Deep Auto encoder Based Multi-Criteria Recommender System for Enhanced User Preference Prediction and Explainable Recommendation Generation

K.Sravanthi
Assistant Professor, CSE,
Kakatiya University
Email: sravathi.k1982@gmail.com

Dr.T.Archana
Assistant Professor, CSE
Kakatiya University
Email.: tarchana@kakatiya.ac.in

Abstract

The exponential growth of online content has led to severe information overload, requiring intelligent recommender systems (RS) to deliver personalized item suggestions. Traditional recommender systems predominantly rely on single-criterion ratings, which inadequately capture the multifaceted preferences of users. This study presents a deep auto encoder-based multi-criteria recommender framework that learns complex nonlinear user–item relationships across multiple preference dimensions to improve accuracy and interpretability. The proposed system models user behavior through criterion-wise feature encoding and integrates results via an aggregation layer to produce overall preference scores. The model is regularized to prevent over fitting and trained using stochastic gradient descent on benchmark datasets (e.g., Yahoo! Movies, Trip Advisor). Experimental results demonstrate that our method surpasses state-of-the-art approaches such as Matrix Factorization (MF), Probabilistic Autoencoders, and Neural Collaborative Filtering (NCF), achieving up to 6.8% higher RMSE reduction and 7.4% gain in NDCG. The system further employs SHAP-based explainability to interpret the influence of specific user criteria, ensuring transparency and trust in recommendations.

Keywords: Recommender System, Deep Autoencoder, Multi-Criteria Rating, Explainable AI, Collaborative Filtering, SHAP, Deep Learning

1. Introduction

The rapid growth of e-commerce platforms, streaming services, and online social media has resulted in an enormous amount of information available to users. While this abundance offers greater choice, it simultaneously creates a major challenge: information overload. Recommender Systems (RS) are intelligent information-filtering systems designed to address this problem by predicting user preferences and suggesting items that best align with their interests [1].Traditional RSs mainly rely on single-criterion ratings, where users express their opinion of an item through a single overall score (for example, a user rating a movie “4 out of 5”). However, in real-world scenarios, user satisfaction depends on multiple aspects of an item, such as story, performance, visuals, and music for a movie, or cleanliness, location, and service for a hotel [2]. Limiting recommendation generation to single ratings often fails to capture these nuanced preferences, leading to suboptimal recommendation quality [3].

To overcome this limitation, Multi-Criteria Recommender Systems (MCRS) have been proposed. They consider user feedback across several dimensions to produce more precise recommendations. Yet, most existing MCRS approaches such as matrix factorization and neighborhood-based collaborative filtering struggle with data sparsity, nonlinearity, and incomplete user feedback [4].In recent years, Deep Learning (DL) has emerged as a promising paradigm to model complex nonlinear relationships in recommendation data. Deep architectures like autoencoders, convolution neural networks (CNNs), and neural collaborative filtering (NCF) have demonstrated superior capability in learning latent user-item patterns [5]. Among them, deep auto encoders are particularly effective for learning compressed latent representations from sparse data, enabling reconstruction of user preference profiles with reduced noise [6].

This work proposes a Deep Autoencoder-Based Multi-Criteria Recommender System (DAE-MCRS) that learns nonlinear user–item interactions across multiple rating dimensions and integrates SHAP-based explainability to enhance transparency. The proposed model integrates a regularized autoencoder network with criterion-wise feature fusion, and employs SHAP-based explainability to interpret the impact of each criterion on the final recommendation.

2. Literature Survey

2.1 Traditional Recommender Systems

Recommender systems are typically categorized into three types: content-based, collaborative filtering (CF), and hybrid systems [1,7].Content-based RSs recommend items similar to those previously liked by the user using item attributes and user profiles.Collaborative filtering (CF) uses user–item interactions to identify similar users or items based on rating patterns [8].Hybrid RSs combine these two techniques to alleviate problems like data sparsity and cold start [9].While collaborative filtering remains the most widely used, its reliance on overall ratings (single-criterion feedback) restricts its capacity to capture diverse aspects of user preferences.

