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Sentiment-Aware and Explainable AI-Based Cross-Domain Recommendation System

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Abstract: Cross-Domain Recommendation Systems (CDRS) enhance traditional recommendation models by transferring knowledge across different domains, thereby improving the personalization of suggested content. The integration of Explainable AI (XAI) ensures transparency in recommendation systems, addressing concerns regarding trust and interpretability. Additionally, sentiment analysis is crucial in refining recommendations by capturing the emotions embedded in user reviews and feedback. This paper explores the concept of a sentiment-aware and explainable AI-based cross-domain recommendation system by discussing key methodologies, challenges, and potential advancements in the field. The research highlights how a hybrid recommendation model can optimize user satisfaction by balancing accuracy, interpretability, and personalized content delivery.

Keywords: Cross-Domain Recommendation, Explainable AI, Sentiment Analysis, Hybrid Recommendation Model, User Trust.

I. INTRODUCTION

Recommendation systems have become essential to digital platforms, offering personalized suggestions in domains such as e-commerce, streaming services, and online education. These systems utilize artificial intelligence-driven approaches to analyze user behavior, preferences, and historical data to recommend products, services, or content. Traditional recommendation systems operate within a single domain, meaning they rely exclusively on user interactions within that specific platform. However, cross-domain recommendation systems (CDRS) extend this capability by leveraging insights from multiple domains, leading to more comprehensive and refined recommendations.

Explainable AI (XAI) has emerged as a significant enhancement to recommendation systems by providing users with clear, interpretable explanations for why a particular recommendation was made. This transparency not only enhances user trust but also allows for better user engagement and acceptance of recommendations. Furthermore, integrating sentiment analysis into recommendation models adds a layer of personalization by considering the emotional tone of user feedback. By analyzing textual reviews and ratings, sentiment-aware recommendations can better align with user preferences and expectations.

II. BACKGROUND

Traditional recommendation systems primarily rely on user interactions such as clicks, views, ratings, and purchase history. These models are typically based on collaborative filtering, content-based filtering, or hybrid approaches. However, the evolution of recommendation systems has seen an increasing focus on cross-domain strategies, where user preferences from one domain are utilized to make recommendations in another. This approach enhances personalization and reduces the limitations posed by data sparsity and cold-start problems in single-domain systems.

Sentiment-aware cross-domain recommendation systems incorporate additional layers of analysis by examining the sentiments expressed in user feedback. For example, a user who has positively reviewed a set of action movies may be more likely to receive recommendations for action-themed video games. By combining sentiment analysis with explainable AI techniques, these systems can provide more intuitive and trustworthy recommendations. Explainable AI models offer interpretability by justifying recommendations in human-understandable terms, ensuring users are more likely to accept and trust automated suggestions.

Types of Recommendation Systems

Recommendation systems are categorized based on the techniques they use to generate personalized recommendations. These systems analyze user behavior, preferences, and interactions with items to suggest relevant products or services. The primary types of recommendation systems include content-based filtering, collaborative filtering, hybrid recommendation systems, knowledge-based recommendations, context-aware recommendations, social recommendations, and cross-domain recommendations. Each of these systems has unique characteristics, advantages, and challenges.

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1. Content-Based Recommendation System

A content-based recommendation system suggests items to users based on the features of previously interacted items. It relies on the attributes of items and a user's past preferences to determine similar items. This approach is commonly used in movie, book, and music recommendations, where systems analyze keywords, categories, descriptions, or metadata of the items.

However, content-based filtering suffers from a cold-start problem, meaning that new users or items with insufficient historical data receive poor recommendations. It also faces the challenge of over-specialization, where the system keeps recommending similar items without exploring diverse options.

2. Collaborative Filtering-Based Recommendation System

Collaborative filtering does not rely on item attributes but instead focuses on user interactions and preferences. It assumes that users who interacted with similar items in the past will likely have similar preferences in the future. Collaborative filtering is divided into two main types:

a) User-Based Collaborative Filtering

User-based collaborative filtering identifies users with similar preferences and recommends items that were liked by one user to another. For example, if two users have rated similar books positively, the system assumes they have similar interests and recommends books based on the preferences of one user to another. However, this approach suffers from scalability issues, as finding similar users becomes difficult in large datasets.

b) Item-Based Collaborative Filtering

Item-based collaborative filtering finds relationships between items rather than users. It identifies items that are frequently purchased, viewed, or rated together and recommends them to users based on their past interactions. Amazon's recommendation system employs this approach by suggesting products that are frequently bought together. Cosine similarity and Pearson correlation are commonly used techniques to measure the relationship between items.

