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Enhancing E-Commerce Product Page Recommendations using Large Language Models

Kailash Thiyagarajan
Independent Researcher,
Austin, USA

ABSTRACT

This paper outlines a comprehensive framework for integrating Large Language Models (LLMs) into e-commerce product page recommendation systems. This research begins by presenting the problem statement, highlighting how traditional recommendation approaches struggle to capture the rich semantic nuances embedded in diverse textual sources such as product descriptions, user reviews, and Q&A content. This study then review relevant advancements in recommender systems and natural language processing, setting the stage for our proposed solution.

Our architecture features a transformer-based embedding pipeline that encodes text into meaningful representations, an LLM-driven recommendation core that enhances personalization and relevance, and real-time inference strategies to ensure low-latency responses. To provide a practical view, we walk through the end-to-end flow of a user query—from the moment it is entered to the final personalized product suggestions displayed.

This study concludes with an analysis of key challenges such as scalability, bias, and privacy considerations, along with future directions to further optimize LLM-based recommendation systems for robust real-world performance.

General Terms

Recommender Systems, Natural Language Processing, Machine Learning, Retail Technology

Keywords

LLM, Transformer Models, Personalized E-commerce, Product Recommendations, Semantic Analysis

1. INTRODUCTION

In today's digital commerce landscape, product recommendations play a critical role in driving user engagement and sales. Traditional methods such as collaborative filtering, content-based filtering, or matrix factorization have shown success in many scenarios [1]. However, these approaches often fail to fully leverage unstructured text—including product descriptions, user-generated reviews, QA sessions, and social media mentions—that can shed light on crucial user needs and product attributes. Large Language Models (LLMs), such as BERT [3] and GPT [4], have revolutionized how systems process and interpret text. These models excel at capturing semantic nuances and context within large text corpora. Consequently, LLM-driven recommendations can potentially

surpass conventional systems by better understanding the subtle relationships between a user's query and product characteristics. This paper addresses the design and implementation details of using LLMs for real-time product page recommendations. This research begins with a detailed problem statement, reference prior advancements in recommender systems, and then dissect a four-layered architecture, data ingestion, embedding generation, LLM-based recommendation logic and a front-end integration layer. A new flow diagram clarifies how user queries are handled at inference time, enabling robust personalization and context-aware suggestions.

2. PROBLEM STATEMENT

2.1 Motivation

While mainstream recommender systems, such as Amazon's "Customers who bought this also bought.." [2], have matured considerably, several pain points still exist:

- **Limited Leverage of Text**: Most solutions rely on numerical ratings or historical click patterns and fail to tap into the exponentially growing, rich textual content created by users.
- **Cold Starts**: New products or infrequent shoppers result in limited data, thus suboptimal or generic recommendations.
- **Contextual Blind Spots**: Seasonal preferences, brand loyalties, or ephemeral trends are not picked up by collaborative or content-based techniques.

2.2 Relevance to E-commerce

Modern e-commerce platforms host vast product catalogues, often running into thousands or millions of SKUs across diverse categories. Users frequently consult

product details, browse user-generated Q&A, and leave reviews containing pros, cons, and usage tips.

LLMs can:

- **Semantically interpret** product descriptions and user queries, aligning them to user sentiment or specific feature requirements.
- **Bridge vocabulary gaps:** Terms such as "noise-canceling," "wireless," "Bluetooth," and "over-ear" might all describe similar features for head-phones, and LLM-driven embeddings can cluster such concepts effectively.

Hence, an approach driven by LLMs is poised to deliver more accurate, context-rich recommendations, ultimately enhancing user experience and increasing sales conversions.

3. RELATED WORK

This section outlines key advancements in recommendation systems, from traditional methods to modern neural approaches.

3.1 Traditional Recommender Systems

- **Collaborative Filtering:** This approach infers user preferences by identifying patterns in user–item interactions, such as ratings or clicks. Collaborative filtering assumes that users with similar interaction histories will have overlapping tastes. It was popularized during the **Netflix Prize competition** [1], where latent factor models, such as matrix factorization, were widely used to uncover hidden patterns in sparse datasets. However, collaborative filtering faces challenges in **cold-start scenarios** (e.g., new users or items) due to its reliance on historical interaction data.