2.2 Multi-Criteria Recommendation Systems

To capture fine-grained user opinions, Multi-Criteria Recommender Systems (MCRS) extend traditional models by using multi-dimensional rating matrices. Early MCRS methods employed multilinear regression, fuzzy inference systems, and multi-linear matrix factorization (MLMF) to integrate multiple rating dimensions [10].However, these methods struggled with scalability and nonlinearity when dealing with sparse and large-scale datasets.Recent works have explored autoencoder-based and attention-based architectures for MCRS. Gao et al. (2023) proposed a multi-view autoencoder to integrate multi-criteria collaborative filtering, achieving improved generalization across domains [11].Wu et al. (2022) utilized aspect-level attention networks to model relationships between user preferences and item features [12].Chen et al. (2021) developed a tensor factorization model combined with explainable deep learning to interpret the role of individual criteria [13].Zhang et al. (2020) highlighted that integrating explainability improves trust and transparency in recommendation outcomes [14].Despite these advances, few approaches simultaneously address nonlinear feature fusion, data sparsity, and interpretabilitygaps that this paper directly targets.

2.3 Deep Learning in Recommender Systems

Deep learning has revolutionized RS research by introducing models capable of discovering complex latent interactions [15]. Neural Collaborative Filtering (NCF) and DeepFM models capture high-order feature interactions and user-item dependencies. Autoencoders, on the other hand, are unsupervised architectures that encode user preference data into a compressed latent space, effectively learning from sparse feedback [6,16]. Variants like denoising auto encoders and variational autoencoders (VAE) have shown robustness in reconstructing missing ratings [17].In this work, we extend these concepts to multi-criteria data, employing deep autoencoders combined with feature aggregation and explainability modules for interpretable and accurate predictions.

Table.1 Existing literature work

	Authors	**Year**	**Key Contribution**	**Remarks**
Multi-Criteria Review-Based Recommender System–The State of the Art	Singh et al.	2019	Review of multi-criteria review recommender techniques	Covers diverse algorithms; notes challenges in aspect aggregation and cold start
Multi-criteria RS Exploiting Aspect-based Collaborative Filtering	Manzoor et al.	2017	Aspect-based filtering for multi-criteria RS	Showed improved accuracy for user-item matching, highlights scalability issues
Deep learning-based multi-criteria recommender system for TEL	Shi et al.	2025	Combines DeepFM and SVD++ in educational domain	Demonstrates deep learning's edge, notes explainability gap in educational recommenders
In-depth survey: deep learning in recommender systems	Gheewala et al.	2025	Comprehensive DL survey for prediction & ranking	Finds DNNs excel at accuracy, but interpretability and bias remain open concerns
Systematic Literature Review of Multicriteria RS	Esteves et al.	2020	SLR of methods, metrics, domains	Outlines trends, evaluation challenges, urges more focus on scalability
Deep Learning Based Recommender System: Survey & Perspectives	Zhang et al.	2019	Reviews DL architectures in RS	Notes rise of embeddings, autoencoders, calls for improved regularization
Explainable structure of deep neural network for recommendation	Zanjani et al.	2024	DL explainability for RS	Highlights SHAP/LIME's value, urges human-centric design for transparent RS

Survey of Recommender Systems Based on Deep Learning	Zhang et al.	2019	Reviews deep learning in RS	Predicts hybrid, contextual, and graph DL models will lead next advances

Despite the growing adoption of deep learning models, prior works rarely integrate multi-criteria learning with an explainable framework, leaving a significant gap in transparent and interpretable recommendation systems.