Collaborative filtering has its challenges, including the sparsity problem, where a lack of user-item interactions results in incomplete recommendations. Additionally, the system struggles with new user and new item cold-start issues.

3. Hybrid Recommendation System

A hybrid recommendation system combines multiple approaches, such as content-based filtering and collaborative filtering, to improve accuracy and diversity in recommendations. This approach helps overcome the weaknesses of individual methods. Hybrid models can be implemented using various strategies, including weighted hybridization, switching hybridization, or feature augmentation.

4. Knowledge-Based Recommendation System

Knowledge-based recommendation systems use domain knowledge, rules, and expert information to suggest items. Unlike collaborative or content-based filtering, these systems do not require historical interaction data but instead rely on predefined knowledge structures.

Knowledge-based recommenders are useful in domains where personalization requires expert insights, such as legal research, finance, and healthcare. However, maintaining an up-to-date knowledge base can be challenging.

5. Context-Aware Recommendation System

Context-aware recommendation systems incorporate additional factors such as location, time, weather, and device usage while making recommendations. For example, a travel recommendation system may suggest destinations based on a user's current location and the time of year.

These systems often use contextual bandits, reinforcement learning, and multi-armed bandit algorithms to dynamically adapt recommendations based on changing contexts. Context-aware recommendations enhance user experience by providing more relevant and situation-specific suggestions.

6. Social Recommendation System

Social recommendation systems leverage social connections, user interactions, and influence from social networks to make recommendations. These systems analyze a user's friends, followers, and online interactions to determine preferences and suggest items accordingly.

For example, platforms like Facebook, Instagram, and Twitter recommend pages, posts, and advertisements based on a user's social network engagement. Graph-based models, such as Graph Neural Networks (GNNs) and Personalized PageRank, are commonly used to analyze social relationships and provide meaningful recommendations.

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Types of Cross-Domain Recommendation System

Cross-domain recommendation systems extend recommendations across multiple domains by transferring knowledge from one domain to another. These systems are beneficial when users have limited interactions in a specific domain but possess substantial data in another domain.

For instance, if a user frequently purchases fiction books, a cross-domain recommender can suggest fiction movies or audiobooks based on learned user preferences. Transfer learning, domain adaptation, and multi-view learning are commonly used techniques in cross-domain recommendation systems.

1. Single-Target Cross-Domain Recommendation System

A Single-Target CRS aims to improve recommendation accuracy in one domain (the target domain) using knowledge from another domain (the source domain). In this type of CRS, users may have significant interaction history in one domain but little to no activity in another, making direct recommendations difficult.

For example, in an e-learning platform, a user might have an extensive history of reading articles but no prior interactions with video lectures. A single-target CRS can leverage the user's reading preferences to recommend relevant video lectures. Techniques such as transfer learning, domain adaptation, and collaborative filtering with latent factor models help in knowledge transfer between domains.

This approach is particularly useful when a new domain lacks sufficient user interaction data, addressing the cold-start problem effectively. However, ensuring that knowledge transfer does not introduce irrelevant or inaccurate recommendations remains a challenge.

2. Multi-Target Cross-Domain Recommendation System

A multi-Target CRS focuses on simultaneously improving recommendations in multiple domains by transferring and integrating knowledge across them. Unlike the single-target approach, which benefits only one domain, this model enhances recommendations for all participating domains.

For example, a multi-target CRS in an e-commerce platform can analyze a user's purchase history of books, electronic gadgets, and clothing to provide more personalized recommendations across all these categories. Techniques like multi-task learning, shared embedding models, and feature alignment strategies are commonly employed to ensure smooth knowledge transfer.

One of the biggest advantages of multi-target CRS is that it provides a holistic user experience across multiple platforms, increasing engagement and cross-domain interactions. However, managing dependencies between multiple domains and maintaining recommendation quality across different data distributions is a challenge.

3. Dual Transfer Cross-Domain Recommendation System

A Dual Transfer CRS enables bidirectional knowledge transfer between domains. Unlike single-target CRS, where information flows only from the source to the target, dual transfer CRS allows for mutual learning between both domains. This approach enhances recommendation performance in both domains by leveraging shared and complementary user preferences.

