Impact of Auxiliary Information in Generative Artificial Intelligence Models for Cross-Domain Recommender Systems

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Abstract*—Recommender systems (RSs) are significant in enhancing the experiences of users across different online platforms. One of the major problems faced by the conventional RSs is difficulties in getting precise preferences for users, mostly for the users that has limited previous interaction data, and this eventually affects the performance of the conventional techniques to solve the data sparsity problem. To address this challenge, this study proposes an Auxiliary-Aware Conditional GAN (AUXIGAN) model that integrates heterogeneous auxiliary information into both the generator and discriminator networks to enhance representation learning to enhance the performance of the cross-domain recommender systems (CDRS). Most researchers consider only the rating matrix of users-items and ignore the impact of auxiliary information on the interaction functions, which is very significant to the recommendation accuracy to solve data sparsity problems. The proposed novel technique considers features concatenation, attention-based fusion networks, contrastive representation learning, knowledge transfer, and multi-modal embedding alignment techniques to enhance the user-item interaction matrix. Our experiments on benchmark datasets show that the proposed model significantly outperformed state-of-the-art RSs models, the key metrics utilized are: RMSE, Precision, Recall, and MAE, which show the influence of incorporating auxiliary information into the GAN-based CDRS. In conclusion, the integration of auxiliary information on generative adversarial networks models represents a substantial advancement in the field of CDRS, and the results of the proposed models on two real-world datasets show that the proposed model significantly outperforms collaborative filtering and other GAN-based techniques.

Keywords*—*Generative adversarial networks; auxiliary information; cross-domain recommender systems; data sparsity; knowledge transfer

I. INTRODUCTION

With the rapid advancement of internet technology, online e-commerce, e-learning, and social networks have made information overloading a serious challenge, this makes it difficult for the users to get the most preferred items or information. The advent of recommender systems (RSs) has been helping to mitigate the problem of information overloading to some extent. RSs uses machine learning techniques and data analysis to recommend preferred information (contents, news, items, movies, music, tourist etc.) to the users. These systems analyze huge amounts of information about the users' preferences, interests and past behavior by using machine learning techniques like collaborative filtering (CF), clustering, and neural networks to recommend items that are personalized to the users. Netflix, Amazon, Spotify, and Lazada are illustrations of RS. Amazon recommends items based on past purchases, preferences and the browsing history of the user, Netflix suggests movies to its users or customers, and Spotify also provides music and playlists based on preferences and past histories of the users. The main purpose of using RSs is to recommend significant suggestions to the users, centered on their past preferences, behavior, etc. [1], [2]. RSs can be used on diverse domains to solve problems of information overloading, such as e-learning [3], e-commerce, and social networks [4], [5].

Traditional RSs, like content-based and collaborative filtering methods, often struggle with data sparsity challenges, particularly in domains that have limited user-item interactions, but cross-domain recommender systems (CDRS) offer solutions to this problem by transferring knowledge from one domain to the other. CDRS leverages knowledge from one or more source domains to improve the quality of recommendations in the target domain with limited data. The existing methods, which include collaborative filtering and matrix factorization, face sparsity challenges due to difference in user and item distributions across domains. Using generative artificial intelligence models like Generative Adversarial Networks (GANs) model, makes CDRS extract shared latent factors across domains, enabling knowledge transfer that improves accuracy and reduces data sparsity. GANs have been widely recognized for its potential in CDRS due to its ability to learn the distributions of complex data. It has emerged as a vital field of study by improving various domains, such as RSs, creative arts, computer vision, and language processing [6], [7], [8], [9]. GANs have displayed favorable achievement in generating realistic data distributions and capturing complex relationships within complex datasets [10], [11]. The recommendation algorithms of GANs have the potential to address the problem of data sparsity by generating realistic user data [12]. It can also improve users' experience and satisfaction [13] and mitigate cold start problems for new users who have no previous history [14], [15].

Auxiliary information is the additional features beyond the primary user-item interaction data (e.g. ratings, clicks). This auxiliary information includes user demographics, item attributes, social networks, contextual data, and more. It is sometimes called side information. This is an aspect that will be put into consideration in this study. Researchers does not consider this auxiliary information as a crucial aspect that can enhance GANs-based RSs. Most of the researchers concentrate more on the user-item interactions only and ignores the influence of auxiliary information on the interaction functions. Incorporating auxiliary information into RSs can enhance its performance by providing additional information or insight into the user's preferences [16], [17]. Previous research on RSs explored different methods like matrix factorization, Graph Neural Networks [18], [17], [19], [20], [21], Convolutional Neural Networks [22], Deep Matrix Factorization [23], [24], Federated meta learning [2], Deep coupled Autoencoders [25], Collaborative Filtering Neural Network [26], Variational autoencoder [27] across different domains. These methods have shown significant improvement on RSs, but they still struggle with the problem of sparse data. This information features plays significant roles in enhancing the performance of RSs by providing additional context that can improve user-item representation learning, this information can be generated from various sources, such as text, multimedia, and social networks, and its effective integration can address issues like recommendation accuracy, explanation generation, and the data sparsity problem [17].

The contributions and novelty of this proposed study are summarized as follows:

- We introduce a novel model named AUXIGAN, which is a model that enhances traditional GANs by integrating auxiliary information into the generative adversarial networks for recommendations improvement.
- We employ an attention network to determine the significance of various auxiliary information components in shaping user and item interactions to solve the data sparsity problems by integrating various kinds of information extracted from a related embedding network to enhance the performance of recommendations.
- We conducted extensive experiments on real-world datasets (Amazon and Book-crossing) to validate the efficiency and rationale behind our proposed model against several baselines.

To the best of our knowledge, no study has been conducted on a GAN-based model to enhance CDRS with the integration of auxiliary information. The proposed GAN model is the first to put auxiliary information of the users and items into consideration to make the recommended items more personalized.