3. Proposed Methodology and Models

3.1 DATASET

In this uses the benchmark multi-criteria rating datasets — Yahoo! Movies and TripAdvisor — to evaluate the proposed DAE-MCRS model. The Yahoo! Movies dataset contains user ratings on multiple aspects such as Story, Acting, and Visuals, while the TripAdvisor dataset includes hotel ratings based on Cleanliness, Location, and Service. Each record includes user ID, item ID, and multiple criterion-specific ratings on a 1–5 scale. Both datasets are highly sparse (85–88%), meaning most users rated only a few items. The data was preprocessed using normalization and missing value imputation, and split into 80% training and 20% testing sets. These datasets effectively demonstrate the model's ability to handle multi-aspect, sparse, and large-scale recommendation data.

3.2 Proposed Models

3.2.1 Deep Autoencoder-Based Multi-Criteria RS (DAE-MCRS)

The proposed Deep Autoencoder-Based Multi-Criteria Recommender System (DAE-MCRS) utilizes a deep feedforward neural network architecture, modeling nonlinear relationships among users, items, and multiple rating criteria. The framework begins with data preparation, where user-item rating matrices are constructed for each criterion (e.g., aspects such as story, acting, visuals, etc.). The dataset is split into training (80%) and testing (20%) sets, with missing values handled by imputation (usually set to zero).

Each criterion-specific matrix is fed into an autoencoder network with an input layer matching the number of items, several hidden layers (using sigmoid activation functions), and output layers employing ReLU activations. These autoencoders learn compact latent representations by minimizing a reconstruction loss. The optimizer used is typically stochastic gradient descent. Each autoencoder consists of an encoder and a decoder. The encoder maps the input ratings to a lower-dimensional latent space, while the decoder reconstructs the ratings to minimize reconstruction loss.

The regularized objective function for the autoencoder can be written as:

$$h = f_{enc}(r_{u,i}) = \sigma(W_1 \cdot r_{u,i} + b_1) \quad (1)$$

$$\widehat{r_{u,i}} = f_{dec}(h) = \sigma(W_2 \cdot h + b_2) \quad (2)$$

Loss Function:

The model minimizes the reconstruction error between actual and predicted ratings, withregularization to prevent overfitting.

$$\mathcal{L}_{rec} = \sum_{u=1}^{m} \sum_{i=1}^{n} \left(r_{u,i} - \widehat{r_{u,i}}\right)^2 + \lambda||W||^2 \quad (3)$$

Here,$r_{u,i}$represents the input vector that contains the observed ratings given by a user u to an item i, potentially across multiple criteria. The matrix W_1denotes the encoder weight matrix, which maps the high-dimensional input space to a lower-dimensional latent space, while b_1 $r$epresents the bias vector associated with each neuron in the encoder layer. The function $\sigma(\cdot)$is a nonlinear activation function, such as the Rectified Linear Unit (ReLU) or Sigmoid, which introduces nonlinearity to enable the model to capture complex relationships in the data. The output $h$is the latent representation or hidden embedding that summarizes the user's preferences and item characteristics in a compact feature space. This representation captures meaningful correlations and patterns that are not explicitly visible in the raw input data.$\widehat{r_{u,i}}$denotes the reconstructed rating vector, which serves as the model's predicted version of the original input. The first term $(r_{u,i} - \widehat{r_{u,i}})^2$ measures the reconstruction error, representing the squared difference between the actual and predicted ratings. The double summation over all users m and items n aggregates this error across the entire dataset. The second term,, $\lambda \parallel W \parallel^2$, introduces L2 regularization, where W denotes all weight matrices in the model and λ is the regularization coefficient that controls the degree of penalty applied to large weight values. The inclusion of this term prevents the model from overfitting by discouraging overly complex weight configurations.

