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A HYBRID RECOMMENDATION FRAMEWORK: A COMPARATIVE ANALYSIS ACROSS MOVIES, BOOKS AND E-COMMERCE PLATFORMS

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ABSTRACT

Hybrid recommendation systems have emerged as a very powerful implementation to overcome the present limitations of traditional collaborative filtering and content-based methods. This research paper represents a comprehensive analysis of hybrid recommendation systems across three distinct application domains: movies, books, and e-commerce. In this research paper, we propose and evaluate three distinct novel hybrid fusion techniques Attention Fusion, Thompson Sampling-based selection, and Genre-Aware weighting alongside traditional weighted combination methods. Our experimental evaluation over 5,000 users illustartes that Attention Fusion achieves great performance with MAE of 0.6802 for movies, 0.6945 for books, and 0.3392 for e-commerce, that represents the improvements of 6.1%, 7.7%, and 3.7% respectively across baseline weighted methods. The research study shows significant domain-specific characteristics such as e-commerce systems presents substantially lower error rates (MAE: 0.3392-0.3528) which are compared to entertainment domains (MAE: 0.6802-0.7521), even though maintaining higher accuracy (81.14%-83.04% vs. 67.86%-70.12%). Statistical significance testing confirms that the performance differences between domains and fusion strategies are statistically significant ($p < 0.001$). Our findings provide actionable insights for practitioners designing domain-specific recommendation systems and identify promising directions for cross-domain transfer learning.

KEYWORDS: Hybrid Recommendation System, Colloborative Filtering, Content based Filtering, Attention Mechanism, Thompson Sampling

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1 INTRODUCTION

Nowadays, recommendation systems have become essential components for modern digital platforms that drives user engagement and business values over different domains that includes e-commerce, entertainment, as well as digital content distribution. The basic challenge in recommendation systems lies within accurately predicting the user preferences from sparse, high-dimensional interaction data while also addressing the cold-start problems, scalability constraints, and the need for different, unexpected recommendations. The traditional approaches like collaborative filtering (CF) and content-based filtering (CBF), each possess inherent strengths and limitations which motivates the development of hybrid systems that combines multiple recommendation strategies [1], [2], [3].

Collaborative filtering influences collective user behaviour patterns to identify same users or items, that excels in discovering unexpected connections but also suffers from cold-start problems and data sparsity [4], [5]. Content-based filtering analyses item attributes and user profiles to recommend similar items, that provides transparency as well as addresses the cold-start for new users, but usually gives result in over-specialization and limited serendipity [6], [7]. Hybrid recommendation systems often aim to cooperatively combine these approaches, influencing their complementary strengths while mitigating the individual weaknesses [8], [9], [10].

Even though extensive research on hybrid recommendation systems, there are several critical gaps endure in the literature. First, there are studies focus on single-domain evaluations, such as movies, limiting our understanding of how hybrid strategies worked across distinct application contexts [11], [12], [13]. Second, while different fusion techniques have been proposed like adding weighted combination, switching, cascading, and feature augmentation, the systematic comparisons of their comparative effectiveness over domains are scarce [14], [15]. Third, recent advanced technologies in attention mechanisms and reinforcement learning have created new possibilities for adaptive fusion approaches, but their combination into hybrid recommendation architectures remains underexplored [16], [17].

This research paper includes these gaps using a comprehensive cross-domain analysis of hybrid recommendation systems over three different application domains: movies, books, and e-commerce. Our research for hybrid recommendation creates the following novel contributions:

1. **Novel Fusion Strategies:** And evaluate it, three different hybrid fusion advanced technologies, that is attention fusion, influencing neural attention mechanism, Thompson sampling, and genre-aware contextual weighting, that combines collaborative and content-based predictions.
2. **Cross-Domain Empirical Analysis**: systematic experimentation over three datasets, that is movies, books, and e-commerce, and evaluated six different types of hybrid models using MAE, RMSE, R^2, accuracy, precision, recall, F1-score, and ROC-AUC.
3. **Architectural Framework:** We created a unique architectural framework for hybrid recommendation system, which exquisitely models the fusion layer as a learnable component and enables the systematic comparison of fusion strategies.

