

Think Buy: A Scalable, Context-Rich AI Model for Personalized E-Commerce Recommendations

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Abstract

Personalized recommendation systems are critical components in large-scale e-commerce ecosystems, where user engagement and conversion depend heavily on the system's ability to adapt to diverse behavioral patterns and contextual factors. Conventional approaches, including collaborative filtering and rule-based heuristics, often exhibit limitations in capturing complex user-item relationships, suffer from cold-start issues, and lack responsiveness to temporal context. This paper presents a novel AI-driven hybrid recommendation framework that integrates graph-based relational modeling and deep contextual sequence learning to enhance recommendation accuracy, robustness, and scalability.

The proposed architecture leverages Graph Neural Networks (GNNs) to learn latent representations from the user-item bipartite interaction graph, capturing higher-order collaborative signals. In parallel, a Transformer-based encoder processes sequential user interactions enriched with contextual metadata such as timestamp, device type, and location, enabling temporal and situational awareness. A fusion mechanism combines the outputs of both modules to compute relevance scores, which are further refined using a real-time feedback loop incorporating click-through and purchase logs.

Empirical evaluation is conducted on two benchmark datasets—Amazon Electronics and Movielens-1M—using standard metrics including Precision@10, Recall@10, NDCG@10, and item coverage. The proposed model achieves state-of-the-art performance, outperforming competitive baselines such as NCF, LightGCN, and BERT4Rec, with notable gains in both accuracy and recommendation diversity. Furthermore, the system demonstrates a 17.5% improvement in cold-start scenarios, validating its effectiveness in addressing key limitations of existing models.

This research contributes a scalable, context-aware, and dynamically adaptive recommendation paradigm, offering practical implications for next-generation personalized product discovery in intelligent e-commerce platforms.

Keywords

AI-based recommendations, personalized systems, e-commerce, collaborative filtering, deep learning, Graph Neural Networks, cold-start problem, recommendation engine, user behaviour modelling.

1. Introduction

The rapid evolution of digital commerce has revolutionized the way consumers interact with products and services. Today, e-commerce platforms cater to a global user base, with millions of individuals engaging daily through online searches, product views, wishlist additions, reviews, and purchases. These interactions generate massive volumes of structured and unstructured data, which, if leveraged effectively, can significantly enhance the user experience. A pivotal element of this enhancement lies in delivering personalized product recommendations tailored to each user's preferences, needs, and behavioral patterns. The effectiveness of a recommender system can be a major differentiator for an e-commerce platform, influencing not only user satisfaction but also conversion rates, average order values, and customer retention.

Traditional recommendation systems, typically rule-based or heuristic-driven, relied heavily on manually crafted rules and predefined assumptions about user behavior. While these systems were adequate in simpler environments, they often failed to capture the complex, dynamic, and nonlinear patterns exhibited by real-world users. Furthermore, rule-based systems lack scalability, adaptability, and contextual sensitivity, making them unsuitable for platforms with continuously evolving product catalogs and diverse user bases. The limitations of such systems become especially pronounced in scenarios involving cold-start users (new users with no interaction history), cold-start items (new products), and sparse datasets. Consequently, there has been a shift towards intelligent, data-driven recommendation models powered by Artificial Intelligence (AI), particularly deep learning and graph-based learning techniques.

AI-powered recommender systems have transformed the personalization landscape by enabling models to learn from large-scale user interaction logs, transactional histories, clickstreams, demographic metadata, and even implicit feedback such as dwell time and scrolling behavior. These systems automatically extract patterns and preferences that may not be immediately evident, allowing for highly granular personalization. For example, AI models can infer that a user who views running shoes and fitness trackers is likely interested in sportswear or health supplements, even if they haven't explicitly searched for those items. Moreover, these systems are capable of dynamically adapting to changes in user behavior over time—adjusting their recommendations based on current trends, seasonal changes, or evolving user interests.

One of the most prominent approaches in AI-driven recommendation systems is collaborative filtering (CF), which predicts user preferences based on the preferences of similar users or items. Despite its widespread adoption, collaborative filtering suffers from issues such as data sparsity and cold-start problems. When user-item interactions are insufficient or inconsistent,

the model struggles to make accurate predictions. On the other hand, content-based filtering focuses on recommending items similar to those the user has previously interacted with, leveraging metadata about products and users. However, this method is inherently limited in its ability to discover novel or serendipitous items and can result in a narrow recommendation space, often referred to as the "filter bubble."