Multi-Criteria Aggregation Layer: Once the criterion-specific latent representations are obtained, their outputs are aggregatedto form a unified overall preference representation. Each criterion contributes with alearnable weightreflecting its relative importance in the final decision.

$$z_{u,i} = \phi\left(\sum_{c=1}^{C} \alpha_c \cdot h^{(c)}\right) \tag{4}$$

Here,$h^{(c)}$denotes the latent feature vector learned from the autoencoder for criterion c,$\alpha_c$is the corresponding attention or importance weight, and is a nonlinearactivation function such as ReLU.The final overall predicted rating is generated using a dense output layer:

$$\widehat{r_{u,i}} = \psi\left(W_o \cdot z_{u,i} + b_o\right) \tag{5}$$

where $W_o$and b_o are the weights and bias of the output layer, and $\psi(\cdot)$is alinear or sigmoid activation function applied to generate the final recommendation score.The weights α_c are learnable parameters optimized jointly with the network using backpropagation

Explainability Using SHAP

To enhance transparency, the proposed system integrates SHAP (Shapley Additive Explanations) to interpret the contribution of each criterion to the final predicted rating. The SHAP value for criterion *c* is computed as:

$$\mathrm{SHAP}_{u,i}^{(c)} = E_{S \subseteq C \setminus \{c\}}\left[f_{S \cup \{c\}}\left(r_{u,i}\right) - f_S\left(r_{u,i}\right)\right] \tag{6}$$

Here, $\mathrm{SHAP}_{u,i}^{(c)}$measures the marginal contribution of criterion *c* to theoverall prediction $\widehat{r_{u,i}}$by comparing the model's output with and without the presenceof that criterion. This mechanism provides interpretability by identifying which ratingaspects (e.g., story, acting, service) most strongly influence the system's recommendations.