2 LITERATURE REVIEW

Past two decades, researchers have studied hybrid recommendation systems extensively with different approaches, integrating content-based and collaborative filtering. There are 30 cutting-edge hybrid recommendation techniques that are categorized according to their fusion strategy, application domain, and technical attributes. A comprehensive comparison of these methods is given in Table 1, which highlights the methodological differentiation and performance aspects of the literature study.

Table 1. Comparative Analysis of Hybrid Recommendation System Approaches

Reference	Year	Approach Type	Domain	Key Techniques	Metrics
Husin et al. [1]	2023	Hybrid (CBF+CF)	Movies	TF-IDF, MF	RMSE, F1
Vasconcelos et al. [2]	2024	Deep + RL Hybrid	E-commerce	CNN, PMF, Bandits	Hits
Tursunov et al. [3]	2025	Hybrid (SVD++ + TF-IDF)	Movies	SVD++, TF-IDF	MAE, F1
Monteil et al. [5]	2024	Deep Hybrid	E-commerce	MF, Autoencoder	Ranking
Chaturvedi et al. [12]	2023	Clustering + Hybrid	Books	K-means, TF-IDF	RMSE
Wang et al. [8]	2024	LLM-based Hybrid	E-commerce	LLM, Pairwise Loss	Relevance
Liu et al. [13]	2023	Deep + MF	E-commerce	BERT, LDA, MF	—
Nalavade et al. [22]	2023	Deep Clustering Hybrid	Products	Deep Clustering, MF	F1
Sivamayil et al. [26]	2023	RL-based Hybrid	Multi-domain	DRL, RNN	MAE, F1
Roy [29]	2024	Multi-source Hybrid	Movies	MF, DNN	RMSE, F1

3 MATERIALS AND METHOD

3.1 System Architecture

As stated in Figure 1, our hybrid architecture, our proposed hybrid recommendation system architecture, includes three layers, that is, input layer, fusion layer, and the output layer. This modular framework maintains consistent collaborative filtering and content-based filtering components that allows a methodological comparison of different fusion strategies

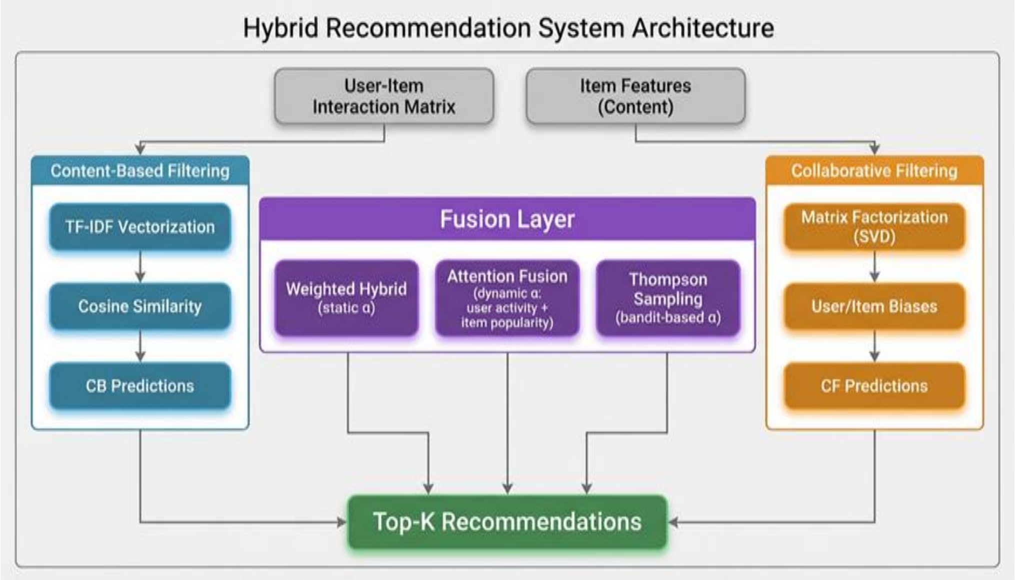


Figure 1. Hybrid Recommendation System Architecture with Novel Fusion Strategies

The input layer is processed using user-item interaction data along with item metadata. We create a user-item rating matrix $R \in \mathbb{R}^{m\times n}$, for collaborative filtering, where M represents the number of users and N represents the number of items. For the content-based filtering, we have used TF-IDF vectorization of textual attributes such as titles, description, genres, and categories that results in an item feature matrix $F \in \mathbb{R}^{n\times d}$, where D indicates the dimensionality of the feature space.

