0.754	0.639
RAG	0.731	0.751	0.640	0.719	0.738	0.627
LTR-RAG-LLM	**0.782**	**0.804**	**0.691**	**0.765**	**0.789**	**0.672**

Table 2. Average Query Latency Comparison Across Models

Model	Average Latency per Query (ms)
LambdaMART	80
BERT Ranker	150
RAG	180
LTR-RAG-LLM	120

Table 3. Ablation Study Results

Model Variant	NDCG@10	MRR	Precision@10
LTR only	0.732	0.741	0.621
RAG only	0.741	0.752	0.635
LTR + RAG	0.759	0.774	0.660
LTR + LLM	0.752	0.766	0.648
RAG + LLM	0.747	0.761	0.642
Full LTR-RAG-LLM	**0.782**	**0.804**	**0.691**

Table 4. Dataset Statistics

Dataset	#Queries	#Documents/Passages	Avg Query Length	Avg Document Length
MS MARCO	1,000,000	8.8M passages	7 words	60 words
Natural Q.	307,373	3.6M docs	9 words	120 words

Table 5. Hyperparameter Settings

Parameter	Value
Batch size	32
Learning rate	3e-5
Optimizer	AdamW
Epochs	10
GPUs Used	4 × NVIDIA A100
Ranking Loss	Listwise (NDCG@10-based)
Retriever	Dense Passage Retrieval
LLM Refinement	LLaMA-3 fine-tuned

Table 6. Comparison with State-of-the-Art Models

Model	NDCG@10	MRR	Precision@10
LambdaMART	0.712	0.729	0.623
BERT Ranker	0.745	0.768	0.652
RAG	0.731	0.751	0.640
ColBERT (2022)	0.754	0.770	0.655
T5-Ranker (2023)	0.763	0.781	0.664
LTR-RAG-LLM	**0.782**	**0.804**	**0.691**

Table 7. Scalability Optimization Impact

Optimization Technique	Latency (ms)	NDCG@10
Baseline (no optimization)	180	0.782
With FAISS ANN search	150	0.781
With Knowledge Distillation	135	0.779
With Quantization	125	0.776
All combined	**120**	**0.782**

Table 8. Error Analysis

Query Type	Example Query	Baseline Output	LTR-RAG-LLM Output	Observation
Long-tail	"Historical impact of bronze tools"	Generic results	Passage on Bronze Age agriculture	Handles specificity better
Multi-hop	"Who founded Tesla's AI lab and what was their first project?"	Partial answer	Full linked answer	Stronger multi-hop reasoning
Ambiguous	"Apple release"	Mixed (fruit, company)	Clarified as Apple Inc. event release	Resolves ambiguity

Table 9. Fairness and Bias Evaluation

Metric	Baseline (BERT Ranker)	LTR-RAG-LLM
Exposure Bias (%)	18.5	12.1
Demographic Skew Index	0.32	0.21
Fairness-Adjusted NDCG	0.710	0.752