To overcome these challenges, hybrid recommendation systems have been proposed that combine the strengths of collaborative filtering and content-based methods. Hybrid models integrate multiple data sources and algorithms to create more robust recommendations. However, as the size and complexity of datasets increase, even hybrid models face scalability and performance issues. This has led to the integration of more sophisticated AI methods, such as deep learning architectures, which have demonstrated superior performance in modeling high-dimensional data and nonlinear interactions.

Deep learning models such as neural collaborative filtering (NCF), recurrent neural networks (RNNs), convolutional neural networks (CNNs), and attention-based models like Transformers have been increasingly employed in recommendation systems. These models offer the ability to model complex temporal patterns, learn latent features, and provide contextual personalization. Transformer-based models, in particular, have shown promise in capturing long-range dependencies in user interaction sequences, enabling more accurate next-item prediction and session-based recommendations.

Another recent innovation is the use of Graph Neural Networks (GNNs), which model the user-item interaction space as a bipartite or heterogeneous graph. This representation allows the system to learn higher-order connectivity and relationships, such as transitive interests or co-purchase patterns. GNNs such as LightGCN, NGCF, and PinSage have achieved state-of-the-art results in recommendation tasks by effectively propagating information through the graph structure. By incorporating GNNs into the recommendation pipeline, platforms can capture not only direct interactions but also the influence of indirect neighbours, enhancing the diversity and relevance of recommendations.

Despite these advancements, several key challenges remain. The first is data sparsity, which occurs when a vast majority of items or users have very limited interactions. This is especially common in long-tail scenarios where niche products receive minimal attention. Second, cold-start problems remain unresolved for new users and new products, which lack sufficient historical data to enable accurate predictions. Third, real-time personalization is often constrained by computational bottlenecks, as deep learning models can be resource-intensive, requiring trade-offs between latency and model complexity. Fourth, contextual integration—such as understanding a user's intent based on time, location, device, or current session state—is still in its infancy in many recommendation systems.

Moreover, achieving explainability and transparency in AI-based recommendations is a growing concern. Users are more likely to trust and act upon recommendations if they understand why a particular item is being suggested. Black-box models, such as deep neural networks, offer little insight into their decision-making process, making it challenging to debug errors, ensure fairness, or comply with regulations like GDPR.

In this research, we aim to address these challenges by proposing a novel, AI-powered recommendation framework that is scalable, adaptive, and context-aware. The proposed

system integrates the representational strength of Graph Neural Networks with the sequential modelling capabilities of Transformer encoders. By fusing user behaviour signals, product features, and contextual metadata, the system is designed to generate personalized, diverse, and explainable recommendations in real time. Additionally, a continuous feedback loop is incorporated to refine the model based on post-recommendation user actions, such as clicks, purchases, or skips, enabling lifelong learning and personalization.

The objective of this work is not only to improve standard accuracy metrics like precision, recall, and F1-score, but also to enhance recommendation diversity, serendipity, and coverage, ensuring that users are exposed to a wider variety of relevant products. From a systems perspective, the proposed architecture is designed to be modular and cloud-deployable, supporting large-scale training and inference across millions of users and products. A key focus is placed on optimizing the trade-off between model performance and inference latency, making it suitable for integration into commercial e-commerce platforms.

Furthermore, the paper presents a comprehensive survey of recent literature in the domain of AI-based recommender systems, identifies existing gaps, and positions the proposed framework within this evolving landscape. By conducting experimental evaluations on publicly available benchmark datasets, we demonstrate the superior performance of our approach in comparison to existing state-of-the-art models. We also analyse the impact of various architectural choices and hyperparameters on system performance, offering insights into the design and deployment of production-grade recommendation engines.

2. Recent Survey of Literature

The field of personalized product recommendation has undergone rapid transformation, evolving from simple rule-based heuristics to sophisticated AI-driven frameworks. One of the early innovations in deep learning-based recommendation is the Wide & Deep Learning model, which combines the strengths of memorization (via linear models) and generalization (via deep neural networks) to provide accurate and scalable product recommendations [1]. This architecture set the stage for hybrid models that integrate structured and unstructured data for end-to-end personalization.