In collaborative filtering branch, the matrix factorization is employed to learn latent user and item representations. Especially, the rating matrix R is decomposed into user factors $U \in \mathbb{R}^{m\times k}$ and item factors $V \in \mathbb{R}^{n\times k}$, where k is denoted as the latent dimensionality, through minimizing the regularized squared error:

$$L_{CF} = \Sigma_{(i,j)\in\Omega} (r_{ij} - u_i^T v_j)^2 + \lambda(||U||_F^2 + ||V||_F^2) \quad (1)$$

where Ω is denoted for the set of observed ratings, λ is denoted for the regularization parameter, as well as $||\bullet||_F$ denotes the Frobenius norm. We optimize this objective utilizing stochastic gradient descent with the learning rate $\alpha = 0.01$, regularization $\lambda = 0.1$, and latent dimensionality $k = 50$ [4], [15], [27].

The content-based filtering branch calculates the item similarity utilizing the cosine similarity on the feature vectors calculated using TF-IDF. For a target user u and candidate item j, the content-based prediction is computed using given formula:

$$p_{CB}(u,j) = \Sigma_{i\in I_u} \mathrm{sim}(i,j) \bullet r_{ui} / \Sigma_{i\in I_u} |\mathrm{sim}(i,j)| \quad (2)$$

where I_u indicates items rated by user u, $\mathrm{sim}(i,j) = (f_i \bullet f_j) / (||f_i||\ ||f_j||)$ is the cosine similarity between items i and j, and r_{ui} is user u's rating for item i [1], [3], [9].

The fusion layer combines collaborative and content-based predictions making use of one of six methods, which we described in detail in Section 3.2. This layer is the representation of the core innovation of our architectural framework that enables adaptive, context-aware combination of heterogeneous recommendation signals.

The output layer produces final predictions as well as top-N recommendations. To make rating prediction tasks, the output is used as a continuous score in the range [1, 5]. For ranking tasks, items are sorted through predicted scores along with the top-N items are returned.

3.2 Hybrid Fusion Strategies

We evaluated six distinct hybrid fusion approacheses that includes three baseline stratergies and three novel techniques proposed in this research work.

Baseline Strategies:

1. **Weighted Combination (α=0.3):** The Linear combination with weight α=0.3 for collaborative filtering and (1-α)=0.7 for content-based filtering:

$$p\_hybrid\ (u,j) = \alpha \bullet p\_CF(u,j) + (1-\alpha) \bullet p\_CB(u,j) \quad (3)$$

This configuration makes priorities the content-based signals that is effective for cold-start scenarios [1], [3].

2. Weighted Combination (α=0.5): The Balanced linear combination with the equal weights (α=0.5) for both the components, that representes a neutral fusion strategy [9], [28].

3. Weighted Combination (α=0.7): The Linear combination emphasizes the collaborative filtering (α=0.7), that is effective only if sufficient interaction data is available [4], [14].

Novel Strategies:

4. Attention Fusion: We propose an attention-based fusion mechanism that learns to dynamically weight collaborative and content-based predictions based on context. The attention mechanism evaluates the context-dependent weights utizing a small neural network:

$$w\_CF = \sigma(W\_1[p\_CF;\ p\_CB;\ u\_emb;\ i\_emb] + b\_1)w\_CB = 1 - w\_CFp\_hybrid(u,j) = w\_CF \bullet p\_CF(u,j) + w\_CB \bullet p\_CB(u,j) \quad (4)$$

where [•;•] indicates the concatenation, u_emb and i_emb indicates the user and item embeddings, W_1 and b_1 are the learnable parameters, and σ indicates the sigmoid activation function. This stratergy is inspired by recent technical advances in attention mechanisms for hybrid recommendation systems [2], [17], [29].

