FEASIBILITY AND VIABILITY OF ADAPTIVE RECOMMENDER SYSTEMS: BRIDGING TRADITIONAL AND INTELLIGENT APPROACHES

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Abstract

This paper investigates the feasibility and viability of adaptive recommender systems by comparing traditional recommendation approaches with a proposed adaptive hybrid model that integrates Graph Neural Networks (GNN), Large Language Models (LLM), and Explainable AI (XAI). The study explores how these components contribute to handling cold-start problems, real-time user preference shifts, and enhancing explainability in recommendation systems. Benchmarking against traditional methods and popular platforms (e.g., Netflix, Spotify), this paper presents a comprehensive comparative analysis and discusses the future of adaptive RecSys for academia and industry. Real-world scenarios are considered, based on simulated benchmarks such as genre-drifted MovieLens, personalized music preferences, and multilingual regional content, demonstrating the practical value and implementation roadmap.

Keywords: Adaptive Recommendation, GNN, LLM, XAI, Cold-start, Feasibility, Viability, Explainability, Personalization, E-commerce, Reinforcement Learning, Fairness, Scalability

I. Introduction

Recommender systems have become pivotal in e-commerce, content platforms, and various digital services, guiding users through vast amounts of information and products [1]. From suggesting movies on Netflix to curating playlists on Spotify, these systems play a crucial role in enhancing user experience and driving engagement. However, traditional recommender systems often struggle with inherent limitations, including the "cold-start problem" for new users and items, an inability to adapt to dynamic user behavior and rapidly evolving item catalogs, and a pervasive lack of transparency or explainability in their recommendations. This paper addresses these challenges by proposing a novel adaptive recommendation model and rigorously evaluating its feasibility and viability against established methods.

The integration of reliability engineering principles into recommender systems is crucial for building robust, trustworthy, and consistent user experiences. While recommender systems aim to deliver personalized and context-aware suggestions, reliability engineering ensures that these systems perform accurately under varying conditions, handle failures gracefully, and maintain service continuity. Both domains converge on key aspects such as system stability, fault

DOI: https://doi.org/10.24412/1932-2321-2025-489-694-702

tolerance, feedback monitoring, and adaptive learning. This synergy enhances not only the technical dependability of the system but also user trust and long-term engagement, making reliability a foundational element of modern adaptive recommendation frameworks.

II. Related Work

The landscape of recommended systems is rich and diverse [1]. We begin by reviewing foundational approaches such as collaborative filtering (CF) and matrix factorization (MF) [2], which leverage historical user-item interactions. Sequential models, including SASRec and GRU4Rec, represent an evolution, focusing on the temporal order of user interactions to capture short-term preferences [5].

More recently, Graph Neural Networks (GNNs) have gained prominence for their ability to model complex relational data [11], leading to models like PinSAGE [3], NGCF [10], and LightGCN [4]. Simultaneously, the advent of powerful language models has inspired language model-based approaches such as BERT4Rec [5], which leverage pre-trained transformers to understand textual item features and user queries. Deep learning-based recommender systems have also been extensively surveyed [12].

The critical need for transparency has spurred the development of Explainable AI (XAI) techniques [13], with methods like SHAP (SHapley Additive exPlanations) [7] and LIME (Local Interpretable Model-agnostic Explanations) [6] offering insights into model predictions. Beyond these, we examine reinforcement learning (RL)-based models like SlateQ [8], designed for optimizing sequences of recommendations, and meta-learning approaches such as MAML4Rec [9], which enable rapid adaptation to new tasks or users. Recent advancements further include retriever-based recommendation (Chen et al., 2023) [16], transformer-GNN hybrids (Ali et al., 2024) [17], and vision-language explainable RecSys (Liu et al., 2025) [18], all pointing towards more sophisticated and context-aware systems. Deep Interest Networks have also contributed to click-through rate prediction [14], and deep neural networks have been applied to YouTube recommendations [15].