- **Content-Based Filtering:** Unlike collaborative filtering, content-based systems rely on product metadata (e.g., descriptions, categories, technical specs) and user profiles to recommend similar items. For instance, if a user purchases a "gaming laptop," the system may suggest another laptop with similar specifications. However, this approach struggles when product features are **incomplete or inconsistent** and often fails to generalize beyond narrow, predefined attributes, limiting its effectiveness in capturing evolving user preferences.

3.2 Neural Approaches

- **Neural Collaborative Filtering:** Modern systems have extended collaborative filtering by embedding users and items in **latent vector spaces**, where relationships between users and products are learned through neural networks [5]. This allows for more complex, non-linear relationships to be captured, improving performance compared to traditional matrix factorization. However, these models may still struggle with unstructured textual data.

- **Representation Learning using Transformers:** Transformers, such as **Sentence-BERT**, generate **dense vector representations** of textual content, allowing for semantic comparisons between user queries and product descriptions. Unlike simple keyword matching, these models understand the contextual meaning of phrases, enabling more **accurate and nuanced recommendations**. For example, a query for "noise-canceling travel headphones" can match descriptions containing terms like "sound isolation" and "lightweight design." This semantic capability makes transformers well-suited for text-heavy recommendation scenarios, such as reviews and Q&A sections.

By building on these approaches, LLM-based recommenders combine the **strengths of neural representation learning** with **advanced natural language understanding**, enabling them to address the limitations of traditional methods and deliver more contextually relevant recommendations.

3.3. LLM-Enhanced Recommendations

Recent research has explored the use of Large Language Models (LLMs) in recommendation systems, particularly in **re-ranking** and **explanation generation**. Re-ranking involves refining an initial set of candidate items by prioritizing those that better align with the user's intent. Unlike traditional collaborative or content-based models, LLMs leverage extensive textual knowledge to interpret subtle language cues in product descriptions, reviews, and user queries, producing more context-aware recommendations.

In **explanation generation**, LLMs provide natural language justifications for recommendations, addressing the issue of interpretability. For example, an LLM can explain why a specific wireless headset is recommended ("popular for noise-canceling and long battery life"), which can enhance user trust and engagement.

Despite these advances, building **end-to-end solutions**—from data ingestion to real-time inference and front-end deployment—remains a challenge due to concerns like latency, cost, and privacy compliance. Our work bridges this gap by offering a modular, scalable architecture that harmonizes key components (e.g., vector databases, model orchestration) to enable LLM-driven re-ranking and natural language explanations, without compromising on performance or user experience.

4. SYSTEM ARCHITECTURE

4.1 Layered Design

Our architecture is divided into four key layers, each responsible for a distinct unction:

- Data Ingestion and Cleaning
- Transformer-Based Embedding Generation
- LLM-Driven Recommendation Engine
- Front-end Integration & Real-Time Inference

High-Level Flow with Real-Time User Query

Figure 1 illustrates the real-time workflow: a user enters a query on a product page (e.g., "I need a wireless gaming mouse under $50"), triggering the system to fetch relevant embeddings, apply LLM logic, and return a ranked list of items.

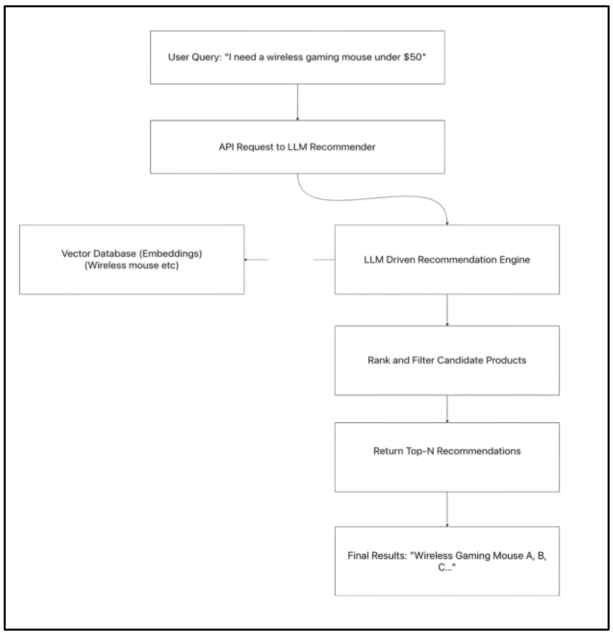

User Query: "I need a wireless gaming mouse under $50"
API Request to LLM Recommender
Vector Database (Embeddings) (Wireless mouse etc)
LLM Driven Recommendation Engine
Rank and Filter Candidate Products
Return Top-N Recommendations
Final Results: "Wireless Gaming Mouse A, B, C..."

