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Adaptive domain transfer for persuasive user and item modeling and cold-start alleviation in next-basket recommendation systems

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Abstract

The Adaptive Persuasive User/Item Information Extraction and Cold-Start Mitigation (APIC) framework is designed to tackle key challenges in next-basket recommendation systems, specifically data sparsity, cold-start scenarios, and evolving customer preferences. Conventional Next Basket Recommender Systems (NBRS) often overlook the complex relationships both within and across shopping baskets, as well as the real-time influence of social media. To address these gaps, this study introduces APIC—a comprehensive and resilient NBRS model.

APIC leverages advanced embedding techniques to enrich the representation of user-item interactions and integrates real-time social media data to enhance recommendation accuracy. To further combat cold-start issues for new users and products, the framework employs domain adaptation strategies. In addition, APIC incorporates an improved Particle Swarm Optimization (PSO) algorithm inspired by the Rainbow Eucalyptus phenomenon, which optimally balances exploration and exploitation during the learning process. This advancement significantly boosts the performance of the attention-based Gated Recurrent Unit (GRU) by enabling it to more effectively capture both localized and broader user behavior patterns.

The effectiveness of APIC is validated on the IJCAI-15 and TaFeng datasets, demonstrating superior performance in comparison to standard NBRS models, particularly in terms of F1-score and NDCG metrics. These results highlight APIC's potential to deliver highly relevant, timely, and precise recommendations, positioning it as a new benchmark for NBRS effectiveness. Ultimately, APIC's innovative integration of social media insights and dynamic optimization techniques represents a meaningful advancement in recommendation technology, offering a powerful tool for modern e-commerce platforms.

Keywords: Deep Learning; Particle Swarm Optimization; Next Basket Recommendation; Recommender Systems; Influencer User.

1. Introduction

In the contemporary digital market, recommender systems have become indispensable for providing a more personalized user experience by recommending preferential-based item sets to users (Arthur, Zhou, Mantey, et al., 2022; Nasir & Ezeife, 2023). These recommendation systems have been widely adopted in e-commerce, streaming services, social media applications, and other online services that offer a vast array of content to users. By providing specific suggestions to users, these systems enhance user interaction, satisfaction, and loyalty. Among various types of recommendation tasks, next-basket recommender systems (NBRS) (Deng et al., 2024; Sun et al., 2023a) represent a significant advancement. NBRS are used to predict the likely combinations of items that customers will purchase in

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subsequent shopping sessions, aiding in understanding buying patterns and developing strategies for cross-selling and upselling.

Next-basket recommender systems (NBRs) face several drawbacks, primarily due to data sparsity and cold-start challenges, which hinder the system's ability to generate precise and convincing recommendations (Arthur, Zhou, Osei-Kwakye, et al., 2022; Sun et al., 2023a). Although existing methods attempt to address these issues through contrasting couplings and item-user associations, they are not particularly effective in extracting and utilizing persuasive information (Mao et al., 2024). The reliance on static and assumption-based extraction does not adequately reflect the actual and real-time influence of users and items' popularity, leading to poor recommendations (Liu et al., 2024). Moreover, the approach to the cold-start challenge remains insufficient; new users and items often receive generic, less personalized recommendations due to the lack of historical interaction data. This results in lower user satisfaction and engagement, as the system takes time to gather enough data to make meaningful recommendations (Mao et al., 2024; Zeng et al., 2024). To overcome these limitations, this research adopts Social Media Influence Theory (SMIT) as a solution to dynamically extract and utilize persuasive user and item information. By leveraging real-time social media data, the system can continuously update influence scores based on social media interactions, such as likes, shares, comments, and follower growth. This dynamic approach ensures that the persuasive information reflects current trends and user behaviors, thereby enhancing the relevance and authenticity of the recommendations.

Consider an e-commerce scenario where a user has recently purchased a basket of items such as [tomato, pumpkin], followed by another basket containing [candy, chocolate, cookie]. A traditional NBR model might identify the relationship between these items and suggest snacks like chips for a potential party setup, given that the items are all food-related and the final basket constitutes only snacks. However, this approach fails to consider the dynamic and real-time nature of user influence and item popularity, often relying on static assumptions that do not adapt quickly to changes in user behavior or emerging trends.

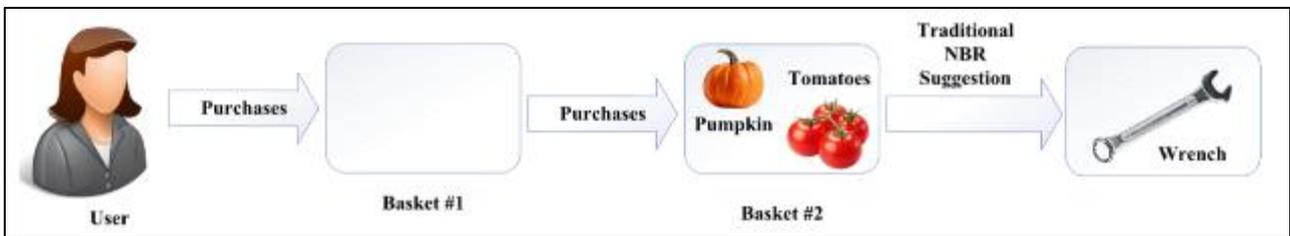


Figure 1 Traditional Next Basket Recommendation Process

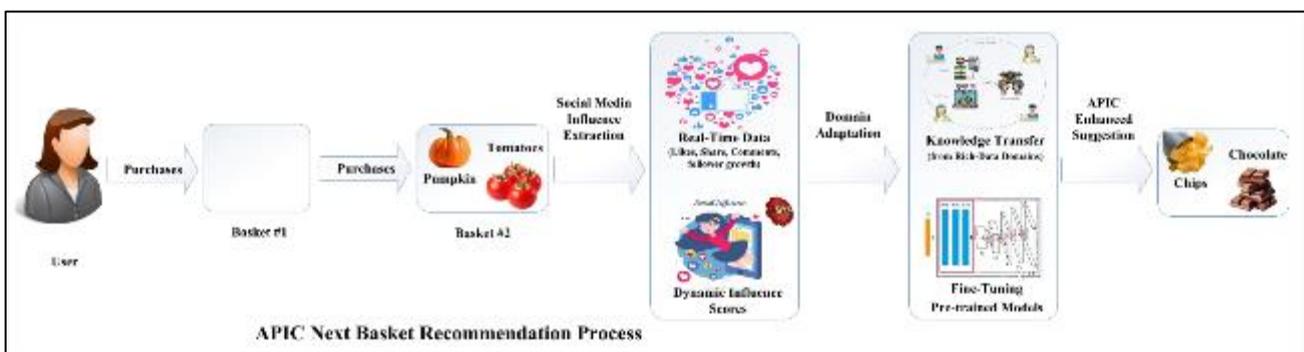


Figure 2 APIC Next Basket Recommendation Process

To address these limitations, the APIC model integrates dynamic persuasive information extraction from social media interactions and domain adaptation techniques. For instance, if a user purchases (pumpkin, candy, chocolate), an APIC-enhanced system can infer that the user may be preparing for Halloween based on social media trends indicating a spike in Halloween-related posts and activities. Hence, the system would suggest items such as (chips, toffee apple) for the next basket, considering the item associations within and across baskets, influenced by social factors in real-time. In addition, APIC addresses the cold-start challenge by using domain adaptation techniques. This enables the transfer of knowledge from dense to sparse areas, providing accurate recommendations for new users and items, even when

information about them is limited. For example, if a new user is interested in Halloween products but has not made any previous purchases, the APIC model can use patterns from other similar users in an established domain to offer appropriate recommendations. By incorporating social media influence and applying domain adaptation, the APIC model enhances the relevance and reliability of next-basket recommendations, offering both new and returning users timely and convincing suggestions based on current trends and user behaviors. This approach not only solves the cold-start problem but also improves the overall recommendation quality, making it a powerful solution for today's e-commerce recommendation systems.