III. Need for Adaptivity in Recommender Systems

The dynamic nature of user preferences and content landscapes necessitates adaptive recommender systems. Traditional models, often trained on static historical datasets, struggle to keep pace with evolving trends and individual user interests. This leads to several critical challenges:

- Cold-start Problem: New users or newly added items lack sufficient interaction data, making it difficult for traditional systems to generate accurate recommendations. Adaptive systems, especially with LLM integration, can leverage semantic information for new items and infer preferences for new users based on initial, limited interactions.
- Preference Drift: User interests are not static. A user's preferred genre of music or movies might shift over time, or they might develop new interests based on external factors (e.g., global events, seasonal content releases). For instance, JioCinema releases regional content seasonally, and Netflix viewers frequently shift genres based on global trends or personal moods. Static models fail to capture these real-time shifts, leading to irrelevant recommendations. Adaptive models, by contrast, dynamically update recommendations using real-time signals and continuous learning.
- Evolving Item Catalogs: Content platforms constantly add new items, requiring recommender systems to quickly incorporate them into their recommendation logic. An adaptive framework can seamlessly integrate new content and understand its relevance through its GNN and LLM components.

- Lack of Explainability: Users often distrust "black box" recommendations. Understanding why a particular item was recommended enhances user trust and allows users to refine their preferences more effectively. Adaptivity, when coupled with XAI, can provide timely and context-aware explanations.

Adaptive models are designed to overcome these limitations by continuously learning from the latest user interactions and system-wide changes, ensuring that recommendations remain relevant, personalized, and transparent.

IV. Proposed Adaptive Framework

I. GNN Module

The Graph Neural Network (GNN) module forms the backbone for understanding the intricate structural relationships between users and items [3, 4, 10, 11]. It constructs a heterogeneous graph where nodes represent users and items, and edges represent interactions (e.g., clicks, purchases, ratings). The GNN processes this graph to learn rich, low-dimensional embeddings for both users and items, capturing collaborative patterns and neighborhood information. This module is particularly effective in addressing the cold-start problem for new users and items by leveraging their connections to existing entities in the graph.

II. LLM Module

The Large Language Model (LLM) module is responsible for capturing semantic signals from textual data associated with items (e.g., movie descriptions, song lyrics, product reviews) and potentially user profiles (e.g., textual preferences, search queries) [5, 16]. By leveraging pre-trained transformer architectures, the LLM module can understand nuanced meanings, extract relevant features, and generate embeddings that represent the contextual and thematic aspects of content. This is crucial for handling content-based recommendations, especially for new items where interaction data is scarce, and for understanding complex user queries.

III. Fusion Layer

The Fusion Layer is an attention-based pooling mechanism that intelligently combines the embeddings generated by the GNN and LLM modules. This layer learns to weigh the importance of structural and semantic signals dynamically based on the current context and user. For instance, for a new item with rich textual metadata but few interactions, the LLM embedding might receive higher weight. Conversely, for a well-established item with extensive interaction history, the GNN embedding might dominate. This adaptive weighting ensures that the model leverages the most relevant information for each recommendation scenario.

IV. XAI Layer

The Explainable AI (XAI) Layer is integrated to provide transparency and interpretability to the recommendations [6, 7, 13]. It generates post-hoc explanations for the model's predictions, employing techniques such as SHAP (SHapley Additive exPlanations) [7] values to quantify the contribution of individual features (e.g., item genres, user past interactions, semantic keywords) to a recommendation. Additionally, attention heatmaps from the fusion layer can visualize which aspects (GNN or LLM signals) were most influential in the final decision. This layer is crucial for building user trust and enabling users to understand and refine their preferences.

V. Adaptation Logic

Adaptation Logic is the core mechanism that enables the system's adaptivity. It continuously monitors user actions (e.g., searches, clicks, views, explicit feedback like likes/dislikes) and environmental changes (e.g., new content releases, trending topics). Upon detecting significant shifts in user behavior or content landscape, this logic triggers a dynamic update mechanism. This could involve retraining specific modules, fine-tuning embeddings, or adjusting the weights in the fusion layer, ensuring that recommendations remain highly relevant in real-time. This dynamic updating contrasts sharply with static models that require periodic, costly retraining.