Structurally, this study begins by introducing the background in Section I. In Section II, we comprehensively review existing research and methods in recommender systems and generative AI models. Section III provides detailed descriptions of our research methodology. Subsequently, Section IV, V and VI showcases the outcomes of our experiments, offering a comparative analysis of various models' performances. Section VII presents the limitations and future directions and finally, Section VIII concludes the study.

II. Related Work

Conventional recommender systems (RSs) which comprise of content-based (CB) methods and collaborative filtering techniques (CF) relies heavily on user-item interactions. CF techniques like matrix factorization [28] perform well in dense datasets but weaken in sparse conditions. CB approaches use item features to recommend similar items, but often require extensive feature engineering [29]. These conventional methods still encounter data sparsity problems compared to the deep learning model techniques, such as GANs.

Generative adversarial networks (GANs) were introduced by [6], which consists of a generator (G) and discriminator (D) in a minimax game, as illustrated in Fig. 1. Recent studies have applied GANs to RSs, and their recommendations are showing promising results [13], [30]. Integrating generative AI models, such as GANs model on CDRSs brings an opportunity to overcome the limitations of traditional RSs [31], [32], [33], [34]. By generating meaningful representations for items or users, generative RSs have the potential to mitigate the cold start issue [31] and enhance accuracy on data sparsity [35]. According to some researchers, the most effective model in adversarial learning is GANs [36]. GANs are capable of capturing shared information across domains due to their ability to generate two different domain data simultaneously, where they resemble each other [37], [38].

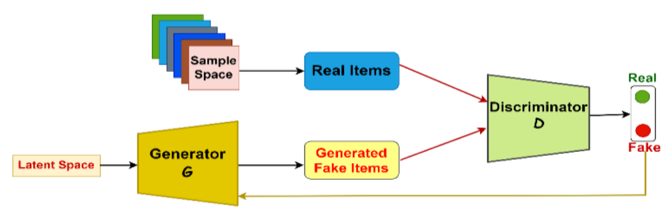

Fig. 1. The illustration of how the generator and discriminator work.

Auxiliary information in RSs is an additional data incorporated to improve relevance and accuracy of recommendations. It plays significant role in enhancing the performance of RSs and it also offers a more personalized, relevant, and context-aware recommendations to the users [39]. Auxiliary information helps to improve and enhance data sparsity [17], [40], [41], [42], [43], [44], [45].

In their study [16], the authors introduced E-EATI model to enhance social recommendation by extracting auxiliary information, aiming to improve recommendation performance by fusing auxiliary information from user or item with BERT model and item2item aggregation operation. The model addresses the project attribute fusion problems in GCN, focusing on signed networks and auxiliary information to enhance recommendation performance. In [46], the author's focus is on enhancing citation recommender systems by integrating auxiliary textual information and BERT into the Neural Citation Network (NCN) model. Their proposed model utilizes a deep neural auto-encoding mechanism with selfattention to learn textual and citation contextual data, this is to improve the citation recommendation performance. Hi-GNN, a Hierarchical Interactive Graph Neural Network for Auxiliary Information-Enhanced Recommendations (AIER) was proposed by [17]. The model addresses the suboptimal performance of AIER by incorporating behavioral and auxiliary information with a hierarchical interaction layer. In their study [47], the authors introduce the Knowledge Graph Attention-assisted Network (HKGAT) as a unique recommendation model that incorporates the knowledge graph into the recommendation model to study higher order connectivity and improve generalization capacity. The HKGAT model utilizes an embedding layer to parameterize each node as a vector and determine the e-weights of each neighbor during the propagation.

In their study [39], the authors focuses on enhancing sequential recommendations by incorporating auxiliary information like item images and textual data to improve user preference understanding. Their proposed algorithm, MFN4Rec, effectively models multi-modal information for accurate sequential recommendation. The authors [48] utilizes Metapath2vec to acquire the low-dimensional representation of music through a music heterogeneous information network. Their proposed model, named MFAE, integrates auxiliary information fusion embedding to alleviate data sparsity and enhance music feature representation. GRU was employed to obtain user feature representation for personalized music recommendation. A novel recommendation method named STRGAN was used in [12]. The model was utilized to address data sparsity issues by incorporating user ratings and social relationships. The model, STRGAN, combines user ratings and social relationships to enhance recommendation accuracy, employing negative sampling methods to align generated recommendations with real data. MA-CVAE in [49] considers tag recommendation by integrating collaborative and multi-auxiliary information for better recommendations. The proposed model addresses the cold-start and sparsity problems in recommenders tagging by coupling social graph information, item content with collaborative information. The model also utilizes deep generative models like Variational Graph Auto-Encoder (VGAE) and Variational Auto-Encoder (VAE) to learn latent embedding from different item auxiliary information. In their study [50], the authors focuses on enhancing implicit RSs by integrating auxiliary information into matrix factorization models to capture different user preferences beyond primary feedback. The proposed method includes pointwise and pairwise models to leverage users' viewing behaviors effectively, with the pairwise model showing superior performance. In [51], the authors focuses on enhancing recommendation systems by addressing issues like sparsity and cold start through a collaborative multi-auxiliary information variational autoencoder (CMVAE).

In our study, we propose a novel model for cross-domain recommender system by incorporating auxiliary information into GAN model. The other component in the model is constructed by converting user behavior history into a multinomial distribution over behaviors. Additionally, we introduce a unique adjustment to the GANs architecture, specifically tailored for recommendation tasks, which has not been explored previously. The details of our model will be presented in the subsequent section.

III. Methodology

This segment presents the proposed model, and this is shown in the architecture of incorporating auxiliary information and rating matrix on the GANs model (AUXIGAN) on CDRS, as shown in Fig. 2.