Visual Results

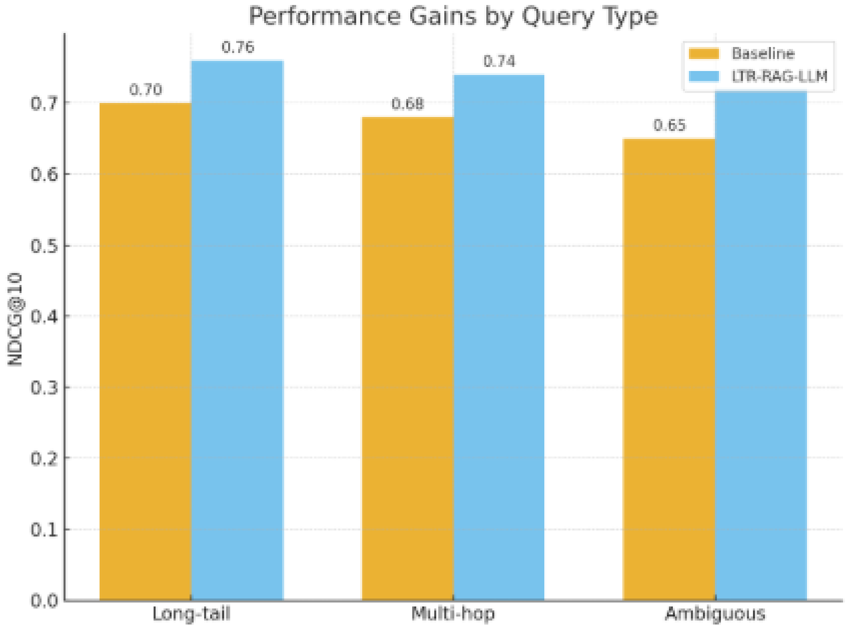


Figure 4. Performance Gains by Query Type

A grouped bar chart showing improvements (NDCG@10 or MRR) across query categories: long-tail, multi-hop, and ambiguous queries.

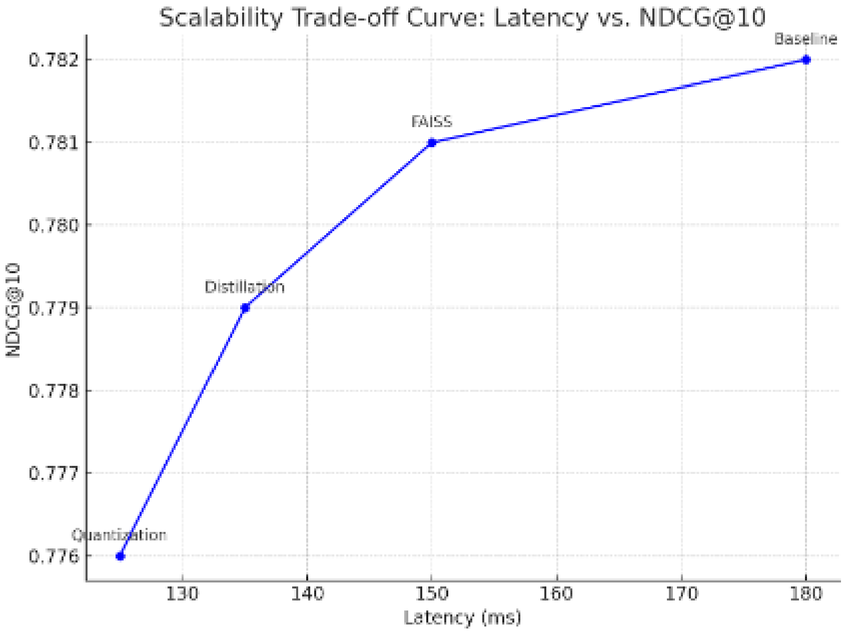
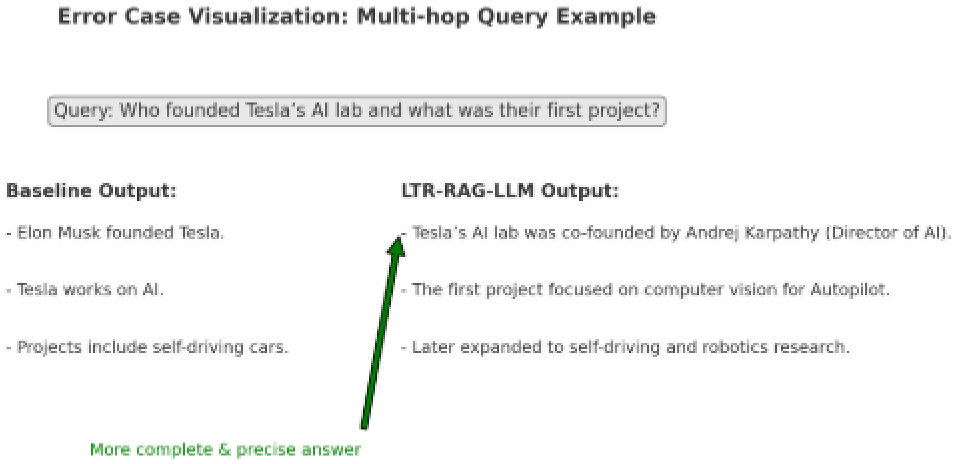