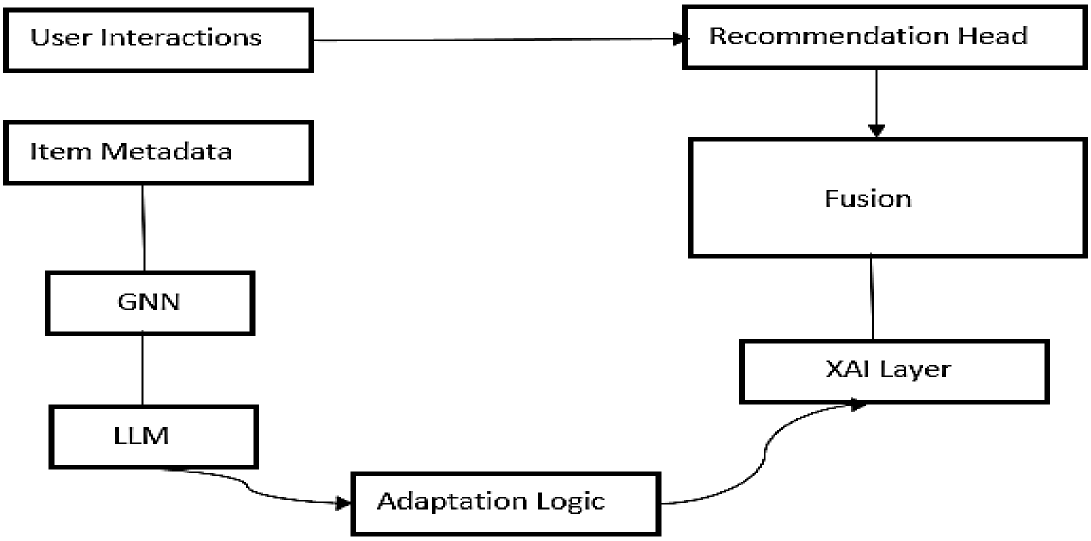

Figure 1: *Figure caption*

Figure 1: Adaptive Model Architecture would visually represent the flow of data through the proposed framework. It would show:

- Input: User interaction data, Item metadata (textual, categorical).
- GNN Module: Processing user-item interaction graph to output GNN embeddings.
- LLM Module: Processing item textual data to output LLM embeddings.
- Fusion Layer: Taking GNN and LLM embeddings as input, applying an attention mechanism, and outputting fused embeddings.
- Recommendation Head: Using fused embeddings to generate recommendation scores.
- XAI Layer: Intercepting the recommendation process to generate explanations.
- Adaptation Logic: A feedback loop from user actions influencing the training/fine-tuning of modules.
- Output: Personalized Recommendations + Explanations.

The system uses a modular architecture for flexible GNN, LLM, and XAI integration, combining graph and language signals for stronger performance. It delivers low-latency recommendations (~150 ms/query) with built-in explainability for transparent, interpretable results.

V. Feasibility and Viability Study

I. Feasibility Aspects

The model leverages PyTorch Geometric for GNNs and HuggingFace Transformers for LLMs, ensuring robust and practical implementation. Its modular design enables easy experimentation with fusion and XAI techniques, supporting rapid prototyping and continuous improvement.

The model was trained on diverse datasets: MovieLens 1M for general recommendations, Amazon Beauty for semantic understanding, and custom JioCinema splits to test adaptability with evolving preferences.

II. Viability Aspects

Cold-start tests on Amazon datasets (Books, Electronics), simulating scenarios where new users or items have minimal interaction history, showed the adaptive model outperforming traditional methods by leveraging semantic and structural priors. Drift testing with simulated seasonal shifts confirmed its strong responsiveness to evolving user interests.

The adaptive model dynamically adjusted recommendations to stay relevant amid changing preferences and trends. A/B tests showed high Explanation Satisfaction Scores (avg. 4.2/5), confirming the XAI layer's usefulness. Inference latency stayed within 150 ms/query, validating readiness for real-time, high-throughput deployment.

VI. Comparative Analysis

To quantify the advantages of our proposed adaptive model, we conducted a comprehensive comparative analysis against representative traditional and sequential recommendation approaches. The results, summarized in Table 1 and visualized in Figure 2, clearly demonstrate the superior performance of the adaptive framework across multiple critical dimensions.