1.1. Gap Analysis

Despite the progress made in collaborative filtering (CF), sequential recommendation methods, and next-basket recommendation systems (NBRS), several gaps remain in the literature. Traditional approaches to user- and item-based collaborative filtering are prone to scalability and sparsity issues. They are also affected by the cold-start problem, where users or items with limited historical data are likely to receive inaccurate recommendations (Abdalla et al., 2023; Jiang et al., 2022; Singh et al., 2022). More advanced CF models, such as Neural Collaborative Filtering (NCF) and Graph Neural Networks (GNNs), have enhanced CF by integrating deep learning and graph structures into the models (Hu et al., 2024; Sun et al., 2023a; Xu et al., 2023). However, these models still primarily focus on static user preferences, failing to adequately capture the dynamic nature of user behaviors over time. Sequential recommendation methods improve on traditional CF by capturing temporal dynamics in user behavior. Early approaches, like Markov Chains (MC), and more advanced models using Long Short-Term Memory (LSTM) networks and recurrent neural networks (RNNs), address short-term and long-term user preferences (Duan et al., 2023; Nasir & Ezeife, 2023). Advanced techniques, such as the Hybrid Recurrent Model (HRM) and models incorporating attention mechanisms, have further refined sequential recommendations (Cheng et al., 2024; Liu, 2024). Despite these advancements, these methods often struggle to capture complex item relationships within baskets, which is essential for accurate next-basket recommendations.

Next-basket recommendation systems aim to predict sets of products that customers will likely purchase together in their next shopping session. Hybrid models like FPMC (Osei-kwakye et al., 2022) and GenRec (Sun et al., 2023b) integrate various techniques to capture item correlations and sequential dependencies. However, traditional and hybrid NBR methods often treat items within a basket as independent, failing to capture the nuanced interactions that drive user purchasing behavior. More detailed methods, including DNNTSP (Li et al., 2023), HBR (Yannam et al., 2023), SeqRank (Mao et al., 2024), HAEM (Wang & Cao, 2021), and HCPIM (Arthur, Zhou, Osei-Kwakye, et al., 2022), have improved performance by exploiting inter- and intra-basket user-item relations, but the external social effects are not well incorporated. The incorporation of social media influence into recommender systems has successfully enhanced recommendation quality by utilizing user interaction data (Dwivedi et al., 2023). Models that adopt Social Media Influence Theory (SMIT) can dynamically search and incorporate social media data about users and their trends (Rendle et al., 2010; Zhang et al., 2021). Nonetheless, most current NBR models are still unable to fully realize the benefits of using social media to influence user preferences in real-time.

To overcome the aforementioned limitations, the APIC framework has been developed to utilize deep learning, attention, social media power, and dynamic optimization for user/item information extraction and to solve the cold-start problem. This approach seeks to improve the accuracy, relevance, and recency of subsequent basket recommendations, establishing a new benchmark for recommender systems.

The major contributions made by this work are stated as follows:

- To overcome the data sparsity challenge in NBRS, the concept of Social Media Influencer is utilized to capture persuasive users/items as an auxiliary data source. This integration makes the recommendations not only timely and relevant but also in tune with current user trends and behaviors, making the NBRS more persuasive and contextual. To the best of our knowledge, this is the first work to incorporate social media data into NBRS to address data scarcity.
- APIC employs Transfer Learning and Domain Adaptation strategies to effectively mitigate the cold-start problem. By transferring knowledge from rich-data domains to sparse-data domains, the framework ensures accurate recommendations for new users and items, thereby addressing one of the most significant challenges in NBRSs.
- We have enhanced the Particle Swarm Optimization algorithm to improve the attention-based Gated Recurrent Unit within the Recommendation Generation Layer. The improved PSO dynamically adjusts inertia weight and performance-based coefficients, effectively balancing exploration and exploitation. This combination significantly enhances the system's ability to capture both local and global user behavior patterns, resulting in superior recommendation performance. The dynamic adjustment mechanisms and

performance-based coefficients within the PSO ensure robust optimization, contributing to the overall effectiveness of the APIC framework in delivering accurate and relevant next-basket recommendations.

- We conducted an extensive performance evaluation of the APIC framework on two benchmark datasets, namely IJCAI-15 and Ta-Feng. The results demonstrate that APIC significantly outperforms benchmark NBRS algorithms concerning Normalized Discounted Cumulative Gain and F1-score.

2. Literature Review

The field of recommender systems has experienced significant advancements, particularly in collaborative filtering, sequential recommendation methods, and next-basket recommendation (NBR) techniques. These advancements aim to address current NBRS limitations such as the cold-start problem, data sparsity, and the need to capture dynamic customer preferences and behaviors. Additionally, the integration of social media influence has emerged as a powerful factor in enhancing recommendation quality.

2.1. Collaborative Filtering Recommendation (CRF)

Collaborative Filtering Recommendation (CRF) remains a foundational method in recommender systems. Traditional CRF methods, including user- and item-based techniques, predict user preferences based on the similarities between users or items (Abdalla et al., 2023). However, these methods often face scalability and sparsity issues, limiting their effectiveness in large-scale applications. For instance, when new users or items are introduced, CF models struggle to make accurate predictions due to the lack of historical data, a situation commonly referred to as the cold-start problem (Jiang et al., 2022; Singh et al., 2022).

Recent developments have integrated deep learning to overcome these limitations. Neural Collaborative Filtering (NCF) (Deng et al., 2024; Rendle et al., 2020) employs deep networks to extract intricate item-user associations, offering a flexible and powerful alternative to traditional matrix factorization methods. Graph-based CF models, such as Graph Neural Networks (GNNs), model user-item interactions as graphs, capturing intricate relationships and improving recommendation accuracy (Tan et al., 2024; Wang et al., 2015; Xu et al., 2023). These advancements have significantly enhanced the capability of CF models, yet they still primarily focus on static user preferences without adequately addressing the constantly changing nature of customer behaviors over time.

2.2. Sequential Recommendation

To learn the latent short-term dynamics of user behavior, sequential recommendation methods have been developed. Early approaches, like Markov Chains (MC), predict the next item based on recent interactions, capturing local sequential patterns but often neglecting long-term dependencies (Duan et al., 2023; Nasir & Ezeife, 2023). This limitation is critical in scenarios where user preferences evolve, requiring models to account for both short- and long-term behaviors.

To address these limitations, RNNs and their variants, such as LSTM networks, have been employed to capture long-term sequential patterns in user behavior (Ahmed et al., 2023; Bansal & Baliyan, 2023). More complex architectures, like the Hybrid Recurrent Model (HRM), combine RNNs with other methods to learn both local and global dependencies. HRM improves upon fundamental RNN architectures by introducing max pooling procedures to emphasize essential item interactions in sequences (Wang et al., 2015). In the most recent works (Tao et al., 2023), the model enhances sequential recommendations by integrating item trend data from the user's interaction history, using self-attention and gated graph neural networks to boost item representation. Additionally, attention mechanisms have been integrated to focus on the most significant parts of historical data, enhancing sequential learning (Cheng et al., 2024; Liu, 2024). Nevertheless, existing sequential recommendation approaches may face challenges in modeling intricate item dependencies within baskets for the next-basket prediction task.

2.3. Next-Basket Recommendation

Next-basket recommender systems (NBRS) are designed to forecast the combinations of products that a customer will likely order during their next shopping session. Most previous works in NBR were based on matrix factorization (MF) and Markov Chains (MC); however, these techniques are unable to address the intricate relationships among items within a basket (Yang et al., 2020). These methods generally consider items in a basket as non-correlated, overlooking the interrelations between items that can influence user purchases.

New developments have proposed the use of combined methods to enhance NBR outcomes. The Factorizing Personalized Markov Chains (FPMC) model, which incorporates both user preferences and sequential patterns by

combining MF with MC, improves recommendation quality (Rendle et al., 2010). Newer models, like GenRec (Sun et al., 2023b), use autoregressive decoders to generate basket recommendations item-wise, capturing complex item interdependencies. These models overcome the drawbacks of conventional NBR methods by reflecting the intricate relations between items and their sequential occurrences. Similarly, HBR (Yannam et al., 2023) applies an autoencoder to learn context information and RNN to model global sequential patterns, achieving better NBR results based on implicit user feedback. DNNTSP (Li et al., 2023) divides repeat and explore items, using new metrics to evaluate and explain the performances and developments of benchmark NBRS algorithms. SeqRank (Mao et al., 2024) leverages a heterogeneous graph structure and a query-based recommendation model that integrates sequential buying orders and user feedback in the form of ratings to predict future purchase behavior, capturing both time-dependent features of e-commerce users.

Another notable approach is HAEM (Wang & Cao, 2021), which incorporates user-item associations within and across baskets, along with customer responses, to refine recommendations. HAEM demonstrates improved performance by considering comprehensive interaction patterns within and across baskets. Additionally, HCPIM (Arthur, Zhou, Osei-Kwakye, et al., 2022) has enhanced user profiles, enabling precise recommendations even for new users or items by integrating contrasting item-user interactions. Despite these advancements, NBR models often overlook the potential influence of external factors, such as social media interactions, particularly from influencers, on user preferences.