Below is the explanation of how the model works; they are broken into key steps:

- Input data and embedding layer: Auxiliary information is utilized to create embeddings for the users (U) and items (I), this process occurs in the embedding layer, where users and items from different domains (source and target) are transformed into a shared latent space, the users-items initial embedding is denoted as input $g_\theta(.)$.
- Aggregation network: Users (Us) and their interacted items (Is) are passed through an aggregation network. This network, which aggregates information for users, is based on their historical interactions with items to generate user-specific representations.
- Generative adversarial networks (GANs): The GANs component comprises a generator $f\theta(\cdot)$ and a discriminator $h\phi(\cdot)$:
  1. *Generator* $f_\theta(\cdot)$: It generates synthetic data (e.g., predicted ratings or embeddings) conditioned on input noise (z) and real data embeddings.
  2. *Discriminator* $h\phi(\cdot)$: It distinguishes between real and generated (fake) data.

The concatenation step combines both generated and real data to further refine the model training, and the objective is to enable domain adaptation and align the learned user and item representations between source and target domains:

- Domain adaptation and transfer layers: The model employs transfer layers to facilitate knowledge sharing between source and target domains. The domain adaptation mechanism ensures that knowledge from the source domain is transferred effectively to the target domain.
- Deep interaction layers: The output from the GANs module is passed into deep interaction layers. These layers processes user embeddings (Ut) from the target domain and utilize the generated ratings matrix (Rn) to interact with Items (It).
- Knowledge transfer: The knowledge transfer component allows the proposed model to learn from one domain and apply the learning to another. This is to help the model to mitigate challenges of data sparsity in the target domain. The knowledge is transferred from

generator to the users (Ut1, Ut2, Ut4, …. Utn,) in target domain.

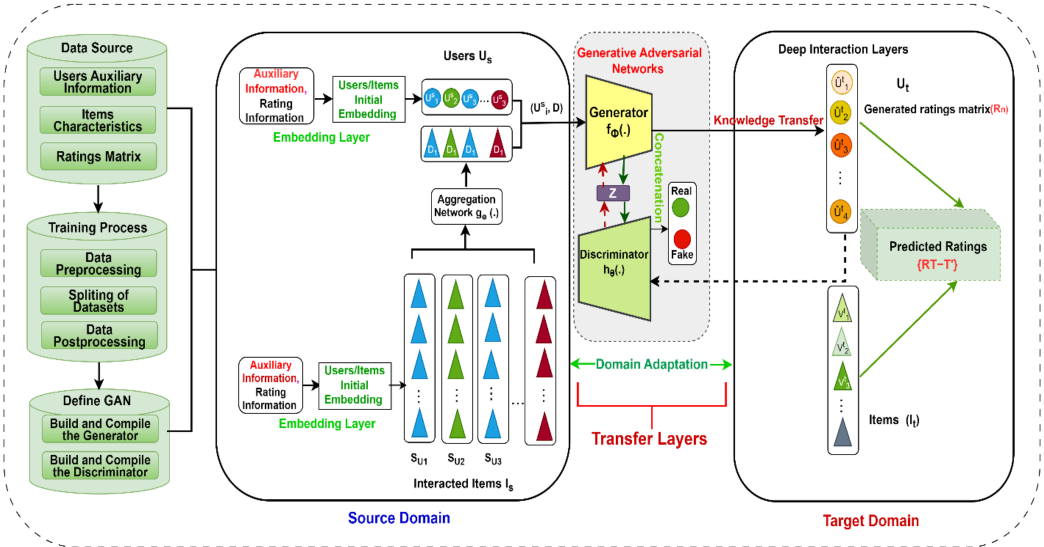

Fig. 2. Proposed AUXIGAN architecture.

- Prediction of ratings: The proposed model generates a predicted ratings matrix (RT-T') for users in the target domain, and the predicted ratings are obtained by interacting with the deep representations of user and item with the influence of auxiliary information.
- User: They are any individual who submits requests to the recommender server to receive predictions of items. To allow this process, the user's profile must be accessible for computations by the recommender server.
- Source domain: The source domain comprises the datasets with a substantial number of user ratings and auxiliary features. This is managed by a data curator who is responsible for the maintenance of the dataset and enabling secure data sharing with other data curators.
- Target domain: The target domain contains the user ratings and auxiliary features that are relatively sparse. A data curator manages this domain to handle encrypted latent profiles received from the source domain.

This proposed GANs architecture is capable of capturing shared information across domains due to its ability to leverage shared knowledge, preserve common semantics, share and transform features, utilize mutual information mechanisms, train simultaneously on the domains, and handle multiple conditional inputs. These capabilities make the proposed GAN model to be highly effective for various cross-domain applications.

A. Problem Formulation

Firstly, this proposed study examines the effect of incorporating auxiliary information into GAN-based CDRS, this is to examine its potential to improve recommendation accuracy, transferability, and robustness. Our assumption is that the two domains have overlapping users and items. When a domain faces the data sparsity problem, the other domain will be facilitated by sharing information for making recommendations. Typically, the domain that may experience this issue is the target domain, while the backing domain is the source domain, indicated by labels (t) and (s), respectively.

Let U = {U_1, U_2, U_3, U_4, U_5, U_{6}…} and I = {I_1, I_2, I_3, I_4, I_5, $I_{6…}$} represent the sets of the users and items. We represent the users and items of the source domain as U_s and I_s, and those of the target domain as U_t and I_t. The conjoint user set between the two domains is U_o= U_s ∩ I_t. We extract a rating matrix R = (r_{ij}) to uncover preferences of the users, where (r_{ij}∈R) signifies the interactions between user (u_i) and item (i_j). The rating matrices for the two domains (source and target domains) are represented as R^s and R^t, respectively.

For the user (u_i,), the sequence of interaction of the items in the source domain can be analyzed as S_{ui} = {I_{t1}^s, …. I_{tb}^s}, where I_{tb}^s represents the b_{th} interaction of the user at timestamp t_b, b∈{1, …., n}. In the proposed model, users and items are transformed into embeddings based on their characteristics, denoted as u_i, i_j $\in \mathbb{R}^d$, where d is the dimension of the embeddings. The aim of this study is to leverage the ratings matrix and auxiliary information from the two domains to improve the recommendation accuracy in the domains. The two domains have user sets U_1 and U_2, item sets I_1 and I_2, and interaction matrices R_1 and R_2.