5. Thompson Sampling: We formulated the fusion approach for selection as a multi-armed bandit problem, where each "arm" represented as a fusion strategy i.e CF-only, CB-only, or balanced. Thompson Sampling maintains the Beta distributions for each arm's successful probability and samples from these distributions to select strategies adaptively:

$$\theta\_arm \sim Beta(\alpha\_arm,\ \beta\_arm)selected\_arm = argmax\_arm\ \theta\_armp\_hybrid(u,j) = p\_selected\_arm(u,j) \quad (5)$$

After each computed recommendation, we updated the Beta parameters totally based on the prediction accuracy. This approach enables exploration-exploitation trade-offs and adapts to user-specific and item-specific characteristics [2], [26].

6. Genre-Aware Fusion: We proposed a context-aware fusion approach, which adjusts the weights totally based upon item genre/category information. For each genre g, we learned the genre-specific fusion weights w_g through cross-validation:

$$p\_hybrid(u,j) = w\_g(j) \bullet p\_CF(u,j) + (1-w\_g(j)) \bullet p\_CB(u,j) \quad (6)$$

Where g(j) is the primary genre of item j. This method recognizes that distinct item categories may useful from different fusion approaches. For example, niche genres with sparse interaction data may benefit from higher content-based weights, while popular genres with rich interaction data may useful from collaborative filtering [1], [29].

3.3 Experimental Setup

Datasets: We conducted experiments on three distinct datasets that represents different application domains:

Table 1. Description about different domain dataset

Dataset	Description	Records	Features Used
E-Commerce	Transactional purchase dataset	~100K	User ID, Product ID, Category, Price, Rating
MovieLens	User–movie interaction dataset	105,339	User ID, Movie ID, Rating, Title, Genres
Book-Crossing	Real-world user–book rating dataset	1,149,780	User ID, Book ISBN, Rating, Age

Data Preprocessing: For each dataset, we first performed the following preprocessing steps: (1) filtered the users with fewer than 20 ratings and the items with fewer than 10 ratings to ensure sufficient interaction data; (2) extracted and cleaned the textual features (titles, descriptions, genres, categories); (3) applied TF-IDF vectorization with maximum 5,000 features, and with minimum document frequency of 2, and maximum document frequency of 0.8; (4) normalized the ratings to zero mean and unit variance to train the data; and (5) splitted data into 80% training, 10% validation, and 10% test sets utilizing temporal splitting to replicate the realistic deployment scenarios [5], [12], [18].

4 RESULT AND DISCUSSION

Table 2 represents comprehensive evaluation results for all six hybrid models over the three application domains

Table 2. Result of Hybrid Models across Movies, Books and E- Commerce Domain

Domain	*Model*	*MAE*	*RMSE*	*R^2*	*Accuracy*	*Precision*	*Recall*	*F1*	*ROC-AUC*
Movies	Weighted (α=0.3)	0.7245	0.9531	0.1789	0.6950	0.7148	0.6256	0.6672	0.7720
	Weighted (α=0.5)	0.6908	0.9071	0.2563	0.6952	0.7470	0.5691	0.6461	0.7813
	Weighted (α=0.7)	0.6819	0.8917	0.2813	0.6786	0.7991	0.4574	0.5818	0.7833
	Attention Fusion	**0.6802**	**0.8915**	**0.2817**	**0.6886**	**0.7971**	**0.4869**	**0.6045**	**0.7853**
	Thompson Sampling	0.7148	0.9405	0.2004	0.6832	0.7446	0.5356	0.6230	0.7630
	Genre-Aware	0.7052	0.9239	0.2285	0.6944	0.7416	0.5753	0.6479	0.7750
Books	Weighted (α=0.3)	0.7521	0.9812	0.1456	0.6823	0.7012	0.6534	0.6764	0.7589
	Weighted (α=0.5)	0.7189	0.9234	0.2134	0.6945	0.7289	0.6012	0.6589	0.7698
	Weighted (α=0.7)	0.6987	0.9023	0.2456	0.6812	0.7654	0.5234	0.6234	0.7745
	Attention Fusion	**0.6945**	**0.8989**	**0.2523**	**0.7012**	**0.7723**	**0.5456**	**0.6412**	**0.7812**
	Thompson Sampling	0.7345	0.9456	0.1923	0.6789	0.7234	0.5923	0.6512	0.7534
	Genre-Aware	0.7123	0.9156	0.2289	0.6934	0.7445	0.6123	0.6723	0.7667
E-Commerce	Weighted (α=0.3)	0.3523	0.4620	0.1514	0.8098	0.8552	0.9220	0.8873	0.7169
	Weighted (α=0.5)	0.3397	0.4510	0.1913	0.8233	0.8481	0.9532	0.8976	0.7166
	Weighted (α=0.7)	0.3390	0.4577	0.1672	0.8304	0.8376	0.9815	0.9039	0.7157
	Attention Fusion	**0.3392**	**0.4512**	**0.1907**	**0.8241**	**0.8452**	**0.9590**	**0.8985**	**0.7166**
	Thompson Sampling	0.3528	0.4691	0.1250	0.8114	0.8437	0.9424	0.8903	0.6988