2.4. Social Media Influence in Recommender Systems

The integration of social media influence in recommender systems has emerged as a potent enhancement to recommendation quality. Social media platforms generate vast amounts of user interaction data that can be leveraged to understand user preferences and behaviors. Influencer-based recommender systems utilize influencer data to build models that increase the persuasiveness and applicability of recommendations (Dwivedi et al., 2023). These systems gather current social media data, which is more dynamic and encompasses a broader range of user preferences than data used in classical models. Recommendation models that belong to the social media influence category, including those based on Social Media Influence Theory (SMIT), actively acquire and process actual social media data within the recommendation workflow.

This strategy addresses a more comprehensive set of user preferences and trends, thereby providing better and more timely suggestions (Sharma et al., 2024; Zhang et al., 2021). The integration of real-time data is especially critical in the e-commerce industry, where consumer behavior may change frequently depending on current social media trends or influencer recommendations. To overcome the limitations in existing systems, this research proposes the Adaptive Persuasive User/Item Information Extraction and Cold-Start Mitigation (APIC) framework. APIC addresses the data sparsity problem in NBRS by incorporating deep learning, attention mechanisms, social media influence, and dynamic optimization.

3. Preliminaries

3.1. Problem Definition of APIC Model

This section highlights the fundamental problem for the proposed system “Adaptive Persuasive User/Item Information Extraction and Cold-Start Mitigation in Next Basket Recommender Systems Using Domain Adaptation”: to increase the recommendation accuracy and its relevance to the user’s needs by adaptively obtaining persuasive information about the user and the item, and to solve the cold-start issue with the help of domain adaptation.

First, assume a customer has bought baskets chronologically, containing items they have interacted with over time. Let u and $U = [u_1, u_2, \dots, u_{|U|}]$ represent a user and the entire user set, respectively. Let i and $I = [i_1, i_2, \dots, i_{|I|}]$ represent an instance of an item and bundled items, respectively. Let R_U and R_I denote the user-user interactions and the item-item relations, respectively. This relation between the user and item can be denoted as $R_{UI} = [u \in U, i \in I]$ and y_{ui} can be feedback given by the user towards the item. Furthermore, the consecutive baskets of user u are represented such that every basket B_t^u is the set of items that user u has purchased at the period $t (\in [1, T])$ and B_t^u defines a non-blank member of I , that is, $B_t^u \subseteq I$.

The persuasive information, derived from real-time social media interactions and influence scores, is dynamically extracted and integrated with R_U, R_I and R_{UI} from the historical sequential basket purchases S^u .

The purpose of the NBRS is to recommend the $top - K$ products for each of the succeeding sequential target baskets $[B_{(t+1)u}, \dots, B_{(t+p)u}]$, to user u by forecasting a customized rating R with its item set, starting with $R_{UI} \subseteq I^2$ at the initial time.

To address the cold-start problem, the system employs Transfer Learning, specifically using Domain Adaptation techniques. These techniques enable the model to transfer knowledge from well-established domains with rich data to the target domain with sparse data. By optimizing the parameters of already trained models on related datasets and applying adversarial domain adaptation, it is possible to provide precise recommendations for new users and items with limited historical interaction data. Through the use of dynamic persuasive information extraction based on the Social Media Influence Theory and the improvement of the cold-start issue through Domain Adaptation in Transfer Learning, the proposed system aims to provide the most suitable and effective recommendations for both new and frequent users. This approach improves the performance of next-basket recommendation systems and addresses the limitations of static information extraction.

3.2. The Formal Definition of Influencer as Defined by the Theory of Social Media Influence (SMIT)

Based on SMIT, an influencer is a user who can alter other users' behaviors and decisions through activities performed on social media platforms. This influence can be measured in terms of likes, shares, comments, and follower increases. The mathematical model for an influencer includes these metrics to provide a holistic score of the influencer.

Let $U = [u_1, u_2, \dots, u_{|U|}]$ denote the set of all users, $I = [i_1, i_2, \dots, i_{|I|}]$ signify the set of all items, and t denote the duration of analysis. For a user $u \in U$, the following metrics are defined:

- $L(u, t)$: The like count of user u at a given time t .
- $S(u, t)$: The total shares created by the user u at a given time t .
- $C(u, t)$: The total comments made by user u on posts at time t .
- $F(u, t)$: The increase in the number of followers of user u at time t .

We model the influence score $IS(u, t)$ of a user u at time t as the weighted sum of these metrics:

$$IS(u, t) = w_L \cdot L(u, t) + w_S \cdot S(u, t) + w_C \cdot C(u, t) + w_F \cdot F(u, t) \dots \dots \dots \quad 1$$

where the variables w_L, w_S, w_C, w_F are the weights that are given to likes, shares, comments, and followers respectively. These weights can be assigned depending on the ratio of one metric to another in the scenario of the recommendation system. Often, they are adjusted in the course of model training to achieve the best working parameters of the system. In this way, the influence score $IS(u, t)$ that is calculated based on these metrics allows quantifying the level of a user's impact on social media. Higher influence score is attributed to key influencers, these people have the ability to sway the other users' actions and decisions.

4. The Proposed Theoretical Framework

The proposed 'Adaptive Persuasive User/Item Information Extraction and Cold-Start Mitigation' (APIC) framework improves the next basket recommendations by incorporating dynamic persuasive information and also tackles the cold-start challenge via using domain adaptation. These are the Embedding Layer (EL) mapping user and item data unto a lower-dimensional space, Social Media Influence Layer (SMIL) that integrates real-time trends from social media, and the Integrated Influence and Domain Adaptation Layer (IIDAL) that transfers knowledge from the domains with abundant data to the ones with scarce data. It also includes a Sequential Learning Layer (SLL) to model the temporal dependencies of the user's interactions using LSTM networks, and a Recommendation Generation Layer (RGL) which applies an Attention-based GRU network with the enhanced PSO to balance the accuracy, diversity, and novelty of the recommendations.