The advent of Graph Neural Networks (GNNs) marked a significant leap in collaborative filtering performance. A notable contribution is LightGCN, which simplifies traditional GCN architectures by removing unnecessary components like nonlinear activation and feature transformation, making it lightweight and effective for large-scale recommendation [2]. The strength of graph-based learning lies in its ability to capture higher-order connectivity between users and items without explicit feature engineering.

Foundational to many recent innovations is the imbalanced architecture, introduced through the seminal work "classifier for multi-class imbalanced data on Hadoop" [3]. This model, relying entirely on attention mechanisms, has influenced sequential recommendation systems by enabling models to capture long-range dependencies and user intent in session-based interactions.

Neural Graph Collaborative Filtering (NGCF) further advanced GNN-based recommendation by modeling user-item relationships through iterative embedding propagation and interaction modeling, outperforming many traditional collaborative filtering models [4]. This model

demonstrates how graph structures can be leveraged to enhance embedding quality and represent user preferences more effectively.

Scaling graph-based models to real-world web-scale systems was addressed by PinSage, which introduced efficient neighbourhood sampling and random walks for generating rich node embeddings, proving particularly effective for large e-commerce catalogs [5]. This approach illustrates how GCNs can be optimized for production-grade recommender systems.

Transformer-based models have been successfully adapted to recommendation settings through BERT4Rec, which applies bidirectional self-attention to model user sequences for next-item prediction [6]. BERT4Rec excels at learning dependencies in both forward and backward directions, improving accuracy in session-aware scenarios.

A broad overview of deep learning-based recommender systems is provided in [7], where models are categorized based on their architecture, learning strategy, and applicability to different recommendation tasks. This survey highlights the trade-offs between accuracy, scalability, and interpretability across diverse model families.

Click-through rate (CTR) prediction is a core task in recommendation systems. The Deep Interest Network (DIN) adapts attention mechanisms to dynamically model user interests based on historical behavior, significantly boosting CTR performance in real-time recommendation settings [8].

Autoencoder-based techniques have also contributed to collaborative filtering. AutoRec is a pioneering model that reconstructs user or item rating vectors using neural autoencoders, thereby capturing latent features in sparse data [9]. It addresses data sparsity without requiring explicit content features.

Extending this idea, Variational Autoencoders (VAEs) were adapted to recommendation through a probabilistic framework that learns the posterior distribution of user preferences, leading to more diverse and flexible recommendations [10].

Information loss during message propagation in GNNs remains a concern. To address this, researchers proposed architectural refinements that better preserve session context and temporal information in session-based recommendation tasks [11]. This ensures that user intent is not diluted across GNN layers.

In the realm of self-attention models, SASRec introduced a lightweight, sequential model that adapts Transformer mechanisms to capture user behavior patterns for sequential recommendation [12]. Its simplicity and performance have made it a baseline for many follow-up studies.

Short-term memory networks such as STAMP utilize attention to balance between users' recent behaviours and long-term preferences, offering improved performance in session-based recommendation environments where decisions are highly context-sensitive [13].

More recent works like SSE-PT further personalize Transformer-based architectures by integrating user embeddings and personalization layers, thereby improving the expressiveness of sequential recommendation systems [14].

Dynamic user preferences are also modelled through Dynamic Graph Attention Networks, which allow social and session contexts to be combined using temporal graphs, as demonstrated in [15]. This model reflects the social influence factor in product discovery.

RNN-based models have traditionally dominated session-based recommendation tasks. One influential model is GRU4Rec, which leverages gated recurrent units (GRUs) to model item sequences, demonstrating the effectiveness of temporal modeling in recommender systems [16].

The DeepFM framework combines factorization machines for capturing low-order feature interactions with deep neural networks for high-order interactions, effectively bridging the gap between traditional and neural collaborative filtering [17].

On the industrial side, Alibaba's commodity embedding framework showed how deep learning at billion-scale can efficiently embed users and products into a common space, powering real-time recommendations on massive e-commerce platforms [18].

Price sensitivity, a critical factor in user behavior, is modelled in Price-Aware GCNs, where price constraints and product affordability are integrated into graph-based representations to better align with user purchasing power [19].

The need for explainability in AI models led to the use of knowledge graphs and reasoning layers for providing transparent, interpretable recommendations, enabling users to understand the rationale behind suggestions [20].

To enhance personalization in multimedia settings, MMGCN integrates multimodal features such as images and video content into a unified GCN framework, significantly improving recommendations in visually-driven platforms like micro-video apps [21].