B. Proposed Cross-Domain Recommender Systems Model

The proposed AUXIGAN model in this study primarily consists of two main networks and components: generator and discriminator with rating matrix and auxiliary information. If I ={I_1, I_2, I_3, I_4, I_5…, I_n} and U = {U_1, U_2, U_3, U_4, U_5,…, U_m} which represents a set of "m" items and a set of "n" users correspondingly, the two matrices can then be created from user

(U), Item (I) and their interactive information which are the rating matrix M = $(r_{u,i})_{m\times n}$, and the auxiliary information matrix M′ = $(\hat{r}_{u,i})_{m\times n}$, $r_{u,i}$ is the rating of user (U) on item (I), and $\hat{r}_{u,i}$ represents the interaction between users (U) and items (I). If items (I) has been rated by users (U), then $\hat{r}_{u,i}$ = 1, otherwise $\hat{r}_{u,i}$ = 0.

C. Model Architecture

In this study, we propose a CDRS framework that integrates a ratings matrix and auxiliary information with GANs, named AUXIGAN. The proposed model shown in Fig. 3 comprises four major components: auxiliary information, rating matrix (embedding layer), items feature aggregation, GANs {Generator (G) and Discriminator (D)} structure, and predictions.

D. Structure of GANs

We utilized the method of mapping to establish the connection from source domain to target domain; this involves training the GAN on users-items ratings and auxiliary information. At this stage, the interactive relationship between users and items is considered, also the auxiliary information related to the users is also put into consideration.

E. Aggregation of the Items Feature

Items are crucial in RSs, alongside users, in addressing data sparsity issues. When users have limited or no ratings for items in the target domain, it requires leveraging their interactions with items in the source domain, along with their auxiliary information. Given that different items interacted with by users can have varying impacts, we employ an attention mechanism to aggregate item features, which are based on their contributions and the user's auxiliary information. The proposed models make use of the concatenation between the generator (*G)* and discriminator (*D*); the generator constructs probable user-item interactions in the target domain, guided by auxiliary information, meanwhile the discriminator distinguishes between real interactions and those generated by the generator.

- Generator function as in Eq. (1):

$$G(z, a_{u,} a_{i\,,}) \rightarrow \sigma(W_g .ReLU\big(V_{g\,.[z,x]}\ \big))$$

$$\sigma(\ W_g.ReLU(V_{g\,.[z,x]}\,)) = \hat{r}_{u,i}$$

$$\text{Therefore, } G(z, a_{u,} a_{i\,,} \rightarrow \hat{r}_{u,i}) \tag{1}$$

Generator loss function:

$$L_G\text{: } LG = -Elog(1 - D(G(z, a_u, a_i)))] \tag{2}$$

The generator loss function was trained to minimize the likelihood of the discriminator by correctly identifying fake data.

- Discriminator loss function:

The discriminator loss function was equally trained to maximize the likelihood of correctly identifying real and synthetic data.

$$D(y) \rightarrow \sigma(W_d\,.ReLU\big(V_{d.y}\ \big))$$

$$\text{Let } \sigma(W_d\,.ReLU\big(V_{d.y}\ \big) = [0,1]$$

Therefore in Eq. (3):

$$D(ru, i, \hat{r}u.i\,) \rightarrow [0,1] \tag{3}$$

where, Discriminator Loss (L_D):

$$LD = -E[log(D(r_{u,i}) + log(1 - D(G(z, a_u, a_i) \tag{4}$$

F. Training Procedures

The training of the model involves alternating between updating the generator to fool the discriminator and updating the discriminator to correctly classify between the real and generated interactions. The loss functions are defined as Eq. (5):

$$LD = -E[log(D(r_{u,i})) + log(1 - D(G(z, a_{u,} a_i)))] \tag{5}$$

where, $E[\dots]$ defines a minimization problem for the discriminator's loss, this is the fitting standard practice in GANs training, where the discriminator's objective is to minimize its loss. Eq. (2) and Eq. (4) illustrate the loss function for the generator and discriminator in the GANs setup. The discriminator (*D*) produces output with a probability close to 1 for the real data $r_{u,i}$. The logarithm of this probability measures how confident the discriminator is that $r_{u,i}$ is real, as in Eq. (6):

$$log(1 - D(G(z, a_{u,} a_i))) \tag{6}$$

The generator (*G*) produces a synthetic data point $G(z, a_{u,} a_i)$ using the noise vector (*z)* and attributes (a_u) and (a_i). The discriminator (*D*) is trained to give an output of a probability close to 0 for synthetic data. Taking the logarithm of one minus the probability measures how confident the discriminator is that $G(z, a_{u,} a_i)$ is fake. The discriminator is trained to differentiate between real data points $r_{u,i}$ and generated data points $G(z, a_{u,} a_i)$.

The discriminator also aims to maximize this loss function, which means:

- Maximizing $log(D(r_{u,i})$ to ensure that it correctly identifies real data.
- Maximizing $log(1 - D(D(z.a_u,\ a_i)))$ to ensure that it correctly identifies generated (fake) data.

Table I highlights the breakdown of the different notations utilized in this study.

G. Data Representation

The proposed AUXIGAN model addresses challenges in traditional GAN models, specifically their struggle to accurately model the distribution of user and item rating matrices in a single iteration, to mitigate the instability of training and mode collapse, the model adopts a structured approach, where the discriminator (*D*) guides generator (*G*), both *G* and *D* are implemented using a multi-layer perceptron (MLP). In our proposed model, the generator (*G)* is tasked to make fake vectors based on varying user condition vectors R_t^u

at different time point *t*. These fake vectors are evaluated by *D* using the Wasserstein distance metric against real vectors from the dataset to enhance the model's robustness. This iterative process helps to improve the reliability and diversity of generated user-item interactions, addressing the limitations of traditional GANs. The following steps are equally followed for the data representations.

- Step 1: Generate fake samples with the generator.