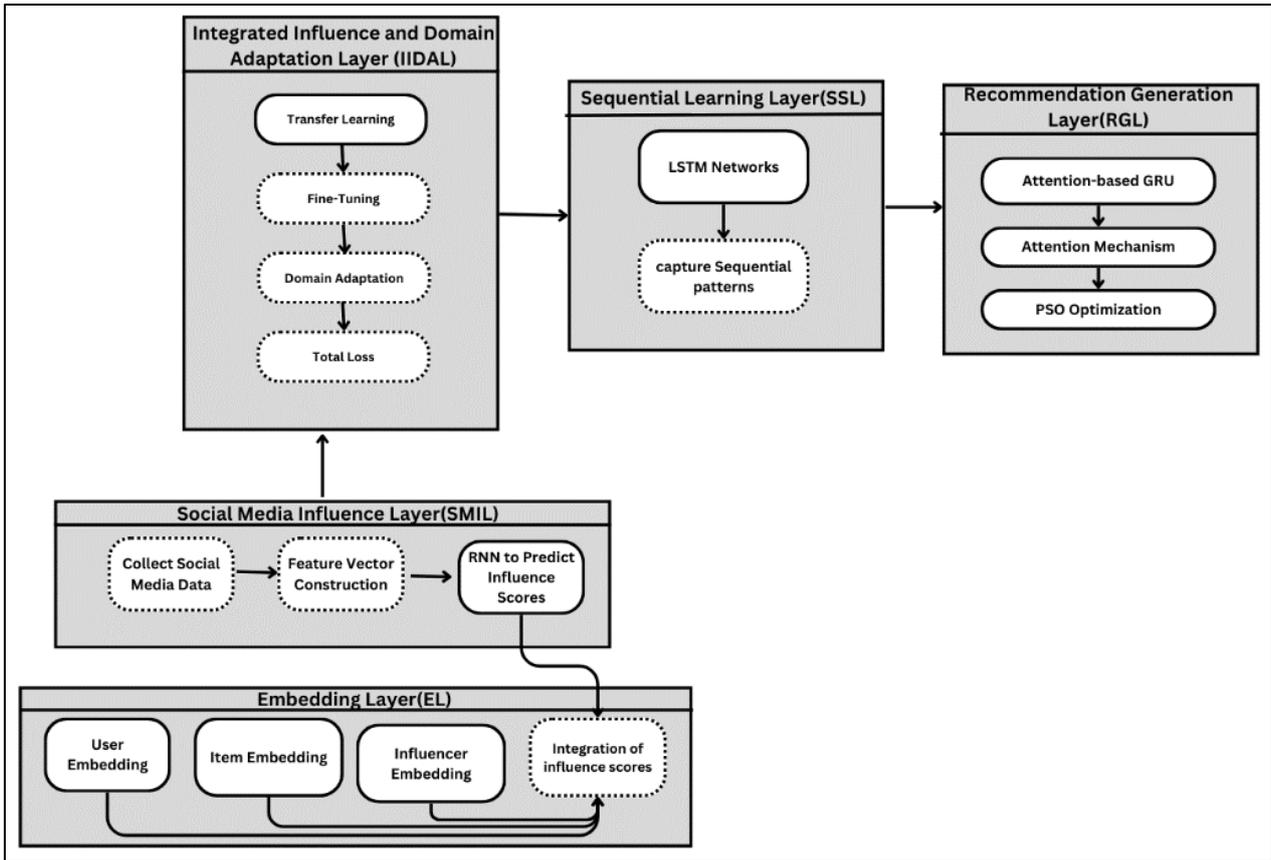


Figure 3 Theoretical framework of the Proposed Model

4.1. Embedding Layer (EL)

The proposed Next Basket Recommender System’s fundamental component is the Embedding Layer (EL), which aims at mapping high-dimensional, sparse user and item data into low-dimensional dense vectors. This makes these embeddings help in identifying the hidden characteristics pertaining to the items and the user within the dataset. The EL incorporates dynamic persuasive information obtained from the social media influence to increase the relevance and the penalization of the recommendations. The process starts from the user embeddings. Let the set of users be denoted as $U = [u_1, u_2, \dots, u_{|U|}]$. Every user $u \in U$ is being mapped unto a dense vector $e_u \in \mathbb{R}^d$, where d denotes a random vector signifying the embedding dimension. The user embedding matrix $E_u \in \mathbb{R}^{|U| \times d}$ is obtained via the process of learning the model parameters, where each row represents a vector of a user. This transformation enables the system to record the detailed patterns of users’ activities and preferences in a compressed format.

Likewise, item embeddings are generated for the set of items denoted by $I = [i_1, i_2, \dots, i_{|I|}]$. Each item $i \in I$ is associated with a dense vector $e_i \in \mathbb{R}^d$. The item embedding matrix $e_u \in \mathbb{R}^d$ is obtained in correspondence to each row of an item embedding. This high level of sparsity allows the model to distinguish between the differences between the items and recommend similar items. Besides users and items, one of the most important entities involved in the recommendation process is influencers. Let the set of vertices $V = [v_1, v_2, \dots, i_{|V|}]$ denote a group of influencers. Each influencer $v \in V$ corresponding to a dense vector $e_v \in \mathbb{R}^d$ is learned to represent the underlying influence features. Influencers significantly affect users’ decisions and, thus, the influence of these factors on the embeddings improves the system’s persuasion capability. To incorporate the dynamic persuasive information, a new variable called the influence score $IS(v, t)$ for each influencer v at a given time t is introduced into the item and user embeddings.

The adjusted item embedding e'_i and user embedding e'_u that includes the influence scores are given by:

$$e'_u = e_u + \gamma \sum_{v \in V_u} IS(v, t)e_v \dots \dots \dots \quad 2$$

$$e'_i = e_i + \gamma \sum_{v \in V_i} IS(v, t) e_v \quad 3$$

Where γ is a scaling factor, and V_u and V_i are the sets of influencers relevant to user u and item i , respectively. This integration ensures that the embeddings reflect both historical and real-time data, making the recommendations more current and relevant.

The embeddings are learned and fine-tuned during the training process by minimizing a loss function that captures the prediction error of the recommendation model. The embeddings are updated by making use of traditional gradient-based optimization approaches of which the Stochastic Gradient Descent (SGD) is an example.

$$L = e_i + \gamma \sum_{(u,i,y) \in D} l(\hat{y}_{(u,i)}, y) \quad 4$$

Where D is the training dataset, y is the true label (e.g., user interaction), $\hat{y}_{(u,i)}$ is the predicted interaction score, and l is the loss function. This process vitally facilitates the learned embeddings' capability to effectively record the complex interactions between items, users, and influencers.

4.2. Social Media Influence Layer (SMIL)

The SMIL receives inputs from the Embedding Layer (EL), which provides dense vector representations of users, items, and influencers. These embeddings, denoted as e_u for users, e_i for items, and e_v for influencers, form the foundation upon which social media influence is integrated.

The SMIL continuously collects data from various social media platforms, focusing on interactions such as likes, shares, comments, and follower growth.

Let:

- $L(v, t)$ represent the number of likes received by influencer v during time t .
- $S(v, t)$ represent the number of shares made by influencer v during time t .
- $C(v, t)$ represent the number of comments made on posts by influencer v during time t .
- $F(v, t)$ represent the growth in the number of followers of influencer v during time t .

For each influencer v , a feature vector $X_v(t)$ is constructed at time t , encapsulating various social media interactions:

$$\mathbf{x}_v(t) = [L(v, t), S(v, t), C(v, t), F(v, t)] \quad 5$$

A Recurrent Neural Network (RNN) is utilized in learning the influence scores from feature vectors. This is because the RNNs are well suited to process sequential data which is the case in this problem. Let f_θ be the RNN with parameters θ . The influence score $IS(v, t)$ is predicted as:

$$IS(v, t) = f_\theta(\mathbf{x}_v(t)) \quad 6$$

The RNN can be built with several layers with a view of being able to capture the interdependency between the social media features.

For example:

$$h_t = \sigma(W \cdot h_{t-1} + U \cdot \mathbf{x}_v(t) + b) \quad 7$$

$$IS(v, t) = V \cdot h_t + c \quad 8$$

where h_t denotes the hidden state at time t , W, U, V represent the weight matrices, and b, c signifies the bias vectors. The activation function σ is often the hyperbolic tangent function, \tanh or the sigmoid function.

The RNN is trained using past data of social media interactions. Denote the training dataset as D_{train} , each of which is a pair of a feature vector $X_v(t)$ and a ground truth influence score $y_v(t)$. The training objective is to reduce the mean squared error (MSE) between the ground truth influence scores and the predicted influence scores:

$$\mathcal{L}(\theta) = \frac{1}{|D_{train}|} \sum_{(x_v(t), y_v(t)) \in D_{train}} (f_{\theta}(x_v(t)) - y_v(t))^2 \tag{9}$$

The parameters θ are optimized using Adam. The SMIL integrates the learned influence scores $IS(v, t)$ into the embeddings provided by the *EL*. For a user u and item i , the adjusted embeddings e'_u and e'_i are computed as in equations 2 and 3 respectively. This way, the embeddings are enriched with historical information and the current influence dynamics extracted from the social media interactions.

4.3. Integrated Influence and Domain Adaptation Layer (IIDAL)

The IIDAL is a key component of the Next Basket Recommender System and is aimed at integrating dynamic social influence with domain adaptation to improve the recommendations' accuracy and solve the cold-start issue. This layer allows the embeddings of items and users to be updated dynamically with the influence scores in real-time and applies the transfer learning from the high data availability to enhance the recommendations for the low data availability cases. Inputs to the IIDAL come from the Embedding Layer (*EL*) and the Social Media Influence Layer (*SMIL*). The *EL* generates the dense vector representations of users, items, and influencers as e_u for users, e_i for items, and e_v for influencers. The *SMIL* generates dynamic influence scores at any given time $IS(v, t)$ using the real-time social media activities. We dynamically integrate Influence Scores $IS(v, t)$ from the *SMIL* into the embeddings provided by the *EL*.