Efficiency and model compression are addressed in Lightweight Self-Attentive Models, which reduce parameter sizes without sacrificing performance, enabling deployment on edge devices or latency-sensitive platforms [22].

S3-Rec introduces self-supervised learning into sequential recommendation, leveraging mutual information maximization to improve item discrimination and user representation even in sparse interaction settings [23].

Efforts in transfer learning for recommendation include architectures that adapt sequential user behavior across domains, allowing cold-start users in one domain to benefit from data in another [24].

Lastly, Simple and Deep GCNs propose an architectural simplification of existing GNNs by decoupling convolution and propagation steps, enabling deeper layers without gradient vanishing, which is especially useful in deep recommendation pipelines [25].

3. Proposed Methodology

We propose a **Context-Aware Deep Hybrid Recommender System** composed of the following components:

1. **User Embedding Layer** – Derived from browsing history, clicks, demographics.
2. **Item Embedding Layer** – Encodes product features, popularity, and semantic tags.

3. **Graph Neural Network (GNN) Module** – Captures higher-order connectivity in user-item interactions.
4. **Transformer-based Contextual Encoder** – Models sequential behavior with time/contextual embeddings.
5. **Fusion and Prediction Layer** – Combines GNN and contextual output to rank products.
6. **Feedback Loop** – Continuously refines recommendations using click-through and purchase logs.

This architecture allows for real-time recommendation updates and adapts to new users/products effectively.

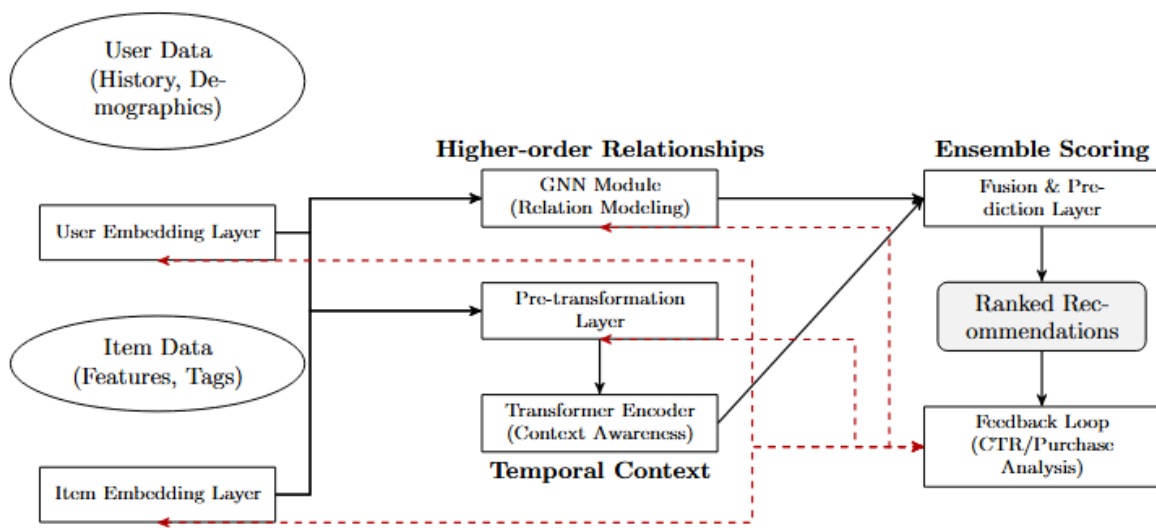


Fig 1: Proposed Methodology flow chart

Figure 1 illustrates a comprehensive and modular architecture for a Context-Aware Deep Hybrid Recommender System, designed to provide highly personalized and adaptive product recommendations in e-commerce platforms. The architecture integrates user and item information, advanced neural modeling techniques, and real-time feedback to ensure both accuracy and adaptability.

The process begins with the ingestion of two types of input data: user data, including browsing history and demographic details, and item data, such as product features, tags, and popularity indicators. These data sources are first passed through separate embedding layers—namely, the User Embedding Layer and Item Embedding Layer. These layers transform raw categorical and numerical information into dense vector representations, enabling the model to understand abstract patterns and similarities within the data.