Data representation on user *(u)* involves concatenating the conditional rating vector R_t^u, which includes noise, with its corresponding embedding vector v_t of *t*. This concatenated vector serves as the conditional input; additionally, random noise (z_u) is injected into the generator (*G)* as in Eq. (7):

$$G(R^u_{t,}, zu, vt) \ = \ \sigma(W_g \, . \, ReLU(V_g \, . \, [R^u_{t, \ zu, \ vt]})) \quad (7)$$

Therefore, generator (*G)* considers only the loss gradients of rated items by ensuring more efficient learning by focusing on the user's observed interactions with items and the auxiliary features. It assists the generator *(G)* to denoise in the latent vector space to achieve an initial fake rating vector $\hat{R}_0^u$, which is a complete dense matrix.

- Step 2: Training of the discriminator

Firstly, the discriminator (D) was trained so that sharing of the real samples $R^u_{t-1,}$ will be known and obtained through the forward process given R_0^u and R_t^u. Then, the discriminator (D) also identified the distribution of the fake samples through the backward process, as shown in the proposed architecture. That is, the sampling of R^u_{t-1} by using subsequent distribution q(R^u_{t-1} | $R^u_{0,}$, $R^u_{t,}$) given that ($R^u_{0,}$and $R^u_{t,}$) exit. Here, the transfer layer plays a significant role by filtering out the unrated item vectors to obtain the distribution of fake samples R^u_{t-1}. The discriminator loss LD and generator loss LG are defined as:

Discriminator Loss (LD) as in Eq. (8) :

$$L_D = -E_x \sim pdata[LogD(x)] - Ez \sim pz \, [\log(1-D(Gz,x)))] \quad (8)$$

Generator Loss (LG) as in Eq. (9):

$$LG = -Ez \ \sim pz[logD(G(z,x))] \quad (9)$$

- Step 3: Optimization process

The optimization process involves updating the parameters of the generator (*G*) and the discriminator (*D*) using gradient descent. Adam with modified hyperparameters was utilized for the optimization process.

The latent item variables can be accomplished by combining the user's information and items information and latent auxiliary variables, as: $vj = v_d\Delta \ + \ z_i$.

H. Incorporating Auxiliary Information

To handle varying lengths of auxiliary information (p_u) for different users effectively, an attention mechanism was utilized to enable each piece of auxiliary features given inversely to the user-item interaction. Through this approach, latent vectors were derived for auxiliary features of the users (*U*) and items (*I*), denoted as x and y, respectively. This allows more representation, where the attention mechanism dynamically weights the importance of different elements within the auxiliary information vectors, for the enhancement of the model's ability to capture diverse user-item interactions effectively. Auxiliary information's numbers (p_u) for different users typically vary; to utilize this, it's necessary to convert these varying-length vectors into a fixed-length vector. The simplest technique is to find the average of all embedding vectors; therefore, we utilized an attention mechanism to influence in diverse ways the user-item interaction, and the latent vectors of the auxiliary information of the users (*U*) and items (*I*) through x and y were then obtained as Eq. (10) and (11):

$$x = \sum_{i=1}^{pu} wd \; x_i \quad (10)$$

$$y = \sum_{i=1}^{qu} vd \; y_j \quad (11)$$

where, *wd* and *vd* represent weights and attentions of *i-th* user's auxiliary features and *j-th* item's auxiliary features, we therefore parameterized *vd* as an attention function with **u**, **v** and **y***j* as input in Eq. (12):

$$vd \ = \ fu \, (\boldsymbol{u}, \boldsymbol{v}, \boldsymbol{y}i) \quad (12)$$

One of the advantages of parameterizing is that, weights of auxiliary features depend on the auxiliary information and the pairing of user-item. Then, Multi-Layer Perception (MLP) was utilized for the parameterization of attention functions: $f_\Phi(.)$ *and* $h_\theta(.)$. Then the attention functions are as follows, as in Eq. (13 and (14):

$$fu \, (\mathbf{u}, \mathbf{v}, \mathbf{x}i) = \ h_u^T \Phi \, \{W_u \begin{bmatrix} u \\ i \\ xi \end{bmatrix} \ + \ b_u\} \quad (13)$$

$$fu \, (\mathbf{u}, \mathbf{v}, \mathbf{y}i) = \ h_u^T \Phi \, \{W_I \begin{bmatrix} u \\ i \\ yi \end{bmatrix} \ + \ b_I\} \quad (14)$$

Where $W_{u,}$ b_u, $W_{I,}$ b_I and Wu, represents weight matrix and the bias vectors for the user-item auxiliary attention functions accordingly. The symbol (Φ) represents the non-linear activation functions, h_u and h_I are the weight vectors that aggregate the output layers of the attention networks to obtain the final attentions weight.

I. Prediction of the Model

After the convergence of the model, we employed a three-step process for predictions. Firstly, in Step 1, noise *(/z/)* was added to the vector of the sparse rating of users *T* times to obtain R_T. This step helps to incorporate noise present in the user-item rating matrix. In Step 2, initial predictions $\hat{R}_0$ were generated in the latent vector space using the conditional vector R_T. Finally, in Step 3, we applied denoising ($T' < T$) times to get the final prediction outcomes ($R_{T-T'}$). This approach aims to preserve personalized information while retaining some of the noise introduced in the latent vector space. This strategy is beneficial for capturing more user preferences and effectively enhancing the personalized performance of the CRRS.

IV. Experimental Setup

The datasets and metrics utilized to evaluate the performance of the proposed model are described in this section. The model is compared with other state-of-the-art methods after conducting the experiments.

A. Dataset Preparation

The experiments were conducted using Book-crossing and Amazon datasets, these datasets provide the necessary features to test the efficiency of the proposed model. Statistical details of the datasets are summarized in Table I. The table provides details of datasets (Amazon and Book-crossing), with a focus on their auxiliary information features utilized to enhance recommendation algorithms. Each of the datasets was randomly divided into two subsets: 80% for the training set and 20% for the testing set. The experiments involved training the model with the training data, while the testing set was utilized to validate the efficiency of the recommendations, optimize and adjust parameters of the model.