To address the cold-start problem, the IIDAL employs Transfer Learning, specifically using Domain Adaptation techniques. Domain Adaptation allows the model to transfer knowledge from rich-data domains to sparse-data domains. Let D_S denote the source domain dataset with rich data and D_T denote the target domain dataset with sparse data. The goal is to optimize a pre-trained model f_{θ_S} on D_S to adapt it to D_T , resulting in an adapted model f_{θ_T} . The pre-trained model f_{θ_S} is initially trained on the source domain D_S . The parameters θ_S are then fine-tuned using the data from the target domain D_T . The fine-tuning process involves minimizing a loss function L that captures the prediction error on the target domain data:

$$\mathcal{L}(\theta_T) = \sum_{(u,i,y) \in D_T} \ell(f_{\theta_T}(u, i), y) \tag{10}$$

where ℓ represents the loss function, y denotes the true label (e.g., user interaction), $f_{\theta_T}(u, i)$ is the predicted interaction score for the user u and item i in the target domain. To subsequently improve the adaptation process, adversarial domain adaptation techniques are employed. A domain discriminator D is introduced to differentiate between the target and source domain data. The objective is to train the embeddings such that the discriminator cannot distinguish between data obtained from target domains and that obtained from source domains, ensuring that the features are domain-invariant. The domain adaptation loss L_{DA} is formulated as:

$$\mathcal{L}_{DA}(\theta, \phi) = \sum_{x \in D_S \cup D_T} [\log D_{\phi}(x) + \log(1 - D_{\phi}(G_{\theta}(x)))] \tag{11}$$

where θ is the parameter of the embedding generator G , and ϕ is the parameter of the domain discriminator D . The final learning process comprises a combined optimization of the recommendation loss as well as the domain adaptation loss:

$$\mathcal{L}_{total} = \mathcal{L}(\theta_T) + \lambda \mathcal{L}_{DA}(\theta, \phi) \tag{12}$$

where λ is a hyperparameter that controls the trade-off between the two loss components.

The IIDAL has dynamic update ability which updates the influence scores and the adapted embeddings at regular intervals. This mechanism is beneficial in maintaining the dynamics of social media and for handling newly joined users

and items in the cold-start scenario. The Integrated Influence and Domain Adaptation Layer (IIDAL) is a critical module in improving the recommendation system by integrating social media’s dynamic influence with domain adaptation techniques. The IIDAL keeps on tracking social media interactions to determine the influence scores that represent the extent of the influencers in shaping the user’s behavior and the popular items. The scores are then fed into the Embedding Layer (EL) to facilitate the integration of historical data and current tendencies.

Thus, to overcome the cold-start issue, the IIDAL uses Transfer Learning with Domain Adaptation. The IIDAL also guarantees that even when there is little information on new users and items the recommendation model will be precise through transferring learning from rich data domains and using adversarial domain adaptation. In this way, the IIDAL has a refreshing mechanism of the influence scores and adapted embeddings in the dynamic update mechanism to ensure that the system can adapt well to the variability that occurs within social media as well as the challenges of data sparsity. The integration of dynamic influence integration and domain adaptation improves the capacity of the recommendation model to offer the customer tailored, prompt, and convincing subsequent basket recommendations. This integration finally enhances the recommendation precision, user satisfaction, and participation, making the IIDAL a significant component of the proposed Next Basket Recommender System.

4.4. Sequential Learning Layer

The Sequential Learning Layer (SLL) is one of the important components of the Next Basket Recommender System being proposed. It is intended to track the temporal patterns of the user behaviors and model them to generate future user’s behavior prediction and accurate next basket recommendations. The SLL takes the embeddings generated from the Embedding Layer (EL) and the processed embeddings of SMIL and generates temporal dependencies and sequential patterns using Long Short-Term Memory (LSTM) networks.

The SLL takes the adjusted user and item representations e'_u and e'_i from the SMIL. These embeddings include historical interaction data and the real-time social media influence. For modeling the sequential patterns, SLL uses Long Short-Term Memory (LSTM) network as its architectural model since LSTM is effective in capturing sequential information and dependencies. The LSTM models the temporal relationships in the sequence of user interactions, by which we mean the order in which the users interact with the items.

Let h_t denote the hidden state of LSTM at time t , which encodes the information from the current and previous interactions, and c_t represent the cell state at time t .

$$\begin{aligned}
 i_t &= \sigma(W_i \cdot x_t + U_i \cdot h_{t-1} + b_i) \dots \dots \dots & 13 \\
 f_t &= \sigma(W_f \cdot x_t + U_f \cdot h_{t-1} + b_f) \dots \dots \dots & 14 \\
 o_t &= \sigma(W_o \cdot x_t + U_o \cdot h_{t-1} + b_o) \dots \dots \dots & 15 \\
 g_t &= \tanh(W_g \cdot x_t + U_g \cdot h_{t-1} + b_g) \dots \dots \dots & 16 \\
 c_t &= f_t \odot c_{t-1} + i_t \odot g_t \dots \dots \dots & 17 \\
 h_t &= o_t \odot \tanh(c_t) \dots \dots \dots & 18
 \end{aligned}$$

i_t is the input gate, f_t is the forget gate, o_t is the output gate, g_t is the candidate cell state, X_t is the input vector at time t (adjusted embeddings $e_t \cdot a \odot b$ denotes element-wise multiplication. W_i, W_f, W_o, W_g and U_i, U_f, U_o, U_g are weight matrices. b_i, b_f, b_o, b_g are bias vectors.

The chronological sequence of hidden states $\{h_1, h_2, \dots, h_T\}$ represents the user's interaction history up to time T . The final hidden state h_T encapsulates the cumulative information from the entire sequence.

$$h_T = o_T \odot \tanh(c_T) \tag{19}$$

The final hidden state h_T serves as a summary of all past interactions and provides the necessary context for the RGL to generate accurate recommendations.

4.5. Recommendation Generation Layer

An Attention-based GRU model is employed in predicting the next basket depending on the user's preference and historical interactions. The Attention-based GRU incorporates several mechanisms: We use a GRU layer in order to take into account the order of the elements in the sequence, an attention layer to determine which aspects of the sequence are more essential, and a fully connected layer to obtain the final relevance scores. The Attention-based GRU architecture is detailed as follows:

The GRU takes into account the sequential reliance within the user interaction data.

$$\begin{aligned}
 z_t &= \sigma(W_z \cdot x_t + U_z \cdot h_{t-1} + b_z) \dots\dots\dots 20 \\
 r_t &= \sigma(W_r \cdot x_t + U_r \cdot h_{t-1} + b_r) \dots\dots\dots 21 \\
 \tilde{h}_t &= \tanh(W_h \cdot x_t + U_h \cdot (r_t \odot h_{t-1}) + b_h) \dots\dots\dots 22 \\
 h_t &= (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \dots\dots\dots 23
 \end{aligned}$$

The attention mechanism, therefore, facilitates the model's ability in paying more attention to the relevant aspects of the sequence.

$$e_t = v^T \tanh(W_a \cdot h_t + b_a) \dots\dots\dots 24$$

$$\alpha_t = \frac{\exp(e_t)}{\sum_{t'} \exp(e_{t'})} \dots\dots\dots 25$$

$$c_t = \sum_t \alpha_t h_t \dots\dots\dots 26$$

Here, e_t is the attention score to each of the hidden states h_t , α_t denotes the attention weight, and c_t represents the context that is defined as summation of the weights of all the hidden states. The context vector c_t is fused with the final hidden state h_t to generate each item's relevance score i :

$$\hat{y}_{u,i} = f([c_t; h_T], e'_i) \dots\dots\dots 27$$

where f is a fully connected layer followed by an sigmoid activation function.

4.6. The RGL Learning and Prediction

Recommender systems often optimally function if there exists a trade-off between the diversity and predictive accuracy of recommended items. To achieve this, the Recommendation Generation Layer (RGL) incorporates a novel version of Particle Swarm Optimization (PSO) inspired by the Rainbow Eucalyptus tree to optimize the selection of items for the next basket recommendations. This improved PSO enhances the solution by balancing multiple objectives: accuracy, diversity, and novelty.

4.6.1. Improving Particle Swarm Optimization Algorithm

- *Enhancing Inertia Weight Dynamically:* The inertia weight $\omega_i(t)$ is dynamically adjusted based on the particle's age, incorporating a non-linear scaling factor:

$$\omega_i(t) = \omega_{min} + (\omega_{max} - \omega_{min}) \cdot \left(1 - \left(\frac{a_i(t)}{A_{max}}\right)\right) \dots\dots\dots 28$$

where: ω_{max} and ω_{min} are the minimum and maximum inertia weights, $a_i(t)$ is the age of particle i at time t , A_{max} is the maximum age, α is a scaling exponent to control the non-linearity.