For instance, in a music streaming and podcast platform, a user’s preference for certain music genres can be used to recommend relevant podcasts, while their podcast listening history can be used to suggest similar music tracks. Graph-based models, reinforcement learning, and shared latent space representations are commonly used to enable dual transfer learning.

While dual transfer CRS can significantly boost personalization, aligning feature representations and handling differences in data distribution between the two domains remains a major technical hurdle.

4. Hybrid Cross-Domain Recommendation System

A Hybrid CRS integrates multiple cross-domain techniques to maximize recommendation effectiveness. This approach combines content-based, collaborative filtering, knowledge-based, and deep learning techniques to ensure efficient knowledge transfer across domains while minimizing data sparsity and cold-start issues.

For example, an AI-powered personal assistant that integrates shopping, entertainment, and fitness tracking can use a hybrid CRS to recommend workout gear based on the user’s movie preferences or suggest healthy meal plans based on their online grocery shopping behavior. Hybrid CRS often utilizes attention mechanisms, neural collaborative filtering, and heterogeneous information networks to enhance recommendation accuracy.

One of the biggest advantages of hybrid CRS is its ability to provide more diverse and personalized recommendations, leading to a better user experience. However, the complexity of integrating multiple recommendation models and maintaining consistency across different domains requires significant computational resources and expertise in multi-modal learning and domain-specific feature engineering.

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III. LITERATURE SURVEY

Numerous studies have contributed to the development of cross-domain recommendation systems, with research focusing on various methodologies such as sentiment analysis, reinforcement learning, tensor factorization, and knowledge graph integration. Recent studies have shown that incorporating sentiment-based recommendations can significantly improve the accuracy and relevance of suggested items. For instance, research on Amazon datasets has demonstrated that sentiment analysis can enhance recommendation precision by extracting emotional cues from textual reviews.

Reinforcement learning has been employed to refine knowledge graphs, allowing for better representation of user preferences and item attributes. Tensor factorization techniques have been utilized for collaborative filtering in datasets such as MovieLens and BookCrossing, enabling the identification of latent user preferences across multiple domains. Other approaches, such as aspect transfer networks, address cold-start problems by adapting user preferences from one domain to another.

Explainable AI has also played a crucial role in improving recommendation systems by making the decision-making process more transparent. Studies on adaptive explainability have shown that users are more likely to trust recommendations when provided with justifications for why a particular item was suggested. Natural language processing (NLP)-based techniques have further enhanced interpretability by generating personalized explanations in human-readable formats. The integration of knowledge graphs has also improved sentiment-based recommendations by linking user reviews with structured information, enabling more accurate and meaningful suggestions.

The study presented in [1] introduces a novel Cross-Domain Recommendation System (CDR) that leverages Sentiment Analysis and Feature Mapping (SAFM) to improve recommendation accuracy. The proposed system analyzes user reviews from multiple domains to extract sentiment-based user preferences, which are then mapped across domains to enhance recommendation quality. The authors employ Natural Language Processing (NLP) techniques to classify sentiment polarity and transfer this knowledge between domains using latent feature representations. The experimental results on the Amazon cross-domain dataset show a significant improvement in accuracy compared to traditional collaborative filtering methods. However, the study highlights limitations such as the overfitting of feature mapping to specific datasets and the need for real-time sentiment analysis techniques to improve scalability.

The work presented in [2] focuses on adaptive and explainable recommendations using aspect extraction from textual reviews. The authors propose AdaReX, a recommendation model that employs transformer-based deep learning models to extract user preferences from review texts. The system is designed to adapt dynamically to user sentiment changes and explain recommendations through keyword-based justifications. The study validates its approach using Amazon and Yelp datasets, demonstrating that sentiment-aware recommendations improve user engagement and trust. Despite its effectiveness, the authors note a major research gap: the lack of a unified approach for handling multiple sentiment-based signals and the need to explore alternative feature extraction techniques for better generalizability.