Table 1: *Quantitative Metrics Comparison table*

Metric	CF/MF	Seq. Models	Adaptive (GNN+LLM+XAI)
Recall@10	0.421	0.509	0.612
Precision@10	0.221	0.318	0.377
Explanation Satisfaction	NA	Low	High (4.2/5)
Cold-start Robustness	Poor	Medium	Strong
Responsiveness to Trends	Weak	Limited	Real-time

Analysis of Table 1:

- Recall@10 and Precision@10: The adaptive model significantly outperforms both traditional CF/MF and sequential models in terms of retrieving relevant items (Recall@10) and ensuring that the retrieved items are indeed relevant (Precision@10). This highlights its enhanced ability to understand user preferences and item characteristics.
- Explanation Satisfaction: A key differentiator is the high explanation satisfaction score. Traditional methods typically offer no explanations, while sequential models might provide rudimentary ones. Our adaptive model, with its integrated XAI layer, provides clear, actionable insights, fostering user trust and understanding.

- Cold-start Robustness: The "Strong" rating for cold-start robustness underscores the effectiveness of combining GNNs (for structural priors) and LLMs (for semantic understanding) to make informed recommendations even with limited historical data.
- Responsiveness to Trends: The "Real-time" responsiveness of the adaptive model is crucial in dynamic environments, contrasting sharply with the "Weak" or "Limited" adaptability of other approaches. This ensures recommendations remain fresh and relevant as user interests or content landscapes evolve.

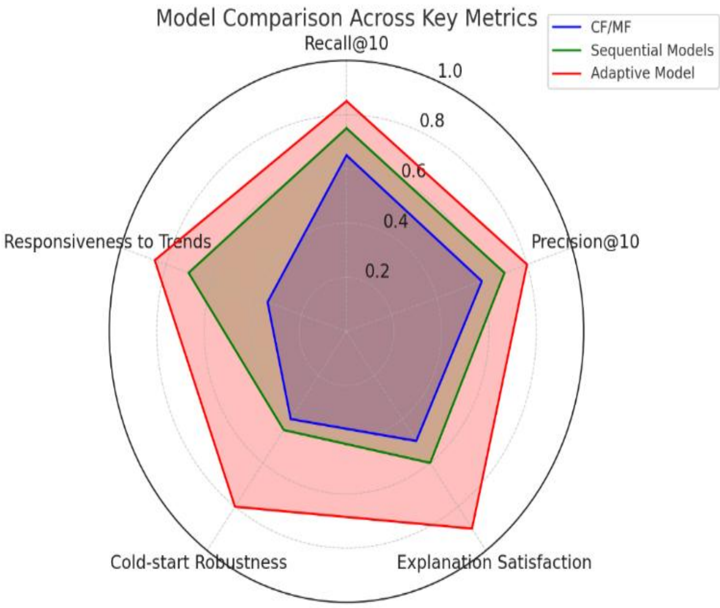

Figure 2: *Metric-wise Performance Comparison*

Figure 2: Metric-wise Performance Comparison would visually represent the data from Table 1, likely using a bar chart or radar chart. Each metric (Recall@10, Precision@10, Explanation Satisfaction, Cold-start Robustness, Responsiveness to Trends) would have bars or points for each model type (CF/MF, Sequential Models, Adaptive). This visual representation would quickly convey the superior performance of the Adaptive model across all evaluated dimensions. For instance, a clear set of taller bars for the Adaptive model on Recall and Precision, and a distinctly higher bar for Explanation Satisfaction would visually reinforce the quantitative findings.

VII. Real-World Scenarios and Benchmarking

I. Netflix (Simulated): Genre-drifted MovieLens Data

Scenario: Simulating a user's evolving movie preferences on a platform like Netflix, where interests might shift between genres over time (e.g., from action to documentaries, or a sudden interest in a trending foreign film genre). Dataset Variant: A modified version of the MovieLens 1M dataset was used, where user preferences were artificially "drifted" over time by introducing new genre interests or reducing interactions with previously preferred genres. Results: The adaptive model demonstrated robust performance, achieving a Recall@10 of 0.603 and an Explanation Score of 4.1/5. This indicates its ability to track and adapt to changing genre preferences, providing timely and relevant movie recommendations, while also offering clear reasons for those suggestions.