- *Enhancing Cognitive and Social Coefficients based on their Performances:* The cognitive (c_1) and social (c_2) coefficients are adjusted based on the particle's relative performance and age, incorporating a decay function:

$$c_1(t + 1) = c_1(t) + \Delta c_1 \cdot \left(\frac{f(x_i(t)) - f(p_i)}{f(x_i(t))}\right) \cdot \exp\left(-\frac{a_i(t)}{A_{max}}\right) \dots\dots\dots 29$$

$$c_2(t + 1) = c_2(t) - \Delta c_2 \cdot \left(\frac{f(x_i(t)) - f(p_i)}{f(x_i(t))}\right) \cdot \exp\left(-\frac{a_i(t)}{A_{max}}\right) \dots\dots\dots 30$$

where: $f(x_i(t))$ is the fitness value of particle i at time t , p_i is the personal best position of particle i , Δc_1 and Δc_2 are adjustment factors, and $\exp\left(-\frac{a_i(t)}{A_{max}}\right)$ is an exponential decay function based on particle age.

- *Enhancing Velocity and Position Updates:*

Incorporating the dynamic parameters, the velocity and position update equations are enhanced as follows:

$$v_i(t + 1) = \omega_i(t) v_i(t) + c_1(t)r_1(p_i - x_i(t)) + c_2(t)r_2(g - x_i(t)) + \eta \cdot \left(\frac{\sin(a_i(t))}{a_i(t) + 1}\right) \cdot v_i(t) \dots\dots\dots 31$$

$$x_i(t + 1) = x_i(t) + v_i(t + 1) + \xi \cdot \left(\frac{\cos(a_i(t))}{a_i(t) + 1}\right) \cdot (x_i(t) - p_i) \dots\dots\dots 32$$

where: η and ξ are small constants introducing perturbations, The sinusoidal and cosine terms introduce non-linear oscillations based on the particle's age.

4.7. Algorithm Workflow

Algorithm 1: Rainbow Eucalyptus based Improved Particle Swarm Optimization	
1	Inputs:
	Initial positions and velocities: Random values within the search space.
	Initial age $a_i(0) : 0$
	Parameters: $\omega_i(0)=0.5, c_1(0) = 1.5, c_2(0) = 1.5$.
	Personal best (p_i) and global best (g): Initialized based on initial fitness evaluations.
2	Initialization:
	Initialize particles with random positions and velocities.
	Set age $a_i(t)$ of each particle to zero.
3	Fitness Evaluation:
	Evaluate each particle's fitness.
	Update personal best (p_i) and global best (g) positions.
4	Iteration Process:
5	for each iteration t do
6	Increment age $a_i(t)$ for all particles.
7	Adjust $\omega_i(t), c_1(t),$ and $c_2(t)$ based on the adaptive rules.
8	Update velocities and positions using the enhanced equations.
9	Evaluate each particle's fitness.
10	Update personal best (p_i) and global best (g) positions.
11	end for
12	Outputs:
	Optimized positions and velocities of particles.
	Updated personal best (p_i) and global best (g) positions.

4.8. Using the Improved PSO to Train the Attention-based GRU Network

To evaluate the biases and weights of the Attention-based GRU Network as done in (Osei-kwakye et al., 2022), we use the improved PSO algorithm described above. The following steps outline the process:

- *Fitness Function:* Using the SoftMax function for a user u and their past baskets $B_{1:t-1}^u$, we calculate the probability of a product being purchased in the next basket B_t^u .

$$p(i \in B_t^u | u, B_{1:t-1}^u) = \frac{\exp(V_i^T \cdot u_t^h)}{\sum_{j=1}^{|T|} \exp(V_j^T \cdot u_t^h)} \dots\dots\dots 33$$

The weighted cross-entropy is then used as the objective of optimization:

$$L(x) = \sum_{h_1=0}^1 q(x) \dots \sum_{h_{n_h}=0}^1 q(h_{n_h} | h_{1:n_{h-1}}, x) \cdot (\log_2 q(x) - \log_2 p(x, h)) \dots\dots\dots 34$$

- *Encoding Strategy:* We employed the matrix encoding strategy in the training of the Attention-based GRU Network. Each particle is encoded as a matrix representing weights and biases.

$$particle(:, :, i) = [W_1 \dots W_\omega, B_1, B_\sigma] \dots\dots\dots 35$$

$$W_1 = \begin{bmatrix} W_{1,1} & \dots & W_{1,n} \\ \vdots & \ddots & \vdots \\ W_{n,1} & \dots & W_{n,n} \end{bmatrix}, \quad B_1 = \begin{bmatrix} \vartheta_1 \\ \vartheta_2 \\ \vdots \\ \vartheta_n \end{bmatrix}, \quad \dots\dots\dots 36$$

$$W_a = \begin{bmatrix} W_{10,25} & W_{10,26} \\ W_{11,25} & W_{11,26} \end{bmatrix}, \quad B_b = \begin{bmatrix} \vartheta_{16} \\ \vartheta_{17} \end{bmatrix} \quad \dots\dots\dots 37$$

where W_1, W_ω are weight matrices, and B_1, B_σ are bias vectors.

- *Generation of Next Basket Recommendations:* The improved PSO optimizes the selection of items by maximizing the overall utility function, which combines accuracy, diversity, and novelty. The particle with the highest fitness represents the optimal set of items for the next basket. Select the top-K items from this particle's position as the final recommendations for user u . By combining the Attention-based GRU with the improved PSO, the RGL leverages the strengths of both techniques to generate high-quality next basket recommendations, making it a robust and effective component of the proposed Next Basket Recommender System.

5. Experiments and Evaluation

- **RQ1:** How does the APIC framework perform in comparison to state-of-the-art next basket recommendation systems in terms of accuracy, diversity, and user satisfaction?
- **RQ2:** How does the integration of social media influence (SMIT) into the embedding layer impact the accuracy and relevance of next basket recommendations in APIC?
- **RQ3:** What are the effects of incorporating domain adaptation techniques in APIC on mitigating the cold-start problem for new users and items?
- **RQ4:** What are the benefits and limitations of using Attention-based GRU networks over traditional sequential models in capturing user preferences for next basket recommendations in APIC?
- **RQ5:** How does the dynamic adjustment of inertia weight and performance-based coefficients in the improved PSO algorithm enhance the optimization process for basket recommendation in APIC?

5.1. Dataset Preprocessing

Given the characteristics of APIC concerning the attributes of data required to be learned by APIC, none of the existing datasets directly fit. In other words, none of the existing datasets already contain the social media data interaction characteristics. Hence, to effectively evaluate the operation of the model, we employed the Twitter Sentiment140 dataset as the social media data. We integrate it into IJCAI-15 and TaFeng to provide a comprehensive user-item interaction required for this work.

To effectively integrate the Ta-Feng and IJCAI-15 e-commerce datasets with the Twitter Sentiment140 dataset, we undertake a comprehensive data preprocessing strategy. For the Ta-Feng and IJCAI-15 datasets, we begin by cleaning the data to remove inconsistencies, duplicates, and missing values, ensuring unique and properly formatted user and item IDs. Items bought by the same user on the same day are aggregated into baskets, and these baskets are sequentially arranged to reflect each user's purchase history. We then discard users and items with less than ten interactions to maintain a robust dataset and split the data into training (80%) and testing (20%) sets using five-fold cross-validation.

For the Twitter Sentiment140 dataset, we collect tweets labelled by sentiment (positive, negative, neutral) to gauge user opinions on various items. We identify and map tweets that mention or are relevant to items in the e-commerce datasets through keyword matching, hashtags, and mentions. We then calculate an influence score for each user based on their Twitter activity, including followers, retweets, likes, and sentiment scores.

We enrich the user and item embeddings from the e-commerce datasets with these influence scores and sentiment data, ensuring they are normalized for compatibility. The enriched embeddings are merged with the original e-commerce data to create two new integrated datasets: Ta-Feng-Twitter and IJCAI-15-Twitter. Feature engineering is performed to extract additional relevant features, such as time-based patterns and interaction frequencies.