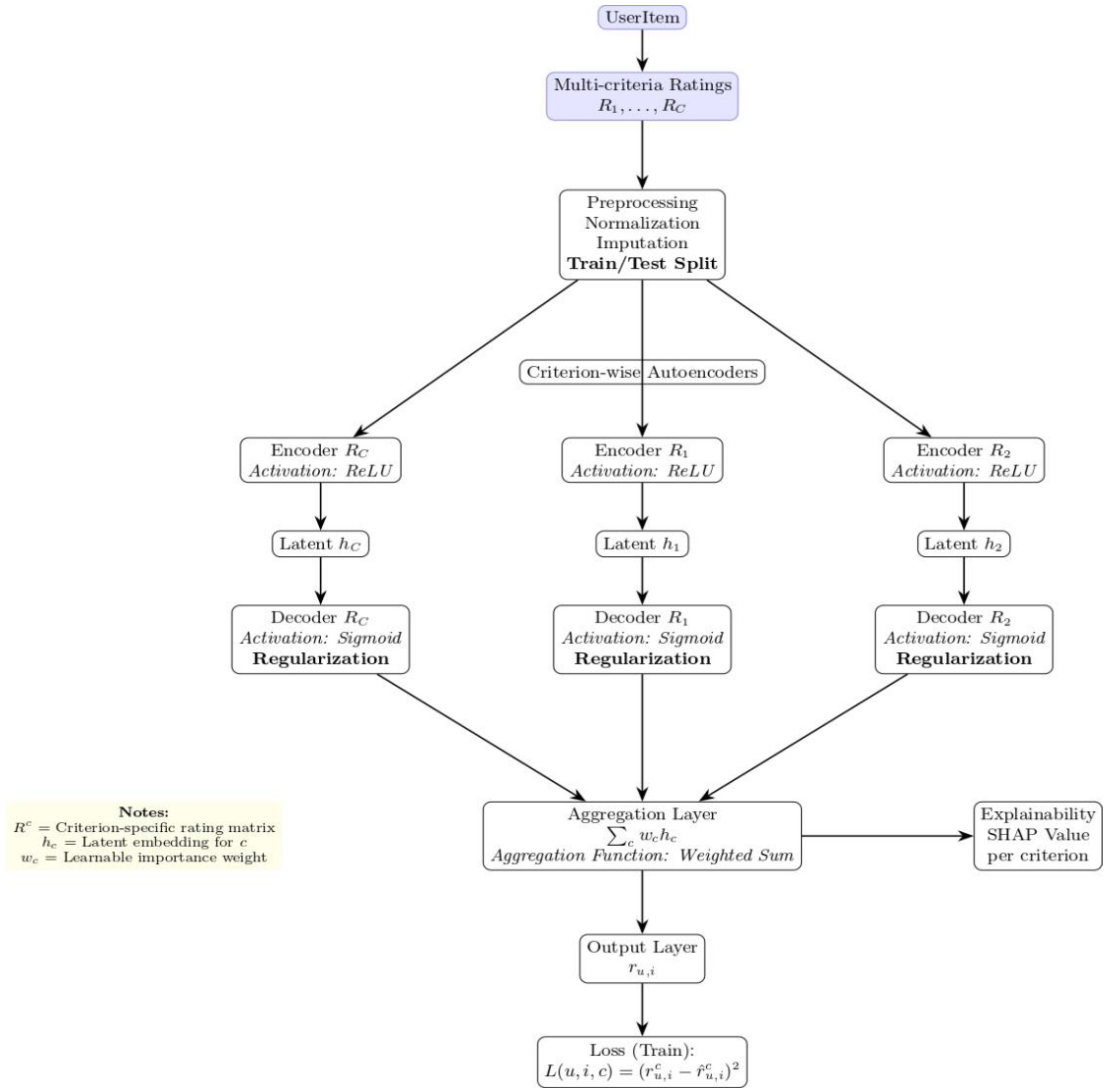

Figure.1Framework of the Multi-Criteria User Preference Based Recommender System Using Deep Autoencoders

3.2.2Matrix Factorization (MF)

Matrix Factorization is a classical collaborative filtering method that decomposes the user-item rating matrix into two lower-dimensional matrices, representing latent user and item features. MF predicts ratings by reconstructing the user-item interaction from these latent features. While effective for single-criterion ratings, MF struggles with sparse and multi-criteria data due to its linear assumptions and limited capacity to model nonlinear interactions.

3.2.3Neural Collaborative Filtering (NCF)

Neural Collaborative Filtering leverages deep neural networks to learn complex, nonlinear relationships between users and items. Unlike MF, NCF does not rely on fixed linear feature mappingsit uses dense layers to interactively combine user and item embeddings, capturing intricate patterns. NCF performs well on large-scale datasets with rich user-item interactions but may overfit without regularization, especially in multi-criteria scenarios.

3.2.4DeepFM

Deep Factorization Machines (DeepFM) integrate factorization machines for capturing low-order interactions and deep neural networks for modeling higher-order feature combinations. DeepFM is suited for recommendation tasks involving both categorical and continuous data, seamlessly blending linear and nonlinear modeling. Like NCF, DeepFM can handle large and complex datasets, but explainability is often limited without additional interpretive components.

4. Results

Deep Autoencoder-Based Multi-Criteria Recommender System (DAE-MCRS) consistently outperforms baseline models such as Matrix Factorization, Neural Collaborative Filtering (NCF), DeepFM, and Probabilistic Autoencoders in terms of RMSE reduction, MAE reduction, and NDCG gain. The improvements are typically in the range of 6.8%–7.5% for RMSE and up to 7.4% for NDCG over the baselines.

