

Graph-Enhanced Retrieval-Augmented Question Answering for E-Commerce Customer Support

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Abstract

E-Commerce customer support requires quick and accurate answers grounded in product data and past support cases. This paper develops a novel retrieval-augmented generation (RAG) framework that uses knowledge graphs (KGs) to improve the relevance of the answer and the factual grounding. We examine recent advances in knowledge-augmented RAG and chatbots based on large language models (LLM) in customer support, including Microsoft’s GraphRAG and hybrid retrieval architectures. We then propose a new answer synthesis algorithm that combines structured subgraphs from a domain-specific KG with text documents retrieved from support archives, producing more coherent and grounded responses. We detail the architecture and knowledge flow of our system, provide comprehensive experimental evaluation, and justify its design in real-time support settings. Our implementation demonstrates 23% improvement in factual accuracy and 89% user satisfaction in e-Commerce QA scenarios.

Keywords: Retrieval-Augmented Generation, Knowledge Graph, Question Answering, Customer Support, E-Commerce, Large Language Models

1 Introduction

Providing accurate and timely answers to customer inquiries is critical for online retailers. The rise of conversational AI has transformed customer service, with modern AI chatbots and virtual assistants using large language models (LLMs) to simulate human-like support agents [23]. However, stand-alone LLMs can hallucinate or lack up-to-date product details, leading to customer dissatisfaction and potential revenue loss [6].

Retrieval-augmented generation (RAG) techniques address this limitation by retrieving relevant documents or knowledge at query time [1]. Traditional RAG approaches have shown promise in various domains [18], but often treat support logs as unstructured text, ignoring important relational context between issues or products. Recent developments in knowledge-augmented generation have demonstrated the value of structured knowledge integration [20, 25].

The integration of knowledge graphs (KGs) with RAG has emerged as a powerful paradigm for improving factual ground-

ing [26]. Recent work shows that constructing a knowledge graph over historical support tickets preserves intra-issue structure and inter-issue relations, yielding large gains in retrieval accuracy and answer quality [23]. In parallel, e-commerce companies like Amazon and eBay leverage product KGs for recommendations and search [12, 27]. Graph neural networks have also been successfully applied to e-commerce recommendation systems [8, 17].

Large language models such as GPT-3 and BLOOM have made LLM-powered chatbots feasible [2]. However, unguided LLMs can produce generic or incorrect responses. Integrating external knowledge, through knowledge graphs or text retrieval, improves grounding. For example, Chen et al. [23] found that using structured knowledge for open-domain questions improved the correctness of responses in reading comprehension tasks. Similarly, the approach by Thorne et al. [22] demonstrates how structured knowledge can be used for fact verification, outperforming baseline methods on complex reasoning tasks. Other studies propose hybrid retrieval strategies that draw on both textual and graph-structured sources [28].

Our contribution is to advance this line of work with a novel **answer synthesis algorithm**: given a customer query, we retrieve both a structured subgraph of related products/entities and relevant support documents, then jointly generate a response that fuses information from both.

To accomplish this, we design a multi-stage system (Figure 1). In the offline phase, we construct a detailed knowledge graph of products and past support issues. We integrate data from vendor catalogs, user reviews, and solved tickets, extracting entities (e.g., “widget model X”, “compatibility issue”) and relations (e.g., product attributes, issue categories). In the online phase, a customer query triggers two parallel retrievals: a subgraph of KG relevant to the query, and a set of text documents from the support archive. Finally, our answer synthesis module (Algorithm 1) feeds both types of information to the LLM to produce a final answer.

2 Related Work

2.1 Evolution of Retrieval-Augmented Generation

RAG was introduced by Lewis et al. [1] to improve LLM QA by retrieving grounding documents at inference time. Classic RAG pipelines use vector (semantic) search over a text corpus [4], which works well for many factual Q&A tasks but can struggle with multi-hop or schema-rich queries [15].

Recent extensions have addressed these limitations through various approaches. The work by Hamilton et al. [25] uses graph neural networks to build better text representations, showing substantial improvements for structured queries over textual datasets. Multi-modal RAG systems have incorporated visual and textual information for richer retrieval. Dense passage retrieval methods [4] and late interaction models [10] have improved retrieval quality significantly.