The study [3] by Sirawit Sopchok, et al presents an explainable cross-domain recommendation system using relational learning. It introduces two methods: Method1, which employs Pearson correlation to find similar users and generate recommendations, and Method2, which enhances this by incorporating item attributes using the ProbFOIL algorithm. Method2 achieves 73% accuracy, outperforming Method1's 60%, and generates 21% more novel and unexpected recommendations based on the SRDP metric. The system ensures interpretability by defining recommendation rules in ProbLog, making the results more transparent. However, the study identifies scalability challenges when integrating more domains and data. The authors suggest future research should address computational complexity while maintaining diverse and explainable recommendations. The system was validated on the Amazon product dataset, focusing on music and movie preferences. The study emphasizes the importance of explainability in recommendation models and highlights the need for further scalability optimizations.

The study [4] by Sung-Jun Park et al introduces a novel recommendation framework that integrates sentiment analysis with knowledge graphs (KG) using reinforcement learning to enhance both accuracy and explainability. The authors construct a Sentiment-Aware Knowledge Graph (SAKG) by analyzing user reviews and ratings, capturing sentiment information in the relationships between entities. They develop a Sentiment-Aware Policy Learning (SAPL) approach, which leverages reinforcement learning to improve item recommendations and reasoning over the SAKG. Experimental results demonstrate that SAPL outperforms existing methods in recommendation accuracy while also providing more convincing explanations through an interactive interface that presents textual justifications and related reviews.

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Unlike traditional knowledge graph-based recommendation systems, this approach uniquely considers sentiment in the entity relationships, making the explanations more relevant. However, the study acknowledges that further improvements in explainability could be achieved by enhancing the interactive interface.

The research fills a gap in prior explainable recommendation models that neglected sentiment-aware relationships, showing the potential of reinforcement learning in sentiment-driven recommendation systems. The study is validated using three real-world datasets containing user reviews and ratings, further demonstrating the effectiveness of the proposed framework.

Li Chen et al. [5] investigate the impact of integrating sentiment analysis from product reviews into recommendation explanation interfaces. Their study reveals that sentiment-based explanations significantly enhance users' product knowledge, preference certainty, perceived information usefulness, recommendation transparency, and purchase intention. Through a between-subjects experiment, the authors compare a prototype system with sentiment-based explanations to a traditional system with only static product specifications. Additionally, an eye-tracking study demonstrates that users notice more product categories and compare products more effectively when sentiment-based explanations are present. The study finds that users inherently prefer sentiment-aware explanations, as they provide deeper insights into product features. This research highlights the need for enhanced transparency in recommender systems but does not explicitly discuss limitations, datasets, or future directions. The study's results suggest that sentiment-based interfaces can improve user engagement and decision-making processes in recommendation systems.

Fenfang Xie et al.[6] propose RESTER, a multitask learning framework that leverages review-level sentiment information to improve both rating prediction and explanation generation in recommendation systems. Unlike traditional models that rely on template-based explanations, RESTER incorporates sentiment polarity analysis from user reviews, enhancing the transparency and interpretability of recommendations. The model integrates user and item features, review attributes, and sentiment scores into a multitask learning framework, leveraging the correlation between rating prediction and explanation generation. Experimental results on three domain-specific datasets show that RESTER outperforms existing methods in both accuracy and explanation quality. The study identifies a gap in current models, which often neglect sentiment-aware explanations, focusing solely on review retrieval. However, it does not explicitly discuss software tools or future research directions. Overall, RESTER demonstrates that incorporating sentiment-rich data can significantly improve both recommendation accuracy and user experience.

The CATN [7] framework leverages user and item reviews to extract fine-grained aspects and model their correlations across domains for cold-start users. It employs an aspect-specific gate mechanism with convolutional layers for aspect extraction and cross-domain review-based preference matching. The model enhances user representation using auxiliary documents from like-minded users, helping alleviate data sparsity issues. CATN effectively transfers user preferences across domains, outperforming state-of-the-art baselines. The study uses the Amazon review dataset (Books, Movies & TV, and Music) with preprocessed interaction data. Global-sharing aspect representations and cross-domain aspect correlation learning further improve performance. Future work suggests exploring graph-based approaches Fast Explainable Recommendation Model [8] is an explainable recommendation model that integrates fine-grained sentiment analysis of review data to improve accuracy and interpretability. The model constructs three matrices—user-rating, user-aspect sentiment, and item aspect-descriptive word frequency—and employs matrix factorization for reconstruction. The approach enhances recommendation efficiency and generates explanatory texts and diagrams for interpretability. FSER is evaluated on Yelp and Public Comment datasets, outperforming classical, tensor, and neural network models. The study highlights the challenge of explaining implicit features in matrix factorization-based models. It emphasizes the need for explainable models that balance efficiency and accuracy. Future research directions are not explicitly mentioned. This survey [9] provides a comprehensive review of explainable recommendation research, its history, taxonomy, evaluation, and applications. It distinguishes between model-intrinsic and model-agnostic explainable approaches, highlighting their advantages and tradeoffs. The study identifies challenges such as balancing explainability and effectiveness, limited evaluation methods, and predefined explanation types. Future directions include developing deep learning models with explainability, integrating knowledge graphs, and generating diverse natural language explanations. The survey traces the evolution of explainable recommendations from early collaborative filtering to advanced deep learning techniques. It suggests combining online evaluation with user studies to assess explanation effectiveness.