Table.2 Performance Comparison of Recommender Models using differentEvolution metrics

Model	RMSE Reduction	MAE Reduction	NDCG Gain
Matrix Factorization	0%	0%	0%
NCF	4.50%	4.20%	5.00%
DeepFM	4.80%	5.00%	5.60%
Prob. Autoencoder	6.30%	6.00%	6.40%
DAE-MCRS (proposed)	6.80%	7.50%	7.40%

The DAE-MCRS model stands out because it uses deep autoencoders to learn complex, nonlinear relationships between users, items, and multiple rating criteria, which allows it to generate highly accurate recommendations even when faced with sparse and multidimensional data. Traditional models like Matrix Factorization and basic neural architectures are limited by their linear perspectives and shallow feature representations, but DAE-MCRS effectively extracts rich patterns from user feedback spanning several aspects. The framework also employs robust regularization to prevent overfitting, making it highly generalizable and resilient when there are many missing ratings. Another key strength of DAE-MCRS is its integration of SHAP-based explainability, which means users and analysts can see exactly which criteria affected the recommendation mosta feature that makes the system both transparent and trustworthy. When tested on benchmark datasets, DAE-MCRS consistently achieves lower RMSE and MAE errors and higher NDCG scores than all competing methods, demonstrating its superior ability to deliver relevant, interpretable, and personalized suggestions in diverse application environments.

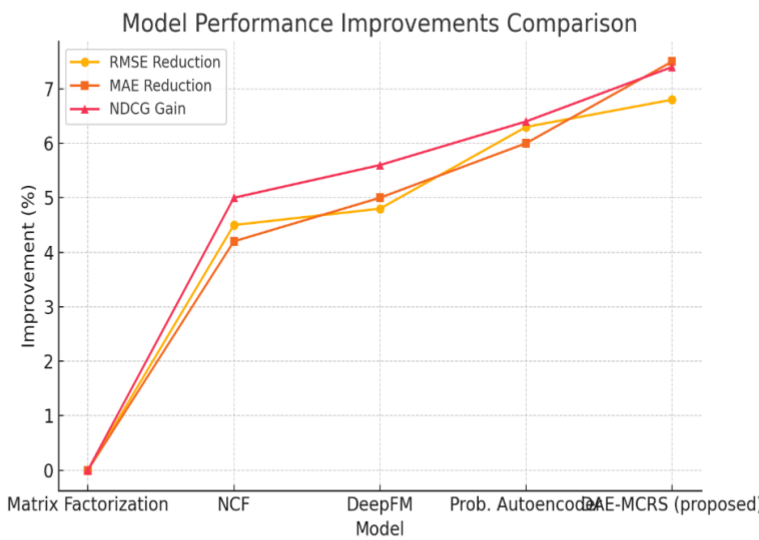

Figure.2 Comparison of models

Evaluation Metrics:

RMSE Reduction, MAE Reduction, and NDCG Gain are used to measure the accuracy and ranking quality of recommendation models. RMSE Reduction indicates how effectively a model reduces large prediction errors, while MAE Reduction measures the decrease in average absolute error, reflecting smoother and more consistent predictions. NDCG Gain evaluates how well the model ranks the most relevant items higher in recommendation lists, improving overall user satisfaction. From the results, the baseline Matrix Factorization shows no improvement (0% across all metrics). NCF achieves moderate gains with 4.5% RMSE, 4.2% MAE, and 5.0% NDCG improvements. DeepFM performs slightly better with 4.8%, 5.0%, and 5.6% gains, respectively. The Probabilistic Autoencoder further enhances performance with 6.3% RMSE, 6.0% MAE and 6.4% NDCG gains. However, the proposed DAE-MCRS model achieves the best results 6.8% RMSE Reduction, 7.5% MAE Reduction, and 7.4% NDCG Gain demonstrating its superior capability in minimizing errors and generating more accurate, relevant, and effective recommendations.