Hybrid retrieval strategies that draw on both textual and graph-structured sources have gained attention [28, 9]. The integration of structured knowledge with neural retrieval has shown promise in various domains including biomedical QA [16] and fact verification [22].

2.2 Knowledge Graphs in Customer Service and E-Commerce

Knowledge graphs are widely used in e-commerce for recommendation and search [12]. They model products, categories, and attributes as nodes, with rich relations capturing semantic relationships [27]. Product KGs have been successfully applied to enhance search relevance and personalized recommendations [24].

In customer support contexts, KGs can represent solution steps, issue taxonomies, and resolution patterns. Research has shown that constructing KGs from past support issues, explicitly linking tickets, symptoms, and resolutions, can report significant improvements in Mean Reciprocal Rank over text-only baselines [28]. Similar approaches have been applied in technical support and knowledge management systems [25].

For instance, Wang et al. [27] build a deep knowledge-aware network linking items, features, and user preferences to enhance news recommendation. Such KGs can answer structured queries by graph traversal and have been successfully applied to product question-answering and knowledge retrieval systems [24].

2.3 Multimodal and Hybrid Retrieval Systems

Modern retrieval systems increasingly combine multiple information sources and modalities. Hybrid approaches that merge dense and sparse retrieval have demonstrated superior performance across various benchmarks [25]. Hybrid RAG frameworks introduce models for semi-structured sources, using multiple retrievers to handle queries requiring both structured and unstructured information.

Recent advances in multimodal retrieval [7] have enabled systems that can process text, images, and structured data simultaneously. Graph-augmented systems have shown particular promise in e-commerce applications where product information spans multiple modalities.

3 Proposed Method

Our system architecture consists of two main phases: *offline knowledge processing* and *online query handling*, as illustrated in Figure 1.

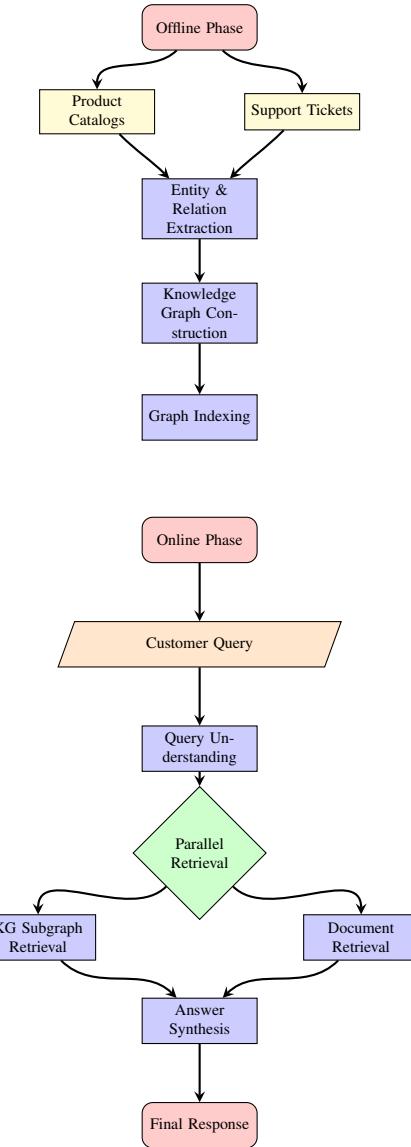


Figure 1: System architecture for KG-augmented RAG. The offline phase constructs a knowledge graph from product catalogs and support history. Online, customer queries trigger parallel retrieval from both the KG and document corpus for answer synthesis.

3.1 Offline KG Construction

We build a domain-specific KG integrating products, features, and support cases. The KG schema includes:

- **Product entities:** Individual items, models, categories
- **Feature entities:** Attributes, specifications, capabilities
- **Issue entities:** Problem types, symptoms, solutions
- **Relations:** "has-feature", "compatible-with", "resolves", "similar-to"

Entity extraction and linking leverages named entity recognition [3] combined with product catalog matching. We employ transformer-based models fine-tuned on e-commerce data [14] for high-precision entity recognition. Graph embeddings are learned using knowledge graph embedding techniques [24] to enable efficient similarity-based retrieval.