Sentiment analysis is widely used in the medical field to extract insights from patient-generated text data. Zucco et al. [10] reviewed existing sentiment analysis models, emphasizing the challenge of deep learning's lack of interpretability. They discussed various explainable models and highlighted the need for more research in this area. The study pointed out that while deep learning achieves high accuracy, its decision-making process remains opaque. Explainable sentiment

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analysis can enhance trust and usability in medical applications. The authors suggested developing new explainable models to bridge this gap. Future work should focus on balancing accuracy and interpretability in sentiment analysis.

Chen et al. [11] introduced a hierarchical sequence-to-sequence (HSS) model for generating personalized natural language explanations in recommendation systems. The model improves both recommendation accuracy and explanation quality compared to template-based methods.
An auto-denoising mechanism was incorporated to filter out non-explanatory user reviews. The study addressed the challenge of generating expressive, free-text explanations instead of relying on predefined templates. Their approach enhances the transparency, trustworthiness, and persuasiveness of recommender systems. However, the complexity of natural language explanations remains an open research challenge. Future work should focus on improving expressiveness while maintaining computational efficiency.

Suzuki et al. [12] proposed a recommendation method that combines knowledge graphs and review text to improve explainability. The system models user-item interactions using a recurrent neural network or factorization machine. An attention mechanism is applied to extract relevant aspects from review text, enhancing recommendation quality. The study demonstrates that knowledge graphs can provide interpretable paths between users and items. Integrating textual data with structured knowledge helps generate meaningful explanations. However, challenges remain in ensuring the accuracy and reliability of explanations. Future research should refine these methods to create more user-friendly explainable recommendation systems.

Diwali et al. [13] provide a comprehensive review of sentiment analysis techniques and explainable AI (XAI) methodologies. The paper highlights the challenge of interpretability in deep learning-based sentiment analysis models. It discusses various techniques used to enhance explainability in sentiment analysis models. A key focus is the limited research on developing interpretable deep learning models for sentiment analysis. The study reviews existing literature on explainability in sentiment analysis and suggests future research directions. It emphasizes the need for techniques that allow deep learning models to describe their internal workings.

Li et al. [14] present a Bi-LSTM model with an attention mechanism for sentiment analysis of Amazon product reviews. The study focuses on sentence-level sentiment analysis and the interpretability of sentiment analysis models. Attention weights help identify key product aspects influencing user sentiment. TF-IDF is used to extract frequent aspect terms, while BERT generates word embeddings. The authors identify high recall on biased datasets as a limitation and suggest future improvements. The dataset used is "Amazon Musical Instruments Reviews," with 10,261 reviews. The model utilizes Python's NLTK, scikit-learn, and BERT for embeddings.

Li et al.[15] propose PETER, a personalized Transformer model for explainable recommendations. PETER simultaneously generates personalized natural language explanations and recommendations. The model integrates user and item IDs into a Transformer-based architecture. It outperforms fine-tuned BERT in text quality and explainability metrics. The paper suggests extending PETER to conversational AI and cross-lingual applications. Datasets used include Hotel, Amazon (Movies & TV), and Yelp.

Zhang et al. [16] introduce the Selective Knowledge Transfer (SKT) framework for cross-domain recommendations. The model selectively transfers user latent factors between domains with overlapping items. Graph co-regularization preserves the intrinsic structure of latent factors to prevent negative transfer. The SKT method improves performance, especially in sparse target domains. Limitations include handling non-overlapping user sets and selecting the best auxiliary domain. Datasets used include Netflix-MovieLens and Goodreads. The model uses an alternating minimization algorithm for optimization.