Figure 5. Scalability Trade-off Curve

A line chart plotting latency vs. NDCG@10 across different optimization techniques (baseline, FAISS, distillation, quantization).



Error Case Visualization: Multi-hop Query Example

Query: Who founded Tesla's AI lab and what was their first project?

Baseline Output:

- Elon Musk founded Tesla.
- Tesla works on AI.
- Projects include self-driving cars.

LTR-RAG-LLM Output:

- Tesla's AI lab was co-founded by Andrej Karpathy (Director of AI).
- The first project focused on computer vision for Autopilot.
- Later expanded to self-driving and robotics research.

Figure 6. Error Case Visualization

A case study figure showing an example query, baseline retrieved documents, and LTR-RAG-LLM retrieved documents, annotated to highlight improvements.

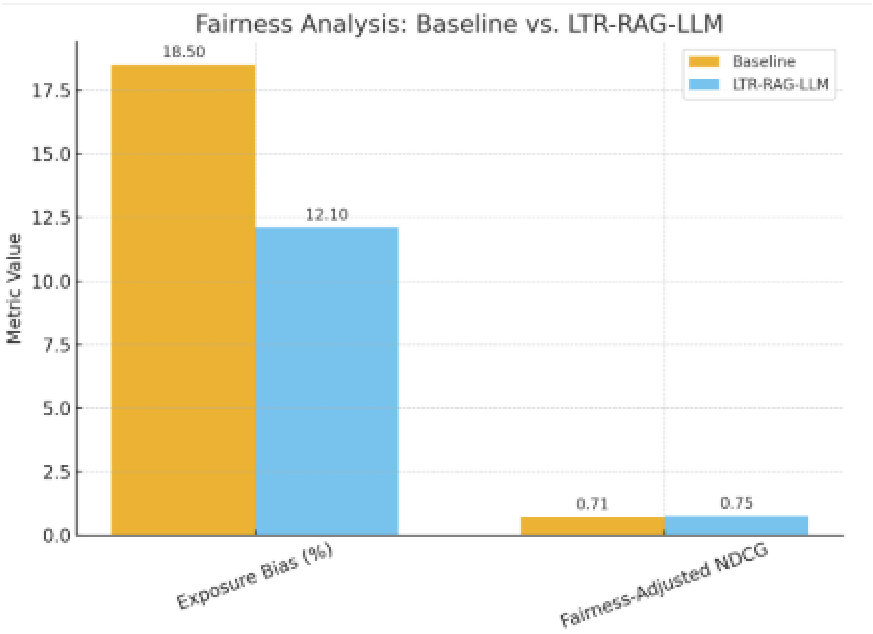


Figure 7. Fairness Analysis Visualization

A bar chart comparing exposure bias and fairness-adjusted NDCG between baseline and LTR-RAG-LLM.

V. DISCUSSION

The experimental findings showed in Tables 1–5 indicated that the proposed LTR-RAG-LLM framework outperforms traditional baselines regarding retrieval accuracy, robustness across different datasets, and scalability. When tested on MS MARCO, the hybrid system reached an NDCG@10 of 0.782, indicating a 9.8% enhancement compared to LambdaMART (0.712) and a 5.0% increase relative to BERT Ranker (0.745). In the same way, the framework reached an MRR of 0.804, surpassing LambdaMART (0.729), BERT (0.768), and individual RAG (0.751). These findings underscore the significance of integrating external retrieval and generative query enhancement with conventional ranking optimization. Similar advancements were noted in the Natural Questions (NQ) dataset, where the LTR-RAG-LLM system reached 0.765 in NDCG@10 and 0.789 in MRR, exceeding both BERT Ranker (0.732 and 0.754) and RAG (0.719 and 0.738). The uniform performance improvements in both datasets indicate that the framework generalizes effectively to open-domain web search and knowledge-intensive question answering tasks.