TABLE I. STATISTICS OF THE DATASETS

Dataset	Ratings	Users	Items	Sparsity	Auxiliary Features
Amazon	1,000,209	3,706	6,040	95.55%	Price, product name, date, brand
Book-crossing	54,694	2,274	3,211	99.25%	Country, city and age

- Clarifications of the Datasets

From Table I, the Amazon dataset has over one million ratings matrix, 3,706 users, and 6,040 items, with 95.55% sparsity. The meaning of this is that only 4.45% of the possible user-item interactions have ratings. Auxiliary data, which includes price, product name, date, and brand, is useful for content-based recommendations. Book-crossing dataset is smaller, with only 54,694 ratings matrix, 2,274 users, and 3,211 items. This dataset has a very high 99.25% sparsity, which means that only 0.75% of all possible user-item ratings are present. Auxiliary data, which includes age, country, and city will help in more personalized recommendations. The *Amazon dataset is considered to be the source domain, while Book-crossing was utilized as the target domain.*

B. Metrics Utilized for the Evaluation

The four commonly utilized evaluation metrics are Precision, Recall, MAE, and RMSE, are utilized to evaluate the performance of the proposed model.

- Precision**:** Precision reflects how the proportions of items recommended are relevant to the user as in Eq. (15):

$$\text{Precision} = \frac{\sum \text{TP}}{\sum \text{TP} + \sum \text{FN}} \tag{15}$$

- Recall**:** It measures the proportion of relevant item that are successfully recommended as in Eq. (16) :

$$\text{Recall} = \frac{\sum \text{TP}}{\sum \text{TP} + \sum \text{FP}} \tag{16}$$

- Mean absolute Error (MAE): This measures the average magnitude of the errors between predicted ratings as in Eq. (17):

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} y_i - \hat{y}_i \tag{17}$$

- Root Mean Square Error (RMSE): It is utilized to evaluate accuracy of the prediction in RS and machine learning as in Eq. (18):

$$\text{RMSE} = \sqrt{\sum_{i=1}^{T} \frac{(\hat{y}-y)^2}{T}} \tag{18}$$

C. Validation of Models with Baselines

To validate the effectiveness of the proposed model, we selected seventeen (17) recommender system models for comparative performance analysis. The baselines include cross-domain recommender systems models, multi-task recommender systems models, and adversarial learning-based recommender systems models, which are related to our recommendations design.

1) Cross-domain recommender systems models.

- DML [52]: Dual Metric Learning introduces a unique latent metric mapping function to derive user preferences by maintaining relationships among users across domains.
- DASL [53]: The model incorporates two innovative components, Dual Embedding and Dual Attention, to facilitate cross-domain recommendations.
- CCCFNet [54]: The Cross-domain Content-boosted Collaborative Filtering Neural Network combines collaborative filtering and content-based filtering using a unified multi-view neural network through factorization.
- CoNet [55]: Collaborative Cross Networks supports knowledge transfer across domains by introducing cross-connections between the base networks.
- EMCDR [56]: The Embedding and Mapping method for Cross-Domain Recommendation (EMCDR) employs a multi-layer perceptron to model the nonlinear mapping function between domains.
- SSCDR [57]: The Semi-Supervised Cross-Domain Recommendation (SSCDR) model learns latent representations for users and items while training a mapping function to capture distance relationships across domains.

2) Multi-task recommender systems models.

- Cross-Stitch [58]**:** The model integrates activations from multiple neural networks and the model learns the best balance between shared and task-specific representations which results to a significant performance boost for categories with limited training data.

- MMOEWD [61]**:** model refines the MMOE structure through soft-parameter sharing techniques. The model optimizes multiple ranking objectives and addresses selection biases by employing a Wide and Deep methodology.
- MMOE [59]**:** It extends the MoE framework. It allows expert sub models to be shared across tasks. The approach enhances trainability by adapting varying randomness in the model initialization and data.
- DARec [63]**:** The Deep Domain Adaptation Recommendation model applies domain adaptation and multi-task learning to deliver cross-domain recommendations. The model identifies and transfers patterns from rating matrices without relying on auxiliary information.

3) Adversarial learning-based recommender systems models.

- RecGAN [60]**:** The model utilizes gated recurrent unit cells to capture latent features of users and items from both short-term and long-term temporal profiles, enhancing recommendation relevance.
- PD-GAN [62]**:** This model generates diverse yet relevant recommendations by sequentially sampling from a DPP kernel matrix. The adversarial training with a discriminator helps recognize or differentiate between generated recommendations and actual user interactions.
- RecSys-DAN [64]**:** This model tackles the data sparsity challenge by learning transferable latent representations for the user, item, and the interactions through adversarial training.
- DAAN [65]**:** The DAAN model combines collaborative filtering through deep adversarial domain adaptation with matrix factorization.
- DSAP-AL [35]**:** This model integrates matrix factorization and adversarial learning to align user and item latent factor spaces.
- CDR-HA [66]**:** The model enhances recommendation accuracy and mitigates data sparsity in the target domain by integrating heterogeneous information network-based adversarial learning with cross-domain adversarial techniques.
- ACDR [67]: The study proposes an Adversarial Cross Domain Recommendation (ACDR) model. The model utilizes adversarial learning for better user embeddings. The model improves recommendation performance on sparse datasets.

Table II highlights the values of each hyperparameter utilized for the proposed model.

TABLE II. HYPERPARAMETER AND THEIR VALUES

Hyperparameters	**Parameter values**
Generator learning rate	0.0001
Discriminator learning rate	0.0001
Latent dimension	128
Batch size	64
Number of epochs	20
Embedding size	100
Dropout rate	0.2
Learning rate decay	0.1
Optimizer	Adam
Activation functions	ReLU
Domain adaptation learning rate	0.0001

V. EXPERIMENTAL RESULTS AND ANALYSIS

A. Results

This subsection shows the experimental results of the proposed model. The experiment was conducted on Book-crossing and Amazon datasets, and the model was compared with the baseline using evaluation metrics: RMSE, MAE and Precision, Recall with 20 epochs on each metric as shown in Fig. 3 to Fig. 6. The proposed AUXIGAN model is the most effective model across all metrics, making it the top choice for high-accuracy recommendations on the datasets. Table III and Table IV show that the proposed AUXIGAN model outperforms the baseline models across all metrics, which makes it the most accurate model for recommendations on the datasets.