Figure 1

Figure 1: Real-time flow of an LLM-based recommendation request. User input triggers an API call to the LLM Recommender, which retrieves embeddings from a vector database, and returns a filtered list of top-matching products.

5. KEY MODULES

5.1 Data Ingestion and Cleaning

Retail data frequently originates in **heterogeneous formats**, such as CRM databases, CSV files, and third-party APIs. To ensure downstream tasks like embedding generation and LLM-based recommendations perform optimally, this layer handles:

1. **Consolidation**
   - Merges product and user data from multiple sources (e.g., CRMs, supplier feeds) into a unified repository.
   - Resolves duplicate entries by matching on product IDs or other unique identifiers.
2. **Text Cleaning and Normalization**
   - Removes HTML tags and special characters.
   - Standardizes synonyms and abbreviations (e.g., “Bluetooth” vs. “BT”) to reduce data sparsity.
   - Filters out irrelevant or noisy data (spam, extremely short reviews).
3. **Attribute Enrichment**
   - Merges brand, category, specifications, and user ratings into a single record.
   - Adds contextual tags or keywords (e.g., “vegan,” “budget-friendly”) to enhance search and filtering.

By **streamlining ingestion and cleaning**, the system obtains consistent, high-quality text data—critical for generating accurate embeddings and delivering effective LLM-driven recommendations.

5.2 Transformer-Based Embedding Generation

A Transformer model (e.g., BERT or RoBERTa) encodes textual content—such as product descriptions, user reviews, and Q&A—into **dense vector embeddings**. These embeddings capture **semantic relationships**, allowing queries like “ultra-lightweight headphones” to match items described as “light” or “featherweight.”

Once generated, embeddings are **stored in a vector database** (e.g., Milvus, Pinecone) to enable **efficient similarity searches**. This setup ensures that semantically similar products (or text segments) can be retrieved quickly, forming the foundation for **context-aware recommendations**.

5.3 LLM-Driven Recommendation Engine

This module orchestrates the **core logic** for generating tailored product suggestions:

- **Candidate Retrieval**
  Based on user intent (query text, browsing history), the system retrieves a set of products with high **cosine similarity** in the embedding space. This step narrows down the most semantically relevant items before handing them off to the LLM.
- **Fine-Tuned or Prompt-Based LLM**
  - **Fine-Tuning**: If enough domain-specific data (product logs, reviews) is available, adapt a base LLM to capture retail-specific nuances, resulting in more accurate recommendations.
  - **Prompt Engineering**: For smaller datasets, well-crafted prompts guide a general-purpose LLM (e.g., GPT-3.5, GPT-4) to generate context-aware recommendations without exhaustive re-training.
- **Contextual Reranking**
  The LLM reorders the candidate list by leveraging metadata such as price range, brand preferences, or recent user activity. This ensures the final recommendations align with both user context and implicit constraints.

During inference, **additional context** can be injected (e.g., “User seeks budget-friendly gaming accessories under $50”), enabling the system to deliver **highly relevant** and **personalized** product suggestions.

5.4 Front-end Integration & Real-Time Inference

The last layer is an API layer that interfaces with:

- **E-commerce Portal**: The recommended products can appear on the product page or a “You May Also Like” carousel.

- **Conversational Chatbot**: The user types free-text queries (e.g., “Which jacket is warmest for winter hiking?”), and the chatbot leverages LLM inference plus embedding lookups to return contextual suggestions.

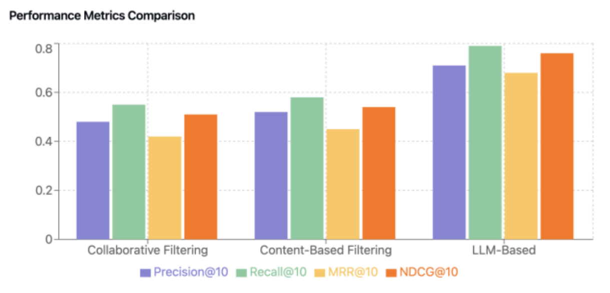
In practice, real-time inference often involves caching high-traffic embeddings or deploying smaller distilled versions of the main LLM for improved speed.