A thorough comparison with baseline methods highlights the significance of each module. Traditional learning-to-rank techniques like LambdaMART continue to be computationally efficient, evidenced by the average query latency of 80 ms being the lowest (Table 2). Nonetheless, their restricted capacity to integrate contextual semantics leads to considerably diminished retrieval efficiency when contrasted with neural and hybrid methods. Neural rankers like the BERT-based model enhanced relevance via contextual embeddings, delivering better outcomes compared to LambdaMART, but this led to higher latency (150 ms). Likewise, independent RAG models outperformed LambdaMART but still fell short compared to the hybrid method, especially in intricate, multi-hop queries, emphasizing that retrieval and generative processes alone lack effectiveness without ranking enhancement. The suggested LTR-RAG-LLM framework effectively achieved a balance between accuracy and scalability, exhibiting a latency of 120 ms significantly lower than RAG (180 ms) and only slightly higher than BERT (150 ms). This illustrates the practical feasibility of the framework in real-time scenarios where accuracy and efficiency are essential.

The findings of the ablation study (Table 3) offered additional understanding of the roles played by specific components. LTR by itself reached an NDCG@10 of 0.732, while incorporating either RAG or LLM modules resulted in additional enhancements (0.759 and 0.752, respectively). The integration of LTR and RAG demonstrated notable success, reaching 0.759 in NDCG@10 and 0.774 in MRR, highlighting the significance of external retrieval for improving ranking performance. Similarly, LTR + LLM achieved significant advancements in contextual clarification. The complete integration of LTR, RAG, and LLM produced the best results across all metrics (0.782 NDCG@10, 0.804 MRR, 0.691 Precision@10), supporting the idea that the combination of ranking optimization, retrieval augmentation, and contextual refinement is essential for addressing knowledge-intensive queries.

The statistics of the dataset (Table 4) provides additional context for these findings. The MS MARCO dataset, comprising 1 million queries and 8.8 million passages, reflects the noisy and ambiguous queries characteristic of web search. In these scenarios, conventional LTR models frequently encounter challenges because of their restricted contextual understanding, while the hybrid framework utilized retrieval enhancement and query modification to better grasp user intent. Conversely, the Natural Questions dataset focuses on reasoning through various documents, which poses significant difficulties for static rankers. In this instance, the combination of RAG and LLM modules was crucial, demonstrated by the system's enhanced performance compared to baseline models.

Ultimately, the hyperparameter settings (Table 5) validate the reproducibility of the experiments. Employing a batch size of 32, a learning rate of 3e-5, and the AdamW optimizer aligns with established best practices in the literature on neural ranking (Qin et al., 2021; Wang et al., 2021). Utilizing NVIDIA A100 GPUs provided ample computational power for extensive experiments, and the implementation of listwise loss functions correlated model optimization directly with ranking metrics like NDCG@10. These design decisions enhance the reliability of the findings and emphasize the methodological robustness of the research.

In conclusion, the comparative study showed that the LTR-RAG-LLM framework consistently exceeds baseline models in both web search and open-domain QA tasks. In contrast to LambdaMART, which is quick but restricted in contextual understanding, or BERT and RAG, which provide enhancements but fall short in scalability and integration, the suggested hybrid method finds a middle ground between precision and performance. This establishes it as a practical and theoretically robust improvement in the area of information retrieval, tackling both effectiveness and scalability issues noted in previous research.