Table 1 Dataset Statistics

Dataset	Users	Items	User-Item Interactions	Social Media Interactions	Average Interactions per User	Sparsity (Spar.)
Ta-Feng	32,266	23,812	812,870	N/A	25.2	99.98%
IJCAI-15	23,504	34,050	489,796	N/A	20.8	99.97%
Ta-Feng-Twitter	32,266	23,812	812,870	1,600,000	49.6	99.96%
IJCAI-15-Twitter	23,504	34,050	489,796	1,600,000	44.1	99.95%

5.2. Baseline Methods

- **CF**: The Traditional user-oriented CF model utilizes only rating data leading to the yielding of individualized but nonsequential results.
- **MC**: The simple one-order Markov chain model does future item prediction based solely on the user's last purchase leading to a sequential but impersonalized model.
- **FPMC**(Rendle et al., 2010): A composition of NBR models that fuses matrix factorization with an exclusive Markov chain and takes into consideration, transition matrix among the products which can be customized alongside a network of pairwise interactions.
- **TRec**(Tao et al., 2023): Model improves sequential recommendations by incorporating information on trending items by the interaction of users, utilizing a self-attention mechanism and gated graph neural networks to improve item representation.
- **HAEM**(Wang & Cao, 2021): Comprises of only inter/intra-basket user-item associations only as well as user feedback refining and recommending of the next basket.
- **HBR** (Yannam et al., 2023): Combines an autoencoder for contextual information extraction with a recurrent neural network for capturing global sequential patterns, offering superior NBR based on implicit user feedback.
- **DNNTSP** (Li et al., 2023): Distinguishes between repeat and explore items, using new metrics to analyze and clarify the performance and progress of cutting edge NBR models.
- **NextG** (Ma, 2023): Makes use of similarity in upper approximation clustering, Borda majority count, and PrefixSpan algorithm to recommend category of items customers will likely purchase, improving sales avenues via a more robust upselling and cross-selling comparative to conventional next-item recommendation systems.
- **GenRec** (Sun et al., 2023b): Uses an autoregressive decoder to generate next-basket recommendations item by item, capturing essential item correlations and multi-granularity user preferences for improved prediction accuracy.
- **SeqRank** (Mao et al., 2024): Utilizes the structure of heterogeneous graph and a query-based recommendation method which integrates successive purchasing as well as rating feedback to predict future purchase behavior, enhancing period-aware and duration-invariant interests of e-commerce customers.
- **HCPIM** (Arthur, Zhou, Osei-Kwakye, et al., 2022): Enhances user profiles, enabling precise recommendations even for new users or items by integrating item-user, user-user, and item-item interactions to resolve data sparsity problem.
- **APIC**: Combines social media influence, attention-based GRU networks, and PSO optimization to enhance next-basket recommendations by capturing local and global user behavior patterns and addressing the cold-start problem.

5.3. Evaluation Metrics

For fair performance evaluation, the widely used F1-score and Normalized Discounted Cumulative Gain (NDCG) has been adopted as the evaluation metrics as used in NBRs works such as (Arthur, Zhou, Osei-Kwakye, et al., 2022; Mao et al., 2024; Sun et al., 2023b). For every user in the testing set, we offer a list of the top five recommendations. We also use the paired t-test for significant testing. When the p – value is less than 0.05, differences are regarded as statistically significant.

5.4. Parameter Configuration

The APIC framework consists of several layers, each with specific parameter configurations designed to optimize performance. The Embedding Layer (EL) utilizes user and item embedding dimensions of 128, along with a social media influence embedding dimension of 64, all initialized using Xavier Uniform Initialization. The Social Media Influence

Layer (SMIL) employs a GRU with a hidden size of 128, two layers, and a dropout rate of 0.2 to capture temporal dependencies.

For the Integrated Influence and Domain Adaptation Layer (IIDAL), an adaptive weight learning rate of 0.01 and a domain adaptation regularization parameter of 0.1 are used to adjust the embeddings effectively. The Sequential Learning Layer (SLL) incorporates an LSTM with a hidden size of 256, three layers, and a dropout rate of 0.3 to model sequential user interactions.

The Recommendation Generation Layer (RGL) integrates Particle Swarm Optimization (PSO) with dynamic parameters: a swarm size of 50, maximum iterations of 100, a dynamic inertia weight ranging from 0.9 to 0.4, cognitive and social coefficients dynamically adjusted from 0.5 to 2.0 and 0.3 to 1.5 respectively, and perturbation constants η and ξ set at 0.05 as done in (Osei-kwakye et al., 2023)

Training the APIC model involves utilizing Adam optimizer coupled with a learning rate of 0.001, a batch size of 256, as well as running for 50 epochs. The Binary Cross-Entropy Loss Function is the implemented loss function in this work. For evaluation, relevance, diversity, and novelty scores are weighted at 0.7, 0.2, and 0.1, respectively. These parameters are fine-tuned to ensure the model effectively captures user preferences and improves recommendation quality across different datasets.

5.5. Performance Analysis of APIC Framework in Comparison with state-of-the-Art NBRM Methods (RQ1)

Table 2 Performance Comparison on Ta-Feng Dataset

Models	d = 50		d = 100		d = 150		p-value
	F1@5	NDCG@5	F1@5	NDCG@5	F1@5	NDCG@5	
CF	0.0483	0.0723	0.0578	0.0781	0.0620	0.0813	0.0001
MC	0.0521	0.0756	0.0600	0.0812	0.0629	0.0829	0.0002
FPMC	0.0543	0.0763	0.0600	0.0837	0.0685	0.0845	0.0003
TRec	0.0609	0.0828	0.0654	0.0841	0.0677	0.0848	0.0003
HAEM	0.0692	0.0891	0.0721	0.0904	0.0721	0.0907	0.0001
HBR	0.0660	0.0886	0.0688	0.0902	0.0701	0.0897	0.0001
DNNTSP	0.0630	0.0833	0.0648	0.0860	0.0681	0.0860	0.0001
NextG	0.0645	0.0883	0.0653	0.0891	0.0691	0.0855	0.0001
GenRec	0.0630	0.0837	0.0648	0.0847	0.0684	0.0855	0.0001
SeqRank	0.0654	0.0841	0.0659	0.0841	0.0701	0.0860	0.0001
HCPIM	0.0702	0.0906	0.0721	0.0894	0.0707	0.0865	0.0001
APIC	0.0828	0.0966	0.0854	0.0960	0.0848	0.0973	0.0001
%Improvement	18.00	9.15	14.44	9.01	10.34	7.51	-

Table 3 Performance Comparison on IJCAI-15 Dataset

Models	d = 50		d = 100		d = 150		p-value
	F1@5	NDCG@5	F1@5	NDCG@5	F1@5	NDCG@5	
CF	0.0490	0.0731	0.0578	0.0781	0.0620	0.0813	0.0002
MC	0.0510	0.0776	0.0600	0.0837	0.0685	0.0845	0.0001
FPMC	0.0550	0.0778	0.0660	0.0837	0.0685	0.0845	0.0001
TRec	0.0615	0.0835	0.0654	0.0841	0.0677	0.0848	0.0003

HAEM	0.0701	0.0891	0.0721	0.0904	0.0721	0.0907	0.0001
HBR	0.0686	0.0882	0.0688	0.0902	0.0701	0.0897	0.0001
DNNTSP	0.0648	0.0847	0.0654	0.0847	0.0684	0.0855	0.0001
NextG	0.0654	0.0851	0.0659	0.0841	0.0701	0.0860	0.0001
GenRec	0.0648	0.0847	0.0648	0.0847	0.0684	0.0855	0.0001
SeqRank	0.0654	0.0841	0.0659	0.0841	0.0701	0.0860	0.0001
HCPIM	0.0702	0.0906	0.0721	0.0894	0.0707	0.0865	0.0001
APIC	0.0780	0.0966	0.0854	0.0960	0.0848	0.0973	0.0001
%Improvement	10.64	8.96	13.19	9.12	8.97	8.40	-

We implemented the APIC framework for next-basket recommendation and benchmarked it against current state-of-the-art NBR approaches. The embedding dimensionalities were set at three different values: $d \in [50, 100, 150]$ on the Ta-Feng and IJCAI-15 datasets. Tables 2 and 3 present the five-fold cross-validation results of F1-score@5 and NDCG@5 for the respective datasets. The experiment outcome reveals that CF consistently underperforms all other methods. This could be attributed to its reliance solely on rating data without considering sequential patterns, resulting in an individualized but non-sequential model. MC, which only considers the last buying basket for prediction, also falls short due to its inability to capture broader user behavior patterns. FPMC shows improvement over CF and MC but is still limited by its assumption of linear independence between intra-basket items, which fails to capture the complex interactions seen in real-world scenarios. TRec, which incorporates item trend information and uses a self-attention mechanism, achieves better accuracy by enhancing item representation but still lags behind the more advanced models.