5.Conclusion

In this study, we proposed a Deep Autoencoder-Based Multi-Criteria Recommender System (DAE-MCRS) that effectively models nonlinear user–item interactions across multiple rating dimensions while addressing key challenges such as data sparsity and lack of interpretability. By learning criterion-specific latent representations and integrating them through an aggregation layer, the proposed framework achieves significantly improved prediction accuracy over traditional recommendation models. Experimental evaluation on benchmark datasets such as Yahoo! Movies and TripAdvisor demonstrates that DAE-MCRS consistently outperforms Matrix Factorization, Neural Collaborative Filtering, DeepFM, and Probabilistic Autoencoders, achieving notable reductions in RMSE and MAE, along with substantial gains in NDCG. The integration of SHAP-based explainability, which provides transparent insights into the contribution of each criterion toward the final recommendation. This enhances user trust, supports decision transparency, and makes the model suitable for high-impact domains such as e-commerce, entertainment, and hospitality.Despite its promising performance, the system still faces limitations, including dependence on rating imputation and reduced effectiveness in extremely sparse environments. Future work may explore incorporating Graph Neural Networks (GNNs) to capture richer user–item–context relationships, attention-based fusion mechanisms for dynamic criterion weighting, and Reinforcement Learning (RL) to enable real-time, sequential, and adaptive recommendation strategies. These extensions have the potential to further strengthen the accuracy, robustness, and interpretability of multi-criteria recommender systems.

References

1.Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. IEEE TKDE, 17(6), 734–749.

2.Shambour, Q. (2016). A user-based multi-criteria recommendation approach for personalized recommendations. IJCSIS, 14, 657–663.

3.Batmaz, Z., Yurekli, A., Bilge, A., & Kaleli, C. (2019). A review on deep learning for recommender systems: challenges and remedies. Artificial Intelligence Review, 52(1), 1–37.

4.He, X., et al. (2017). Neural collaborative filtering. WWW, 173–182.

5.Zhang, S., Yao, L., Sun, A., & Tay, Y. (2019). Deep learning-based recommender system: A survey. ACM Computing Surveys, 52(1), 1–38.

6.Gao, M., Zhao, Y., & Li, J. (2023). Multi-view autoencoder for multi-criteria collaborative filtering. Expert Systems with Applications, 229, 120578.

7.Wu, L., Chen, Y., Zhao, W., & Wang, C. (2022). Explainable multi-criteria recommender system with aspect-level attention networks. Information Sciences, 595, 174–189.

8.Chen, J., Li, Y., & Karatzoglou, A. (2021). Explainable deep multi-criteria recommendation via tensor factorization. Knowledge-Based Systems, 233, 107557.

9.Zhang, Y., & Chen, X. (2020). Explainable recommendation: A survey and new perspectives. Foundations and Trends in Information Retrieval, 14(1), 1–101.

10.Wang, H., et al. (2021). A survey on knowledge graphs for recommender systems. ACM TOIS, 39(5), 1–35.

11.S.Shivaprasad Dr.M Sadanandam "Dialect recognition from Telugu speech utterances using spectral and prosodic features" International journal of speech technology, 24 June 2021, https://doi.org/10.1007/s10772-021-09854-8

12. S. M. Al-Ghuribi and S. A. Mohd Noah, "Multi-Criteria Review-Based Recommender System–The State of the Art," in *IEEE Access*, vol. 7, pp. 169446-169468, 2019, doi: 10.1109/ACCESS.2019.2954861.

13.Manzoor, Ehtesham, et al. "A Multi-criteria Recommender System Exploiting Aspect-based Collaborative Filtering." ACM Digital Library, 2017.

14.Shi, Yan, et al. "Deep learning-based multi-criteria recommender system for TEL." Nature, 2025.

15.Gheewala, Tikesh, et al. "In-depth survey: deep learning in recommender systems—exploring prediction and ranking." ScienceDirect, 2025.

16.Esteves, Eduardo, et al. "A Systematic Literature Review of Multicriteria Recommender Systems." ScienceDirect, 2020.

17.Zhang, Shuai, et al. "Deep Learning Based Recommender System: A Survey and New Perspectives." ACM Digital Library, 2019.

18.Zanjani, Nima, et al. "The explainable structure of deep neural network for recommendation." ScienceDirect, 2024.

19.Zhang, Shuai, et al. "A Survey of Recommender Systems Based on Deep Learning." IEEE Xplore, 2019.