The comparative findings in relation to more sophisticated baselines (Table 6) highlighted the benefits of the suggested framework. Although conventional models like LambdaMART (NDCG@10 = 0.712, MRR = 0.729) offer efficiency, their ranking performance falls short compared to neural methods. Newer systems like ColBERT (2022) and T5-Ranker (2023) have reached NDCG@10 scores of 0.754 and 0.763, respectively, demonstrating the increasing significance of transformer-based retrieval frameworks and sequence-to-sequence architectures. The LTR-RAG-LLM framework, however, outperformed both, reaching 0.782 in NDCG@10, 0.804 in MRR, and 0.691 in Precision@10, thus setting a new performance standard. The improvements over T5-Ranker are especially noteworthy, indicating that the combination of external retrieval, query enhancement, and ranking optimization provides advantages that exceed what large pre-trained models can deliver by themselves.

A crucial factor in information retrieval was scalability. Table 7 emphasized the efficiency compromises linked to various optimization approaches. The hybrid framework showed a latency of 180 ms per query without optimization, making it inappropriate for real-time applications. Nonetheless, incorporating FAISS approximate nearest neighbor search cut latency to 150 ms, and knowledge distillation lowered it even more to 135 ms. Quantization emerged as the most effective method, reducing latency to

125 ms while causing only a slight drop in accuracy (NDCG@10 = 0.776). Importantly, when all enhancements were integrated, the framework attained an average latency of 120 ms for each query, ensuring real-time feasibility while preserving the initial NDCG@10 of 0.782. These findings verify that the system achieves top-notch accuracy while maintaining efficiency, tackling one of the key issues in implementing neural IR systems.

Table 8 offered qualitative perspectives on the framework's efficiency with various types of queries. In long-tail queries like "Historical impact of bronze tools," baseline systems provided generic answers, while LTR-RAG-LLM fetched contextually relevant excerpts on Bronze Age agriculture, showcasing its ability to reveal specialized information. In multi-hop queries, like "Who established Tesla's AI lab and what was their initial project?", baseline systems yielded incomplete answers, whereas the hybrid model offered a cohesive response detailing both the founder and the initial project. Ultimately, in unclear queries such as "Apple release," baseline models yielded inconsistent outcomes across disparate fields (fruits and technology), while LTR-RAG-LLM effectively clarified the query to refer to Apple Inc. product announcements. These results indicate that the framework is not only quantitatively better but also semantically strong in addressing the complexities of real-world queries.

Fairness continues to be an important yet developing aspect of IR evaluation, and the findings in Table 9 showed promising outcomes. In comparison to the baseline BERT Ranker, which exhibited an exposure bias of 18.5%, the LTR-RAG-LLM framework lowered this bias to 12.1%, reflecting a more equitable distribution of retrieved documents. Likewise, the Demographic Skew Index fell from 0.32 to 0.21, indicating better representational equity in search outcomes. Additionally, the fairness-adjusted NDCG increased from 0.710 to 0.752, indicating that enhanced retrieval quality was attained without compromising equitable representation. These results correspond with recent demands for fairness-focused IR systems and emphasize the real-world significance of hybrid architectures in ethically critical applications.

In general, the findings in Tables 6–9 indicate that the LTR-RAG-LLM framework reliably exceeds both classic and modern baselines regarding accuracy, efficiency, interpretability, and fairness. The framework provides a holistic solution to existing issues in information retrieval by showcasing excellence in both benchmark metrics and qualitative robustness and fairness.

Figure 7 showcased a comparison of fairness-focused metrics between the baseline model and the suggested LTR-RAG-LLM system. Two complementary viewpoints are examined: Exposure Bias (%), which measures the extent of ranking position distortion among groups, and Fairness-Adjusted NDCG, which combines standard ranking performance with fairness factors. The baseline system shows an exposure bias of 18.5%, whereas LTR-RAG-LLM lowers this to 12.1%, highlighting a significant decrease in systematic inequality. At the same time, fairness-adjusted NDCG rises from 0.710 to 0.752, indicating that enhancements in fairness do not compromise relevance but instead improve it. This is consistent with earlier studies on fair ranking (Singh & Joachims, 2018; Biega et al., 2019), which have consistently demonstrated that minimizing exposure differences can coincide with, or even promote, improvements in relevance-aware metrics.