Khan et al. [17] propose MD-GCN, a graph convolution-based framework for cross-domain recommendations. The model leverages metadata and user preferences from a richer source domain to address data sparsity. MD-GCN outperforms baseline models in terms of Hit Ratio (HR), NDCG, MAE, and RMSE. The framework is tested on Amazon datasets for Movies, Books, and Music recommendations. It effectively handles the cold-start problem by transferring knowledge from dense to sparse domains. The study emphasizes the importance of metadata in improving recommendation accuracy.

IV. RESEARCH GAPS

Despite significant advancements, several challenges persist in the field of sentiment-aware and explainable cross-domain recommendation systems. One major limitation is the inadequate integration of sentiment analysis into cross-domain recommendations, as most existing models primarily focus on behavioral data rather than emotional context. Additionally, there is a lack of personalized sentiment understanding in recommendation justifications, making it difficult to align recommendations with user expectations.

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Scalability remains a challenge for large-scale real-world applications, as many sentiment-aware models require extensive computational resources to process large volumes of textual data.
Furthermore, ethical concerns and biases in sentiment-aware AI pose risks in ensuring fairness and inclusivity in recommendations. Another pressing issue is the absence of real-time sentiment adaptation, as most current models rely on pre-processed data rather than dynamically adjusting recommendations based on evolving user sentiments.

V. PROPOSED METHODOLOGY

In recent years, cross-domain recommendation systems have received considerable attention due to their capacity to draw on user tastes from a source domain (e.g., movies) to enhance recommendations in a target domain (e.g., books). The conventional methods, however, tend to ignore the contribution of user sentiment in reviews, resulting in less-than-optimal personalization. Furthermore, the unexplainability of such systems decreases user confidence and satisfaction. To overcome these challenges, this paper suggests a Sentiment-Aware and Explainable AI-Based Cross-Domain Recommendation System that incorporates sentiment analysis with deep learning methods but guarantees interpretable recommendations.

The framework for the proposed model has three primary components: sentiment extraction, cross-domain knowledge transfer, and explainable recommendation generation. First, sentiment extraction is done based on fine-tuned BERT or RoBERTa models to obtain aspect-based sentiments of user reviews, retaining subtle opinions (e.g., "The camera is great, but the battery life is terrible"). The acquired sentiment information is then added to a user-item interaction matrix, which enhances the input features for the recommendation model. Then, cross-domain knowledge transfer is handled based on adversarial adaptation or graph-based methods. Adversarial learning facilitates the alignment of user and item latent representations between domains, and graph neural networks spread sentiment-informed preferences over a knowledge graph that links users, items, and sentiment nodes. Lastly, the system provides explainable recommendations through attention mechanisms or natural language explanations, which identify how source domain sentiment informed target domain recommendations (e.g., "We suggest this book because you left positive reviews on similar movies").

In order to ensure the viability of the new method, tests will be done using benchmark corpora like Amazon Reviews and Yelp, comparing recommendation performance (on measures like RMSE, Precision@K, and NDCG) with explainability (through user surveys). The results are likely to prove that cross-domain recommendations taking sentiment into consideration will surpass their baseline counterparts with clearer and explainable suggestions and, thus, greater user satisfaction and trust. This work advances the emerging body of AI-based recommender systems by filling the gap between sentiment analysis, cross-domain learning, and explainable AI.

VI. CONCLUSION

The integration of sentiment-aware AI and explainability in cross-domain recommendation systems represents a significant advancement in personalized content delivery. By incorporating behavioral and emotional data, such systems can improve the accuracy and trustworthiness of recommendations. Explainable AI enhances transparency, enabling users to understand and accept recommendations with greater confidence. However, challenges such as data sparsity, real-time adaptation, and ethical concerns continue to pose obstacles in large-scale implementations.

Future research should focus on developing real-time user profiling mechanisms to enhance the adaptability of recommendations. Efforts should also be made to design bias-free AI models that ensure fairness and inclusivity in recommendations. Expanding the application of sentiment-aware and explainable recommendation systems to domains such as healthcare, education, and public services could further demonstrate their potential in improving user experience and decision-making. A human-centric AI approach, balancing explainability and performance, will be key to driving future advancements in recommendation systems.

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