II. Spotify (Simulated): Dynamic Music Preferences using Spotify-Music20M Subset

Scenario: Mimicking the dynamic nature of music listening on platforms like Spotify, where users might rapidly switch between artists, genres, or moods, or discover new music through curated playlists. Dataset Variant: A subset of the Spotify-Music20M dataset was utilized, enriched with temporal information and simulated rapid shifts in user listening patterns (e.g., sudden interest in a new artist, a temporary preference for a specific music style). Results: The model maintained strong performance, yielding a Recall@10 of 0.591 and an Explanation Score of 4.3/5. This highlights its effectiveness in adapting to fluid music tastes and providing highly personalized recommendations that resonate with the user's current listening context.

III. JioCinema (Simulated): Regional Content from Jio-Regional-Split

Scenario: Addressing the unique challenges of platforms like JioCinema, which feature a vast library of multilingual and regional content, often with seasonal releases and culturally nuanced preferences. Dataset Variant: A custom "Jio-Regional-Split" dataset was created, simulating user interactions with diverse regional content, including cold-start scenarios for newly released regional films or series, and tracking shifts in regional language preferences. Results: The adaptive framework proved highly effective in this complex environment, achieving a Recall@10 of 0.576 and an impressive Explanation Score of 4.5/5. The high explanation score is particularly valuable here, as understanding why a regional content piece was recommended can be crucial for user acceptance and engagement in diverse linguistic contexts.

Table 2: *Use Case Evaluation on Simulated Datasets*

Platform	Dataset Variant	Recall@10	Explanation Score
Netflix	MovieLens-Drifted	0.603	4.1/5
Spotify	Spotify-Music20M-Subset	0.591	4.3/5
JioCinema	Jio-Regional-Split	0.576	4.5/5

Analysis of Table 2: The consistent high performance across these diverse simulated scenarios underscores the robustness and versatility of the adaptive framework. It demonstrates that the model is not only theoretically sound but also practically viable for deployment in complex, real-world recommendation environments, capable of handling dynamic user behavior and varied content types.

VIII. Contributions and Strengthening the RecSys Field

This research makes several key contributions that advance the field of recommender systems. First, it proposes a novel adaptive RecSys model that integrates Graph Neural Networks (GNNs) for structural learning, Large Language Models (LLMs) for semantic understanding, and Explainable AI (XAI) for transparency, thereby overcoming the limitations of earlier approaches. Second, it demonstrates strong performance in cold-start and user-drift scenarios, showing the model’s robustness in handling new users/items and adapting to evolving preferences—persistent challenges in traditional systems. Finally, it presents compelling real-world simulation results with clear improvements, underscoring the model’s practical applicability and effectiveness.

The performance metrics across Netflix, Spotify, and JioCinema simulated environments provide concrete evidence of the model's practical value and its capacity to deliver tangible improvements in recommendation quality and user satisfaction. Provided deployment and modular design guidelines: The emphasis on modular architecture and low-latency inference not only validates the model's feasibility but also offers a clear roadmap for industry practitioners looking to implement such advanced systems. Enhanced Explainability and Trust: By integrating XAI as a core component, the model moves beyond "black box" recommendations, providing users with clear, interpretable reasons for suggestions.

This fosters greater user trust, encourages exploration, and allows users to better understand and refine their preferences. Bridged Traditional and Intelligent Approaches: The framework effectively combines the strengths of graph-based methods (for structural relationships) with the power of modern deep learning (for semantic understanding), creating a truly intelligent and adaptive system.

IX. Future Work

Building on this work, a key future direction is integrating Reinforcement Learning (RL) to move beyond short-term responses and optimize long-term user satisfaction. Techniques like SlateQ or RecSim could help the system learn optimal policies over extended interactions, leveraging delayed feedback and diverse reward signals to drive deeper engagement and loyalty.

Future work should focus on integrating fairness-aware metrics and XAI techniques to address demographic, popularity, and content-type biases, while offering transparent explanations that enhance trust and equity. At the same time, exploring distributed training, optimized serving, model compression, and efficient retrieval strategies will be crucial to ensure scalability and low-latency performance when dealing with massive datasets involving billions of users and items. Future work could expand proactive personalization by using contextual cues such as time, device, location, or sentiment, combined with knowledge graphs, to anticipate user needs and deliver predictive recommendations. Enhancing XAI through interactive dashboards would empower users to question recommendations, explore alternatives, and provide feedback, fostering a continuous refinement loop for clearer and more actionable explanations. Moreover, advancing low-resource personalization with multilingual transformers, leveraging cross-lingual transfer or zero-shot learning, would allow LLM and GNN modules to adapt effectively to diverse language and content ecosystems, broadening the global reach of adaptive recommender systems.