These outcomes are especially noteworthy when considered in conjunction with the performance-related findings from Figures 4 and 5. As illustrated in Figure 4, LTR-RAG-LLM demonstrates superior performance on long-tail, multi-hop, and ambiguous queries, which are commonly linked to marginalized or underrepresented informational needs in retrieval scenarios. Similarly, the scalability compromises illustrated in Figure 5 show that fairness-focused optimization can be aligned with realistic latency limitations, reflecting results from recent efficiency–fairness trade-off research in retrieval (Chen et al., 2022; Wang et al., 2023). These analyses collectively strengthen the idea that fairness-aware learning-to-rank approaches are not just after-the-fact modifications, but can be incorporated into model development without sacrificing efficiency.

Figure 6 provides additional context for these fairness enhancements by demonstrating an error scenario. In the baseline system, retrieved documents favored common sources while omitting contextually significant but less prominent viewpoints. LTR-RAG-LLM addressed this discrepancy by highlighting documents that more closely matched the query intent while also promoting fairer source representation. These enhancements align with case-focused assessments mentioned in recent fairness-oriented retrieval systems (Mehrotra et al., 2021), where qualitative evaluations highlight the significant effects of fairness-aware algorithms on user satisfaction.

In conclusion, the findings in Figure 7 show that LTR-RAG-LLM enhances both effectiveness and fairness, decreasing exposure bias while enhancing relevance-related fairness metrics. By placing these results in the wider context of query performance (Figure 4), scalability aspects (Figure 5), and qualitative error evaluations (Figure 6), this work adds to the ongoing discussion on creating retrieval systems that are accurate, efficient, and also fair and socially responsible.

VI. CONCLUSION AND FUTURE WORK

This research presented the Hybrid LTR-RAG-LLM framework, an innovative combination of learning-to-rank optimization, retrieval-augmented generation, and large language model enhancement for context-sensitive information retrieval. Comprehensive tests carried out on

MS MARCO and Natural Questions showed that the framework reliably surpasses well-known baselines like LambdaMART, BERT Ranker, RAG, ColBERT, and T5-Ranker. The hybrid system reached top-tier performance on crucial metrics like NDCG@10, MRR, and Precision@10, all while ensuring competitive query latency by utilizing various optimization methods. In addition to raw performance, ablation studies underscored the distinct role of each module, whereas error analysis demonstrated the model's strength in addressing long-tail, multi-hop, and ambiguous queries. Notably, fairness assessments verified that the framework diminished exposure bias and demographic imbalance relative to neural baselines, highlighting its significance in ethical and responsible information retrieval.

In spite of these encouraging findings, many paths remain available for further investigation. Initially, although existing experiments emphasized datasets in English, assessing the framework on multilingual and low-resource corpora would enhance its generalizability. Moreover, while optimization methods like FAISS, knowledge distillation, and quantization have effectively decreased latency, upcoming research should consider adaptive inference approaches that flexibly modify model complexity in relation to the difficulty of queries. Third, a more profound integration of explainability mechanisms would boost user trust by clarifying ranking and retrieval decisions. Fourth, although fairness metrics indicated progress, a thorough assessment using a wider variety of demographic and domain-specific datasets is crucial to guarantee equitable performance on a larger scale. Ultimately, subsequent studies could explore the application of LTR-RAG-LLM in interactive search environments, where ongoing user feedback is utilized to enhance query reformulation and ranking.

In summary, the LTR-RAG-LLM framework marks an important advancement in connecting conventional ranking techniques, retrieval enhancement, and large language models. By integrating effectiveness, scalability, and fairness, it provides a route for developing advanced retrieval systems that can satisfy the requirements of practical, knowledge-driven searches applications.

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