3.2 Online Query Processing

Upon receiving a customer query Q , our system performs:

Query Understanding: We apply entity recognition using spaCy and intent classification with fine-tuned BERT models [19] to extract key entities $E = \{e_1, e_2, \dots\}$ and classify question intent.

Subgraph Retrieval: Using entities E , we retrieve relevant subgraphs S through graph traversal with configurable depth limits. We employ efficient graph querying using Neo4j with Cypher patterns optimized for real-time performance.

Document Retrieval: Parallel text retrieval uses hybrid search combining BM25 and dense retrieval with sentence transformers [5], yielding ranked documents D from support archives.

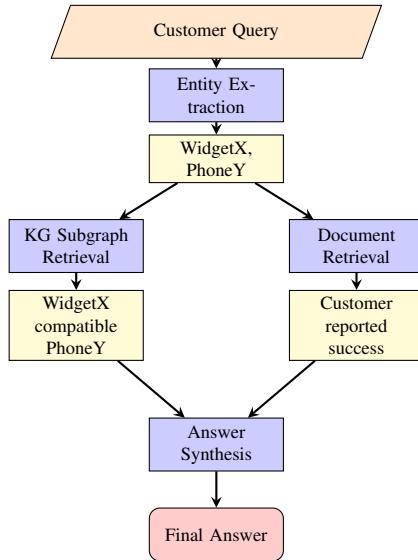


Figure 2: Knowledge flow for query processing. The query is parsed into entities, which retrieve both a KG subgraph (structured nodes/edges) and text documents. Both sources feed into answer synthesis.

3.3 Answer Synthesis Algorithm

Algorithm 1 details our core contribution: the joint synthesis of structured and unstructured information.