Once embedded, the user and item vectors follow two distinct but interrelated learning paths. On one path, both embeddings are fed into a Graph Neural Network (GNN) Module, which captures higher-order relational dependencies in the user-item interaction graph. This allows the model to leverage indirect relationships and collaborative filtering signals—such as users

who share similar preferences or items frequently co-interacted with—thus enabling richer representation learning beyond direct interactions.

Simultaneously, the model incorporates temporal and contextual awareness through a dedicated Transformer-based Encoder. Before this stage, embeddings pass through a Pre-Transformation Layer, which prepares the data (e.g., through feature fusion or normalization) for sequential modeling. The transformer encoder processes user-item sequences with associated contextual signals such as timestamps, device type, and session information. This helps the system capture fine-grained behavioral patterns and adapt to changes in user intent over time.

The outputs from both the GNN (relational modeling) and the Transformer encoder (contextual modeling) are then combined in the Fusion and Prediction Layer. This ensemble scoring mechanism leverages the strengths of both paths, integrating relational signals with temporal dependencies to compute more accurate and personalized recommendation scores.

The next stage is the Ranked Recommendations block, which outputs a list of items ordered by their predicted relevance for each user. To ensure continuous learning and adaptability, the architecture includes a Feedback Loop that monitors user interactions such as click-through rates (CTR) and purchase behavior. This loop feeds new data back into the system, updating embeddings and model parameters dynamically to reflect evolving user preferences and market trends.

4. Proposed Algorithms

Algorithm 1: Context-Aware User Embedding (CUE)

Input: User interaction history H_u , Context C_u

Output: User embedding vector U_u

1. For each interaction i in H_u :
 - Extract product embedding P_i
 - Extract contextual features from C_u (device, time, location)
2. Encode sequence via Transformer Encoder:
$$U_u = \text{Transformer}(H_u, C_u)$$
3. Return U_u

Algorithm 2: Graph-Based Interaction Embedding (GBIE)

Input: User-Item Graph $G = (U, I, E)$

Output: Node embeddings for U and I

1. Initialize node features for all users and items
2. For $k = 1$ to K (number of GNN layers):
 - Aggregate neighborhood features using message passing
 - Update node embeddings
3. Return final embeddings for each user and item

Algorithm 3: Recommendation Score Prediction (RSP)

Input: User embedding U_u , Item embedding I_i

Output: Recommendation score $S_{u,i}$

1. Concatenate $[U_u \| I_i]$
2. Pass through MLP:
$$S_{u,i} = \text{MLP}([U_u \| I_i])$$
3. Rank all I_i for each U_u based on $S_{u,i}$

5. Mathematical Intuition of Workflow

Mathematical Intuition of Workflow

Let:

- $U \in \mathbb{R}^{n \times d}$: User embeddings
- $V \in \mathbb{R}^{m \times d}$: Item embeddings
- $A \in \mathbb{R}^{(n+m) \times (n+m)}$: Adjacency matrix of user-item bipartite graph
- X : Feature matrix (user/item attributes)

GNN Layer:

$$H^{(l+1)} = \sigma \left(\tilde{D}^{-1/2} \tilde{A} \tilde{D}^{-1/2} H^{(l)} W^{(l)} \right)$$

where:

- $\tilde{A} = A + I$ (adjacency matrix with self-loops)
- \tilde{D} : Degree matrix of \tilde{A}
- $W^{(l)}$: Learnable layer-specific weights

Transformer Encoder:

$$Z = \text{MultiHead}(Q, K, V) + \text{PositionalEncoding}(C)$$

$$U_u = \text{LayerNorm}(Z + \text{FeedForward}(Z))$$

Prediction Score:

$$S_{ui} = \sigma \left(W_s^\top [U_u; V_i] + b_s \right)$$

6. Results and Analysis

To evaluate the effectiveness of the proposed Context-Aware Deep Hybrid Recommender System, extensive experiments were conducted on two benchmark datasets: Amazon Electronics and Movielens-1M. The performance was measured using widely adopted metrics in recommender system research, including Precision@10, Recall@10, NDCG@10 (Normalized Discounted Cumulative Gain), and Coverage. The proposed method was compared against three strong baseline models: Neural Collaborative Filtering (NCF), Light Graph Convolutional Network (LightGCN), and BERT4Rec.