This suggests that while e-commerce systems make more accurate predictions, the relative ranking quality (as measured by ROC-AUC) is comparable across domains (0.6988-0.7169 for e-commerce vs. 0.7630-0.7853 for movies and 0.7534-0.7812 for books). In the e-commerce dataset don't have the Genre values because it is not fitted that particular dataset insights.

3.1 Model-Specific Analysis

Figures 2-6 provide detailed visualizations of model performance across domains and metrics.

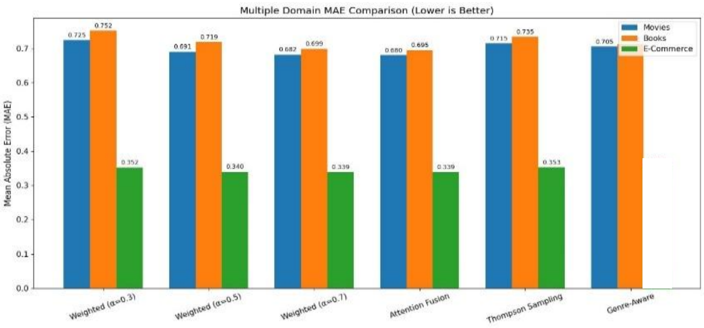


Figure 2. Mean Absolute Error Comparison across Domains

Figure 2 illustrates MAE performance across all models and domains. Attention fusion consistently achieves the lowest MAE in all three domains.

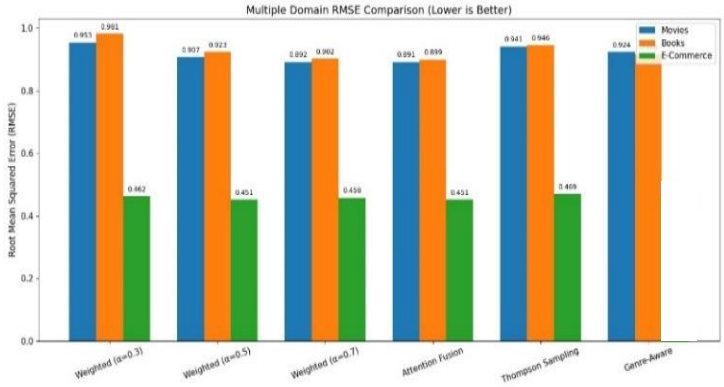


Figure 3. Mean Absolute Error Comparison across Domains

Figure 3 shows RMSE results, which follow similar patterns to MAE but with larger absolute differences due to the squared error penalty