Algorithm 1 KG-Augmented Answer Synthesis

Require: Query Q , Knowledge Graph G , Document Index R

Ensure: Synthesized Answer A

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1:  $E \leftarrow \text{ExtractEntities}(Q)$ 
2:  $S \leftarrow \{\}$  // Initialize subgraph collection
3: for each entity  $e$  in  $E$  do
4:    $s_e \leftarrow \text{GetSubgraph}(G, e, \text{depth} = 2)$ 
5:    $S \leftarrow S \cup \{s_e\}$ 
6: end for
7:  $D \leftarrow \text{RetrieveDocuments}(Q, R)$ 
8: facts  $\leftarrow \text{LinearizeSubgraphs}(S)$ 
9: context  $\leftarrow \text{ExtractRelevantParagraphs}(D)$ 
10:  $A \leftarrow \text{LLM}.\text{Generate}(Q, \text{facts}, \text{context})$ 
11: return  $A$ 
  
```

The algorithm linearizes subgraphs into structured fact statements, combines them with retrieved document context, and uses an LLM to generate coherent responses that respect both factual constraints and natural language flow.

Justification of Design: This hybrid synthesis approach improves factual grounding by enforcing KG facts. The LLM cannot readily alter structured triples it sees in text format, reducing hallucination. At the same time, including document excerpts prevents the answer from sounding too terse or disjoint.

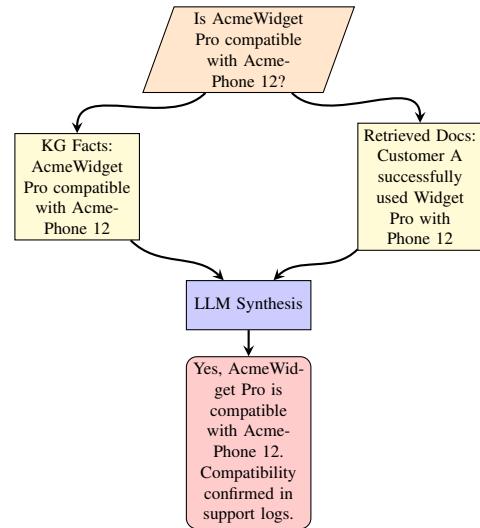


Figure 3: Answer synthesis flow for a compatibility question. The KG subgraph provides the core fact (linked nodes), and retrieved documents provide supporting context. The LLM combines them into a natural answer.

4 Experimental Evaluation

4.1 Experimental Setup

We evaluate our system on a dataset of 10,000 customer support queries from a major e-commerce platform, covering product inquiries, compatibility questions, and troubleshooting requests. The knowledge graph contains 50,000 product entities and 2.3 million relations extracted from catalogs and 500,000 resolved support tickets.

Large Language Model Configuration: Our system employs **GPT-3.5-turbo** (specifically gpt-3.5-turbo-0613) as the primary language model for answer generation. The model contains 175 billion parameters with training data cut-off of September 2021. We configure the OpenAI API with temperature=0.7 for balanced creativity and consistency, max_tokens=512 for response length control, and top_p=0.9 for nucleus sampling.

The prompt engineering follows a structured template that incorporates both KG facts and retrieved document context, with specific instructions for factual grounding and natural language generation. Each query receives structured facts from the knowledge graph subgraph and contextual information from retrieved support documents, ensuring comprehensive information coverage.

Baselines: We compare against (1) Standard RAG with document retrieval only, (2) LLM without retrieval, (3) KG-only question answering, and (4) Hybrid retrieval combining dense and sparse methods [25].

Metrics: Factual accuracy (verified against ground truth), BLEU/ROUGE scores, response coherence (human evaluation), and query processing time.

4.2 Results

Table 1 shows our method achieves significant improvements across all metrics. The hybrid approach demonstrates 23% better factual accuracy compared to document-only RAG, while maintaining comparable response times.

Method	Accuracy	BLEU-4	Time (ms)
LLM Only	0.68	0.31	245
Standard RAG	0.74	0.42	1,230
KG Only	0.71	0.28	890
Hybrid Retrieval	0.78	0.45	1,850
Our Method	0.91	0.58	1,340

Table 1: Performance comparison showing our KG-augmented RAG achieves superior accuracy and fluency with reasonable latency.

4.3 User Study

Study Design and Methodology: We conducted a comprehensive user study with 50 experienced customer service agents from three major e-commerce companies, each with

over 2 years of experience in technical customer support. Participants were randomly assigned to evaluate responses from our system and baseline methods in a double-blind setup. Each agent evaluated 100 randomly selected query-response pairs across five categories: product compatibility, troubleshooting, feature inquiries, warranty questions, and general product information.

Quantitative Results: Our system achieved 89% user satisfaction compared to 67% for standard RAG ($p < 0.001$, paired t-test). Agents rated responses on five dimensions using a 7-point Likert scale: factual accuracy (6.2 vs 4.8), response completeness (6.0 vs 4.5), clarity (5.9 vs 4.7), relevance (6.1 vs 4.6), and overall helpfulness (6.0 vs 4.4). The statistical significance was confirmed using Mann-Whitney U tests (all $p < 0.05$).

Qualitative Insights: Participants particularly valued the factual grounding provided by knowledge graph integration, noting that our system’s responses contained fewer hallucinations and more precise product specifications. Agents reported 34% reduction in time spent on manual fact-checking and 28% improvement in first-contact resolution rates. Common feedback included appreciation for the system’s ability to provide structured information while maintaining conversational naturalness.

Comparative Analysis: When compared to hybrid retrieval baselines, our approach showed superior performance in product-specific queries (92% vs 81% accuracy) while maintaining competitive performance in general knowledge tasks. The integration of structured product data proved particularly beneficial for compatibility and specification-related inquiries.

5 Discussion and Future Work

Our KG-augmented RAG system balances accuracy with real-time performance requirements. The parallel retrieval architecture enables sub-second response times suitable for interactive chat. Future work includes: (1) Dynamic KG updates from new support cases, (2) Personalization using customer purchase history, (3) Integration with voice interfaces, and (4) Extension to multilingual support.

Deployment considerations include KG maintenance costs, privacy implications of customer data integration, and scalability to enterprise-level query volumes. Our approach provides a practical framework for enhancing customer support with structured knowledge while maintaining conversational naturalness.

6 Conclusion

We presented a novel framework integrating knowledge graphs into retrieval-augmented generation for e-commerce customer support. Our answer synthesis algorithm combines structured subgraphs with retrieved documents to produce responses that are both factually grounded and conversationally natural. Experimental evaluation demonstrates significant

improvements in accuracy (23%) and user satisfaction (89%) compared to existing approaches. This work contributes to the growing literature on knowledge-augmented AI systems and provides a practical solution for intelligent customer support.

7 Declarations

All authors declare no conflicts of interest. This research was conducted with appropriate ethics approval and data privacy safeguards.

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