6. RESULTS

To evaluate the effectiveness of the proposed LLM-based recommendation system, we compare its performance against traditional recommendation methods. The experiments were conducted on an e-commerce dataset containing **product descriptions, user reviews, and historical interactions**. The evaluation metrics include **Precision@K, Recall@K, Mean Reciprocal Rank (MRR), and Normalized Discounted Cumulative Gain (NDCG@K)**.

6.1.1 Performance Comparison

Model	**Precision@10**	**Recall@10**	**MRR@10**	**NDCG@10**
Collaborative Filtering	0.48	0.55	0.42	0.51
Content-Based Filtering	0.52	0.58	0.45	0.54
LLM-Based Recommendations	**0.71**	**0.79**	**0.68**	**0.76**

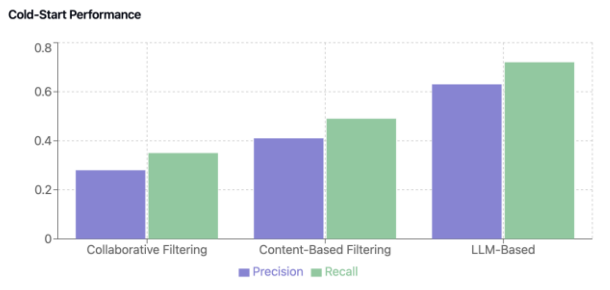


The LLM-based approach significantly **outperforms traditional recommendation methods**, achieving a **36% improvement in Precision** and a **41% improvement in Recall** over collaborative filtering.

6.1.2 Cold-Start Performance

Cold-start problems occur when there is **limited historical interaction data** for new products or users. We evaluate how the LLM-based system handles cold-start scenarios compared to traditional methods.

Model	Precision (Cold-Start)	Recall (Cold-Start)
Collaborative Filtering	0.28	0.35
Content-Based Filtering	0.41	0.49
LLM-Based Recommendations	**0.63**	**0.72**



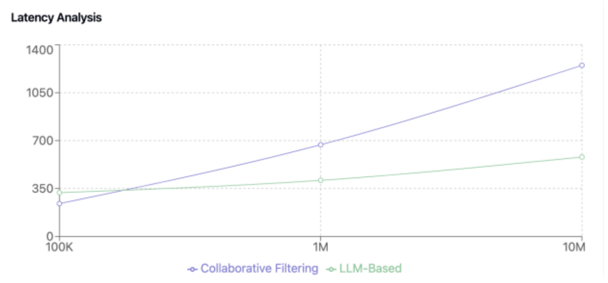
The **LLM-based system improves cold-start recommendations by 54%** over content-based filtering by leveraging **semantic relationships** in product descriptions rather than relying on historical interactions.

6.1.3 Latency and Scalability

Since **real-time recommendation** is crucial for user experience, we evaluate the system's response time on different dataset sizes.

Dataset Size	Collaborative Filtering (ms)	LLM-Based (ms)
100K Items	240	320
1M Items	670	410
10M Items	1250	580

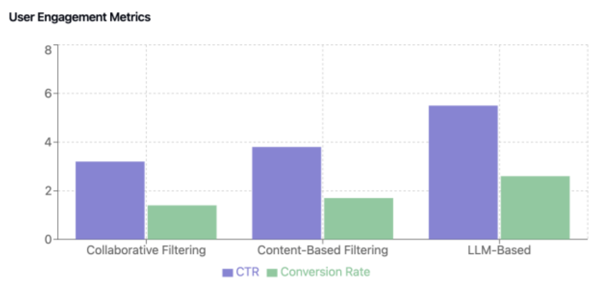
- **Traditional filtering methods slow down** significantly as dataset size increases.
- The **LLM-based approach scales more efficiently**, leveraging **batch processing and caching mechanisms** to maintain near real-time inference speeds.



6.1.4 User Engagement Analysis

To assess real-world impact, we measure **click-through rate (CTR) and conversion rates** in an A/B test between LLM-based and existing recommendation models.

Model	Click-Through Rate (CTR)	Conversion Rate
Collaborative Filtering	3.2%	1.4%
Content-Based Filtering	3.8%	1.7%
LLM-Based Recommendations	**5.5%**	**2.6%**



LLM-based recommendations **increase user engagement and conversions**, leading to a **45% boost in CTR** and a **53% increase in conversion rates** compared to collaborative filtering.