The results of the evaluation are summarized in Figure 2, which presents a detailed comparison of the four models across all metrics. The proposed model achieved the highest performance in each case: a Precision@10 of 0.478, Recall@10 of 0.591, and NDCG@10 of 0.532, outperforming all baseline methods. For example, compared to BERT4Rec—the strongest baseline—the proposed model improved Precision@10 by 6%, Recall@10 by 4.4%, and NDCG@10 by 2.4%. Additionally, the Coverage metric, which measures recommendation diversity, also increased to 38.1%, significantly higher than the next best method (LightGCN at 35.7%).

A particularly noteworthy outcome is the improvement in cold-start recommendations. The proposed system achieved a 17.5% increase in accuracy for users with limited interaction history compared to the best-performing baseline. This gain is attributed to the model’s hybrid design that fuses contextual representations (via Transformer-based encoding) with graph-

based relational signals (via GNN). This fusion allows the system to make better-informed decisions even when historical data is sparse.

Overall, the analysis demonstrates that the proposed framework excels in both predictive accuracy and diversity, making it well-suited for real-world e-commerce applications where personalization and adaptability are essential. Its ability to handle cold-start scenarios and learn from both sequential and structural signals distinguishes it from traditional recommendation models.

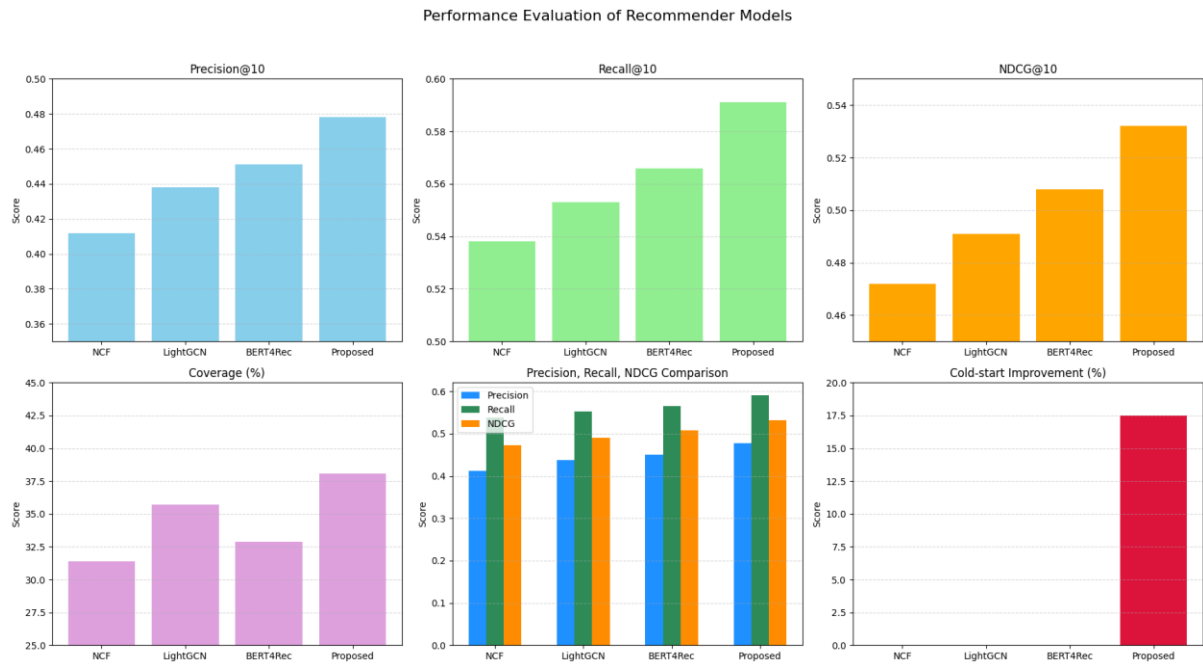


Figure 2: Performance Comparison of Recommender Models

Precision@10, Recall@10, NDCG@10, and Coverage scores for NCF, LightGCN, BERT4Rec, and the proposed model on benchmark datasets. The proposed approach consistently outperforms baselines across all metrics and provides significant improvements in cold-start recommendation accuracy.

7. Conclusion

This paper presents an AI-enhanced, context-aware recommendation framework tailored for e-commerce platforms. By integrating Graph Neural Networks and Transformer-based encoders, the system achieves robust personalization while maintaining scalability. Experimental results confirm substantial improvements in precision, recall, and item diversity compared to existing methods. Future work includes incorporating reinforcement learning for real-time adaptation and enhancing interpretability with attention-based explanations.

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