TABLE III. PERFORMANCE ON AMAZON (MUSIC) - BOOK-CROSSING

Model	**Amazon (Music) - Book-crossing**			
	RMSE	***MAE***	***Precision***	***Recall***
DML	0.2205	0.1706	0.8583	0.9595
DASL	0.2202	0.1705	0.8595	0.9597
CCCFNet	0.2639	0.1841	0.8102	0.8872
CoNet	0.2305	0.1892	0.8328	0.8990
EMCDR	0.2192	0.1789	0.8516	0.9307
SSCDR	0.2295	0.1744	0.8520	0.9341
Cross-Stitch	0.2465	0.1972	0.8339	0.9111
MMOE	0.2388	0.1806	0.8444	0.9234
MMOEWD	0.2332	0.1772	0.8502	0.9278
DARec	0.2376	0.1796	0.8495	0.9318
RecSys-DAN	0.2665	0.1980	0.8287	0.9220
PD-GAN	0.2693	0.2002	0.8260	0.9231
RecGAN	0.2708	0.2007	0.8260	0.9198
DAAN	0.2672	0.1982	0.8291	0.9242
DSAP-AL	0.2663	0.1979	0.8288	0.9238
CDR-HA	0.2679	0.1991	0.8274	0.9233
ACDR	0.1347	0.0995	0.8972	0.9790
AUXI-GAN	**0.0998**	**0.0774**	**0.9666**	**0.9938**

TABLE IV. PERFORMANCE ON AMAZON (MOVIES) - BOOK-CROSSING

Model	**Amazon (Movies) - Book-crossing**			
	RMSE	***MAE***	***Precision***	***Recall***
DML	0.2683	0.2093	0.8714	0.9089
DASL	0.2681	0.2088	0.8717	0.9095
CCCFNet	0.2711	0.2116	0.8664	0.9046

Model	Amazon (Movies) - Book-crossing			
	RMSE	***MAE***	***Precision***	***Recall***
CoNet	0.2685	0.2078	0.8722	0.9046
EMCDR	0.2704	0.2092	0.8729	0.9009
SSCDR	0.2699	0.2100	0.8677	0.9021
Cross-Stitch	0.2791	0.2150	0.8605	0.8929
MMOE	0.2778	0.2127	0.8633	0.8946
MMOEWD	0.2723	0.2111	0.8693	0.8998
DARec	0.2701	0.2095	0.8717	0.9013
RecSys-DAN	0.2769	0.2154	0.8675	0.8979
PD-GAN	0.2796	0.2165	0.8646	0.8958
RecGAN	0.2803	0.2187	0.8627	0.8944
DAAN	0.2722	0.2127	0.8719	0.9005
DSAP-AL	0.2736	0.2138	0.8708	0.8998
CDR-HA	0.2754	0.2166	0.8683	0.8976
ACDR	0.2431	0.1919	0.8846	0.9237
AUXI-GAN	**0.1350**	**0.0908**	**0.9031**	**0.9531**

The performance of experiments is presented in Fig. 3 to Fig. 6. We have the following findings:

Fig. 3 presents evaluation metrics over 20 epochs for the Amazon (Music) - Book-crossing datasets. *Precision* improves over epochs, which indicates better accuracy in recommending relevant items. *Recall* consistently increases, and it reflects improved capacity to capture relevant recommendations. *MAE* remains stable, which suggests a low mean error between the predicted and actual ratings. *RMSE* decreases steadily, which shows reduced prediction errors over the epochs. This demonstrates performance improvements across the evaluation metrics, which indicates the model's effectiveness.

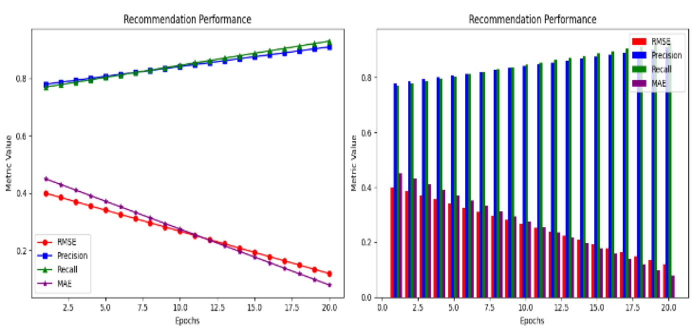

Fig. 3. Performance of proposed model on Amazon (Music)-Book-crossing.

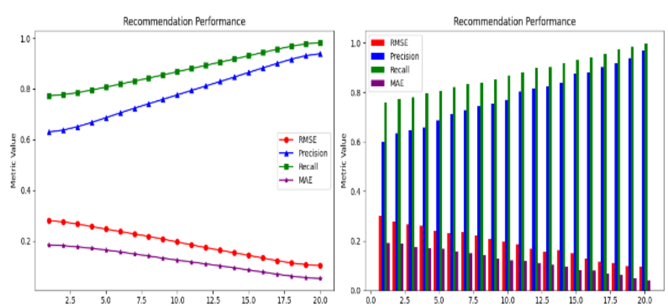

Fig. 4. Performance of proposed model on Amazon (Movie)-Book-crossing.

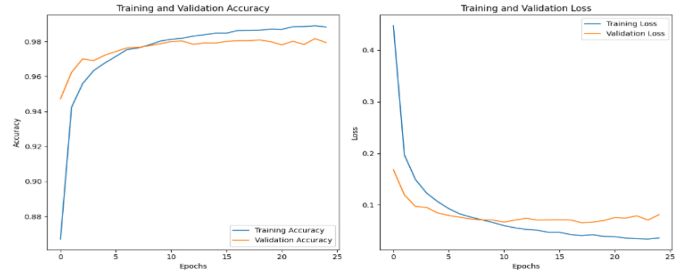

Fig. 5. Training, validation accuracy and validation loss.