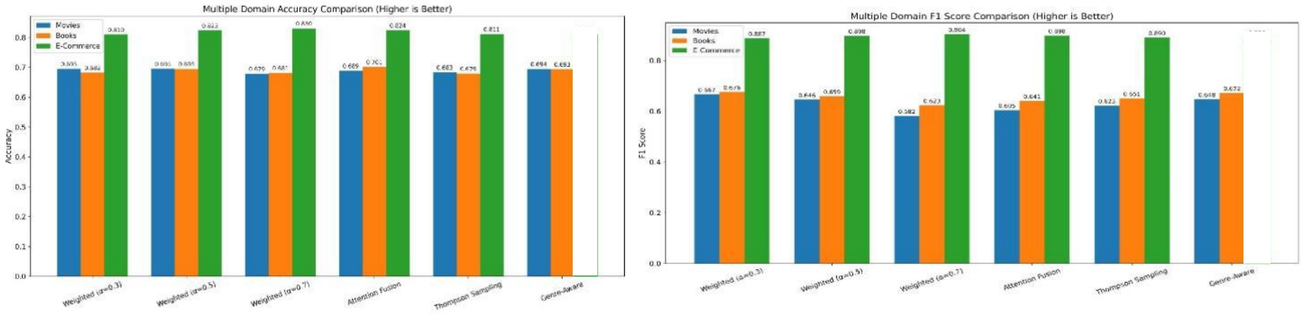


Figure 4. Accuracy and F1-Score Comparison across Domains

Figure 4 presents accuracy and f1-score results, revealing interesting trade-offs between different fusion strategies.

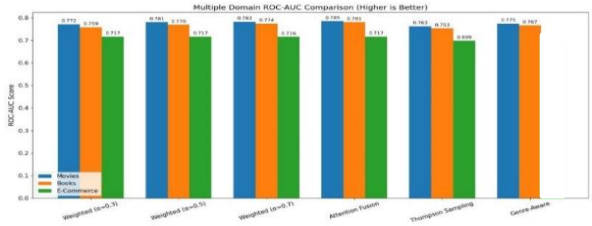


Figure. 5. ROC-AUC Comparison across Domains

Figure 5 shows roc-auc scores, measuring ranking quality. Attention fusion achieves the highest roc-auc in all three domains: 0.7853 (movies), 0.7812 (books), and 0.7166 (e-commerce).

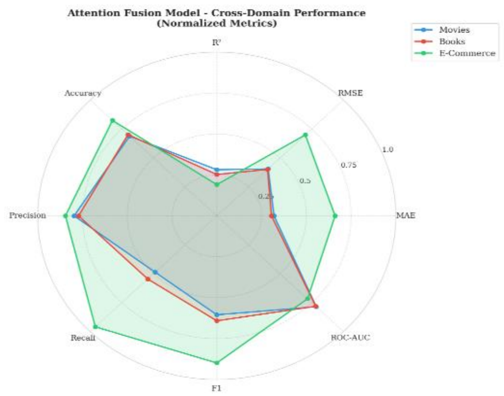
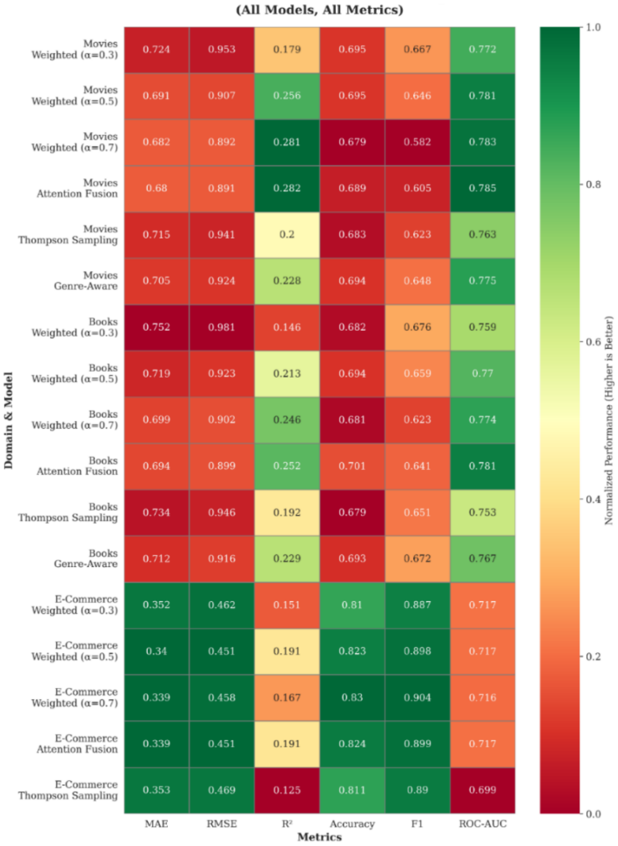