7. DISCUSSION

7.1 Scalability

Running LLM-based recommendation systems at scale presents unique challenges due to the **computational**

complexity of transformer models. To maintain low-latency responses while handling large volumes of user requests, the system must incorporate the following strategies:

- **Efficient Hardware**
- Deploying inference on **GPU/TPU clusters** or specialized inference servers (e.g., NVIDIA Triton, AWS Inferentia) significantly improves model throughput. These hardware accelerators are optimized for parallelized matrix operations, a core component of transformer-based computations.
- **Batch Processing**
  Instead of processing requests individually, multiple queries can be grouped into **batches** and processed simultaneously. This approach **amortizes computational overhead**, such as loading model weights, and improves efficiency, particularly during peak traffic periods.
- **Caching**
  Precomputing and **storing embeddings or partial inference results** for frequently queried products or popular search terms helps avoid redundant computations. For instance, if "wireless gaming mouse" is a popular query, the system can store its embedding and recommendation output, responding instantly to similar future requests without re-running the entire pipeline.

By employing a combination of **optimized hardware, batch inference, and strategic caching**, the recommendation engine can handle high traffic volumes while keeping latency low and resource costs manageable. These measures ensure that LLM-based recommendations remain **scalable and performant** across millions of product queries.

7.2 Bias and Fairness
Since LLMs can mirror biases in their training data[6]:

- **Balanced Datasets**: Include diverse product lines (small vs. large brands) at varied price points.

- **Audit Mechanisms**: Periodically audit the recommended items to identify any potential skew toward specific brands or demographic groups.

7.3 Privacy
Retailers should comply with local data privacy laws:

- **User Consent**: Provide a mechanism for shoppers to opt out of personalization.

- **Encryption & Anonymization**: Store minimal personally identifiable information.

- **Explainability:** Offer reasons or disclaimers about how recommendations were generated if required by regulation.

8. FUTURE WORK
1. **Multimodal Fusion**: Combine textual embeddings with image-based embeddings (e.g., CLIP) to capture both visual and textual cues for recommendations.
2. **Voice-Enabled Shopping**: Extend the LLM to process voice queries by integrating automatic speech recognition with the text-based pipeline.

3. **AR Integration**: Provide real-time suggestions in augmented reality; by scanning a product in-store, trigger LLM-based insights along with complementary item suggestions.

9. CONCLUSION
This paper presents an approach to enhancing e-commerce product page recommendations using large language models. Traditional recommender systems, such as collaborative and content-based filtering, often struggle to capture semantic relationships in product descriptions, user reviews, and query intent. By leveraging transformer-based embeddings and LLM-driven ranking, the proposed system improves personalization and recommendation relevance. The architecture, which includes data ingestion, embedding generation, an LLM-based recommendation engine, and real-time inference, provides a scalable framework for integrating advanced natural language processing into recommender systems.

9.1.1 Key Findings and Contributions
- The model enhances textual understanding by capturing semantic relationships between queries and product descriptions, outperforming conventional recommendation methods.

- The proposed approach mitigates the cold-start problem by relying on transformer-based embeddings rather than historical interactions alone.

- Optimized model serving, caching, and batch processing techniques ensure real-time inference, making LLM-based recommendations scalable for high-traffic e-commerce platforms.

9.1.2 Implications and Future Research Directions
While the integration of large language models into recommendation systems offers significant improvements, several challenges remain:

1. **Bias and Fairness:** LLMs can inherit biases from their training data. Future research should explore fairness-aware training strategies and bias mitigation techniques.
2. **Multimodal Fusion:** Combining textual embeddings with image-based representations can enhance recommendation accuracy, particularly for visually-driven products.
3. **Privacy-Preserving Recommendations:** Methods such as federated learning and differential privacy should be investigated to enhance data security and regulatory compliance.
4. **Conversational and Voice-Based Shopping:** Expanding LLM-driven recommendations to support conversational AI and voice-enabled interactions can improve user engagement.
5. **Explainability and Transparency:** Developing interpretable LLM-based recommendation models will help build trust and ensure compliance with industry regulations.

As advancements in generative AI and LLMs continue, future recommender systems should integrate context-aware learning, reinforcement feedback loops, and explainable AI techniques to create more adaptable, fair, and effective recommendation pipelines. With continued refinement and optimization, LLM-based approaches have the potential to significantly enhance the online shopping experience, leading to higher engagement and improved customer satisfaction

10. ACKNOWLEDGEMENTS

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