Fig. 4 illustrates the evaluation metrics over 20 epochs for the Amazon (Movie) – Book-crossing datasets. The key observations are: *Precision* improves consistently, which indicates better accuracy in recommendations over time. *Recall* increases steadily, which shows improved coverage of the relevant recommendations. *MAE* decreases gradually, demonstrating reduced mean error between predicted and actual ratings. *RMSE* decreases over 20 epochs, indicating less prediction errors. The model demonstrates improved performance across all the evaluation metrics, and Fig. 5 shows the training, validation accuracy and validation loss results.

B. *The Parameter Settings and Model Training*

The relevant hyperparameters used in the proposed model are as follows: we conducted the experiments with Top-N recommendations, whereby N represents the number of items recommended to the users; the parameters are shown in Table II.

C. *Baseline Comparison*

The proposed model demonstrates a better performance compared to state-of-the-art methods across all metrics. Table III and Table IV summarize the results, which indicate that the proposed model not only outperforms the baselines but also opens new opportunities to address the challenges of data sparsity on CDRS.

D. *Data Sparsity Performance*

From the proposed model, as shown in Table IV and Table V, we discovered that the model significantly mitigated data sparsity problems by incorporating auxiliary information into the GANs-based CDRS. In the data sparsity problem, there are improvements in recommendation accuracy, underscoring the influence of auxiliary information to enhance recommendation performance when there is limited data.

VI. Ablation Experiments

As highlighted in Section V, the proposed model demonstrates significant improvements compared to the selected baseline models. These enhancements stem from the innovative design of the model, which integrates auxiliary information into the GAN-based model recommendation techniques. In this segment, we perform an ablation study to validate the contribution of auxiliary information into the proposed model. We removed auxiliary information from the model and used only the rating matrix of the users-items.

The following variations were tested to examine the influence of the auxiliary information:

- Model A (without auxiliary information): The model excludes auxiliary information, which relies solely on GAN-generated interactions.
- Model B (with auxiliary information): The model includes auxiliary information with GAN-generated interactions.

TABLE V. ABLATION STUDY RESULTS ON AMAZON

Model	Amazon (Movie) - Book-crossing datasets			
	RMSE	***MAE***	***Precision***	***Recall***
Model A	0.1980	0.1181	0.9020	0.9720
Model B	**0.0998**	**0.0774**	**0.9666**	**0.9938**

As shown in Table V, the proposed model proves robust performances in transferring knowledge across domains, with increase in recommendation accuracy for data sparsity when auxiliary information is incorporated into the model. Fig. 6 shows the experiments on the Book-crossing and Amazon datasets with evaluation metrics (RMSE, MAE, Precision and Recall) respectively.

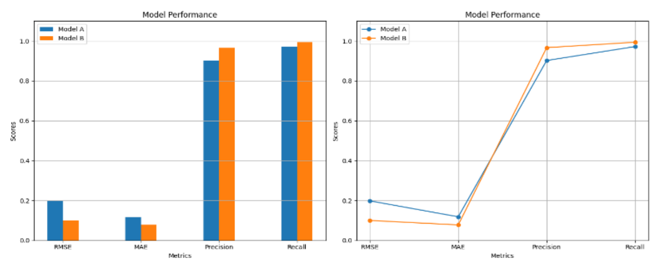

Fig. 6. Ablation results of RMSE, MAE, Precision and Recall on Amazon (Music)-Book-crossing datasets.

VII. LIMITATIONS AND FUTURE DIRECTIONS

This section presents the limitations of the proposed model and future directions that need to be explored.

A. Limitations

1) High computational complexity. Training GANs, especially when integrating auxiliary information, requires significant computational resources and time.

2) Overfitting. With the limited data or excessive auxiliary information, the model may encounter a problem of overfitting in the training set.

3) Hyperparameter sensitivity. The GANs model may require careful tuning of hyperparameters, such as learning rate, embedding dimensions, or loss functions, which may not be practical for all circumstances.

4) Inconsistent quality. The auxiliary information may be noisy, incomplete, or inconsistent.

B. Future Directions

Future directions may focus on integrating more complex auxiliary data and temporal dynamics to further enhance the recommendation accuracy. Since our findings indicates that GAN-based CDRS, when enhanced with auxiliary information can effectively capture user preferences, more personalized and accurate recommendations across different domains, therefore future studies may hybridize the generative AI models such as GANs and VAEs with the incorporation of auxiliary information for better performance.

VIII. CONCLUSION

Our findings from the conducted experiments highlight the positive influence of auxiliary information on GAN-based CDRS; the proposed model demonstrates improvements in data sparsity, recommendation accuracy, and robustness. Auxiliary information not only enhances the quality of recommendations but also enables the model to generalize across domains by addressing challenges of data sparsity. The integration of auxiliary information on GAN-based CDRS achieved a more comprehensive representation of user and item preferences. The adversarial training framework effectively generates realistic user-item interactions, addressing data sparsity issues. The incorporation of auxiliary information assisted the GAN-based model to capture more details about users' preferences and item features. This enhancement led to significant improvements in core recommendation metrics, with auxiliary-enhanced models achieving gains in Precision, recall, RMSE and MAE across the two datasets. These results significantly showed that auxiliary information aids GAN-based models to better understand and represent user-item interactions, especially in the data sparsity problem. This research also encourages more exploration into transfer learning techniques within CDRS. The findings suggest that incorporating auxiliary information could be an introductory approach for the development of advanced multi-domain recommendation solutions on GAN-based models by extending beyond traditional RSs techniques. To the best of our knowledge, auxiliary information has not been integrated into GANs-based CDRS. Previous authors believed that generative AI models such as GANs had the ability to generate new content or items, but GANs model still depends on the data or information it is been trained on. GANs have the capability to generate new, more personalized, accurate, and robust recommendations with the incorporation of auxiliary information on CDRS.

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