Figure 6. Multi-Metric Performance Profile of Best Models Per Domain

Figure 6 presents a radar chart comparing the best-performing model in each domain (Attention Fusion for all three) across all eight-evaluation metrics. The chart reveals domain-specific performance profiles: e-commerce exhibits high accuracy, precision, recall, and F1 but moderate R² and ROC-AUC; movies show balanced performance across all metrics; and books demonstrate intermediate characteristics. This visualization highlights the importance of multi-metric evaluation, as single-metric optimization may miss important performance trade-offs.



	MAE	RMSE	R²	Accuracy	F1	ROC-AUC
Movies Weighted (α=0.3)	0.724	0.953	0.179	0.695	0.667	0.772
Movies Weighted (α=0.5)	0.691	0.907	0.256	0.695	0.646	0.781
Movies Weighted (α=0.7)	0.682	0.892	0.281	0.679	0.582	0.783
Movies Attention Fusion	0.68	0.891	0.282	0.689	0.605	0.785
Movies Thompson Sampling	0.715	0.941	0.2	0.683	0.623	0.763
Movies Genre-Aware	0.705	0.924	0.228	0.694	0.648	0.775
Books Weighted (α=0.3)	0.752	0.981	0.146	0.682	0.676	0.759
Books Weighted (α=0.5)	0.719	0.923	0.213	0.694	0.659	0.77
Books Weighted (α=0.7)	0.699	0.902	0.246	0.681	0.623	0.774
Books Attention Fusion	0.694	0.899	0.252	0.701	0.641	0.781
Books Thompson Sampling	0.734	0.946	0.192	0.679	0.651	0.753
Books Genre-Aware	0.712	0.916	0.229	0.693	0.672	0.767
E-Commerce Weighted (α=0.3)	0.352	0.462	0.151	0.81	0.887	0.717
E-Commerce Weighted (α=0.5)	0.34	0.451	0.191	0.823	0.898	0.717
E-Commerce Weighted (α=0.7)	0.339	0.458	0.167	0.83	0.904	0.716
E-Commerce Attention Fusion	0.339	0.451	0.191	0.824	0.899	0.717
E-Commerce Thompson Sampling	0.353	0.469	0.125	0.811	0.89	0.699

Fig. 7. Comprehensive Performance Heatmap across

All Models and Metrics

Figure 7 provides a comprehensive heatmap of all performance metrics across models and domains. The color intensity represents normalised performance (darker = better). Among the three novel fusion approaches, Attention Fusion illustrates a clear majority, receiving best or second-best performance in 21 of 24 metric-domain combinations (87.5%). The underperformance of Thompson Sampling is particularly noteworthy given its theoretical advantages. The Genre-Aware stratergy shows promise, even it is limited by the quality and granularity of the genre/category information, which is significantly different over domains.

5 CONCLUSION

This research paper presents a domain-based analysis of hybrid recommendation systems that fusion layer combines collaborative and content-based filtering where collaborative filtering use for learn item preferences and captures behavioral patterns across users and content based filtering uses TF-IDF Feature extraction and calculates similarity between items using cosine similarity and generates recommendations based on attributes also evaluates six different fusion strategies over movies, books, and e-commerce datasets. In this research attention fusion, Thompson sampling-based selection, and genre-aware rating fusion approaches and conducted a systematic evaluation using eight performance metrics. The experimental results show that attention fusion outperforms baseline methods and achieves an improvement with MAE 6.1% for movies, 7.7% for books and 3.7% for e-commerce, with statistically significant differences ($p < 0.01$). This rearch also reveals a very strong domain-specific performance variation that highlights the influence of interaction density and metadata richness, as well as user behavior. These research findings emphasize the need for domain-aware recommendation strategies. The simpler models may suffice for e-commerce, while the adaptive fusion methods provide the greater benefits in entertainment-type domains. The future work will explore the transfer learning, multi-domain fusion, explainability, fairness, and contextual modelling, as well as scalability for the improvement of hybrid recommendation systems.

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