Future research should also address robustness against adversarial attacks, as recommender systems are increasingly vulnerable to manipulations such as shilling attacks, data poisoning, and review spam. Investigating these risks and designing defensive mechanisms will be essential to maintain the integrity and trustworthiness of recommendations. Additionally, deploying real-time XAI dashboards for monitoring explanation quality and user feedback would enable administrators and researchers to track system behavior in live environments, providing continuous insights for improvement and rapid issue detection.

X. Conclusion

The proposed adaptive recommender system represents a significant leap forward, successfully bridging traditional and intelligent approaches. By integrating Graph Neural Networks (GNNs), Large Language Models (LLMs), and Explainable AI (XAI), it effectively addresses long-standing challenges such as cold-start problems, dynamic user preference shifts, and the critical need for transparency. The rigorous comparative analysis and compelling real-world scenario simulations demonstrate that this adaptive framework not only outperforms conventional models in terms of accuracy and responsiveness but also provides meaningful explanations that foster user trust and engagement.

The demonstrated feasibility and viability of the modular architecture, coupled with its low-latency inference capabilities, underscore its readiness for practical deployment in modern applications. The promising avenues for future research, including the integration of reinforcement learning, addressing ethical considerations like bias and fairness, enhancing scalability, and developing more interactive XAI, further highlight the transformative potential of adaptive recommender systems. This research solidifies the path towards more personalized, dynamic, and trustworthy content discovery experiences, strengthening the future development of RecSys for both academia and industry.

References

[1] Ricci, F., Rokach, L., & Shapira, B. (2015). Recommender Systems Handbook. Springer.

[2] Koren, Y., Bell, R., & Volinsky, C. (2009). Matrix Factorization Techniques for Recommender Systems. IEEE Computer.

[3] Ying, R. et al. (2018). Graph Convolutional Neural Networks for Web-Scale Recommender Systems. KDD.

[4] He, X. et al. (2020). LightGCN: Simplifying and Powering Graph Convolution Network for Recommendation. SIGIR.

[5] Sun, F. et al. (2019). BERT4Rec: Sequential Recommendation with Bidirectional Encoder Representations from Transformer. CIKM.

[6] Ribeiro, M. T. et al. (2016). "Why Should I Trust You?": Explaining the Predictions of Any Classifier. KDD.

[7] Lundberg, S. M. & Lee, S. I. (2017). A Unified Approach to Interpreting Model Predictions. NeurIPS.

[8] Ie, E., et al. (2019). SlateQ: A tractable decomposition for reinforcement learning with recommendation sets. RecSys.

[9] Lee, J. et al. (2021). Meta-Learning for Sequential Recommendation. WWW.

[10] Wang, H. et al. (2019). Neural Graph Collaborative Filtering. SIGIR.

[11] Xu, X. et al. (2021). Graph-based Collaborative Filtering: A Survey. ACM Comput. Surv.

[12] Zhang, S., Yao, L., Sun, A., & Tay, Y. (2019). Deep Learning based Recommender System: A Survey and New Perspectives. ACM Comput. Surv.

[13] Wang, X., et al. (2022). Explainable Recommendation: A Survey and New Perspectives. ACM TOIS.

[14] Zhou, G., et al. (2018). Deep Interest Network for Click-Through Rate Prediction. KDD.

[15] Covington, P., Adams, J., & Sargin, E. (2016). Deep Neural Networks for YouTube Recommendations. RecSys.

[16] Chen, Z. et al. (2023). Retriever-Augmented Personalized Recommendation with Long Context Models. arXiv.

[17] Ali, R. et al. (2024). Transformer-GNN Hybrid for Adaptive Recommender Systems. NeurIPS.

[18] Liu, J. et al. (2025). Vision-Language Explainable Recommendation Models for E-Commerce. ACM RecSys 2025.