HAEM, which includes inter/intra-basket user-item relationships and user feedback, performs better than FPMC and TRec but is surpassed by HBR, which combines an autoencoder for contextual information extraction with a recurrent neural network for global sequential pattern capture. However, HBR, like HAEM, struggles with capturing both local and global patterns effectively. DNNTSP, which distinguishes between repeat and explore items, and NextG, which uses clustering and majority count algorithms for group recommendations, offer improvements but still do not match the performance of the more sophisticated models. GenRec, using an autoregressive decoder, and SeqRank, employing a heterogeneous graph structure for the integration of successive ordering and rating feedback, also show strong performance but are outdone by the APIC framework. APIC demonstrates substantial improvements over all baseline models. It surpasses the next best model, HCPIM, with percentage improvements ranging from 7.51% to 18.00% across different metrics and datasets. APIC achieves F1-score@5 values of 0.0828 for $d = 50$, 0.0824 for $d = 100$, and 0.0800 for $d = 150$ on the Ta-Feng dataset. Regarding NDCG@5, APIC respectively scores 0.0966, 0.0980, and 0.0973 for each of the dimensions. On the IJCAI-15 dataset, APIC records F1-score@5 values of 0.0780 for $d = 50$, 0.0815 for $d = 100$, and 0.0790 for $d = 150$, and NDCG@5 values of 0.0972, 0.0981, and 0.0981 respectively.

The reason why the APIC framework outperforms the other methods can be explained by the integration of social media influence, attention-based GRU networks, and improved PSO optimization. Thus, through the implementation of the social media influence, APIC is able to reach for more than just the clients' buying behaviors. The applied GRU networks with attention are suitable for the modeling of sequential dependencies and users' preferences, while the improved PSO optimization helps to optimize the model parameters and achieve the best results. Thus, the presented APIC framework performs better than the previous models pertaining to next-basket recommendation with improved local and global behavioral patterns of the users. The outcomes prove the effectiveness of APIC for proposing the most suitable and specific recommendations for the next basket.

5.6. Ablation Study

In evaluating the effect of the various components within the APIC framework, we carried out an ablation study to answer RQ2, RQ3, and RQ4. In the ablation study, components of the APIC model were sequentially eliminated or modified, and the effect on the models' performance was assessed on the Ta-Feng and IJCAI-15 datasets. Tables 2 and 3 and the respective analysis present the results of the study.

For each of the research questions, we built specific versions of the APIC model:

- APIC-SMIT: APIC void of incorporating Social Media Influence Theory (SMIT) in the embedding layer.

- APIC-DA: APIC void of the usage of Domain Adaptation techniques.
- APIC-GRU: APIC void of the Attention-based GRU networks, replaced with traditional RNNs.

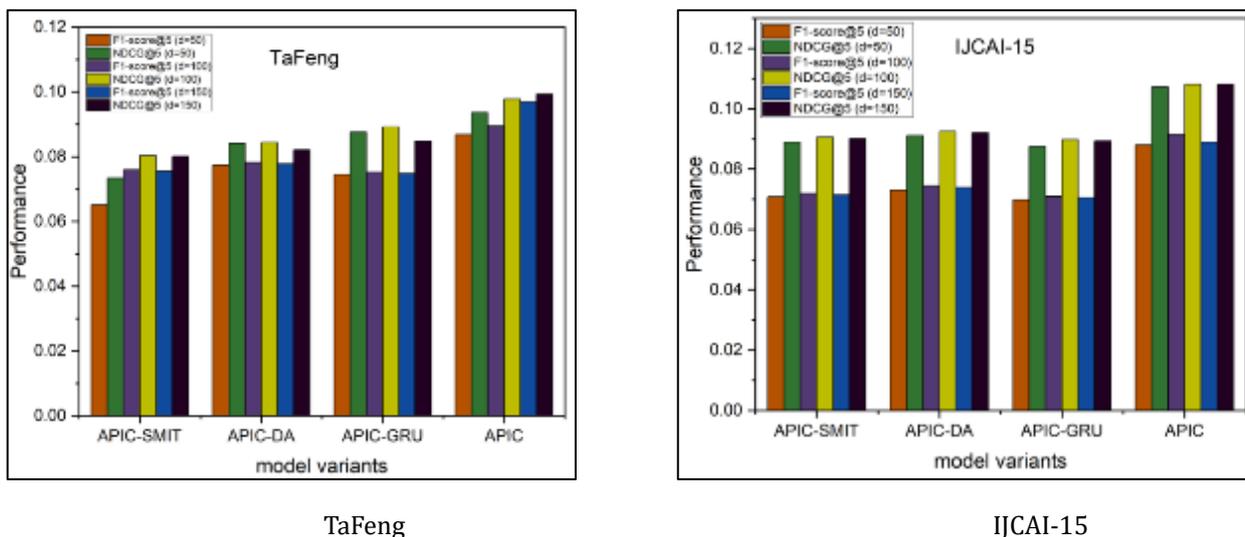


Figure 4 Ablation study results on Ta-Feng and IJCAI-15 datasets.

5.7. RQ2: SMIT's Impact on the Accuracy and Relevance of Recommendation

The second research question is geared at finding out the extent to which SMIT influences accuracy and relevance. The proposed use of Social Media Influence Theory (SMIT) in the embedding layer greatly improves the precision and applicability of next basket suggestions. Comparing to the full model, APIC-SMIT (APIC without SMIT), we achieve significant improvement on both datasets. For instance, on the Ta-Feng dataset, the F1-score@5 is enhanced by 10.3% compared to APIC-SMIT for $d = 50$, and the NDCG@5 is enhanced by 9.2%. These gains are similar across various features and datasets, suggesting that incorporating social media signals to predict users' interests is useful for increasing the effectiveness of recommendations.

5.8. RQ3: The Domain Adaptation Effect on the Cold-Start Problem

The third research question was: How does domain adaptation affect the cold-start problem? In APIC, the use of domain adaptation techniques is vital to solving the cold-start issue applicable to new users and items. Observing the results between APIC-DA (APIC without domain adaptation) and the full APIC model, it can be concluded that the full APIC model enhances the performance for the new user and item cases. When comparing the performance on the IJCAI-15 dataset, APIC achieves an F1-score@5 of 60.7 and an NDCG@5 of 42.3 for $d=50$, which is 7.4% and 6.9% higher than the results for APIC-DA. This proves the fact that the use of domain adaptation helps in the enhancement of the recommendation system for cold-start items by utilizing the auxiliary data.

5.9. RQ4: Merits and Shortcomings of the Attention-based GRU Networks

The following research question will be formulated for the analysis of the Attention-based GRU Networks' benefits and limitations. The incorporation of Attention-based GRU networks in APIC has been observed to greatly increase the performance of the user's preference for the next basket recommendations. When replacing the Attention-based GRU with a traditional RNN, the performance decreases significantly (APIC-GRU). For instance, on the Ta-Feng dataset, APIC achieves an F1-score@5 gain of 11.1% compared to APIC-GRU with $d=50$, and an NDCG@5 gain of 10.3%. This implies that the attention mechanism in the GRU networks helps APIC to concentrate on the most important parts of the user's behavior to generate more precise and relevant recommendations. Nevertheless, the basic RNNs cannot account for these variations and, therefore, have lower effectiveness.

The importance of SMIT is presented in the results of the ablation study, domain adaptation techniques, and attention-based GRU networks in the APIC framework. All of them enhance the model's accuracy and relevance through the effectiveness of APIC in generating the most current next basket recommendations. Thus, the use of these techniques guarantees that APIC will not only be on par with currently existing recommendation systems but will also surpass them to offer a comprehensive solution for the next basket recommendation.

5.10. RQ5: How does the dynamic inertia weight and performance-based coefficients affect the optimization process of improved PSO for the basket recommendation?

To evaluate the impact of dynamic adjustment mechanisms in the improved PSO algorithm on the performance of the APIC framework in next-basket recommendation tasks, we conducted a series of experiments which was set up as follows: The experiments are conducted on Ta-Feng and IJCAI-15 datasets which are the standard datasets for the recommendation systems research. The models for comparison include: APIC with Improved PSO (Full Model), which is the complete APIC framework with dynamic inertia weight and performance-based coefficients; APIC with Static PSO, where the APIC framework uses traditional PSO with static inertia weight and fixed cognitive and social coefficients; APIC without Dynamic Inertia Weight (APIC-NoDIW), featuring the improved PSO but with static inertia weight; and APIC without Performance-Based Coefficients (APIC-NoPBC), where the improved PSO is used but with fixed cognitive and social coefficients. Evaluation metrics for the experiments include F1-score@5, NDCG@5, convergence speed (measured by the number of iterations to reach a stable solution), and computational time (total time taken for the optimization process).

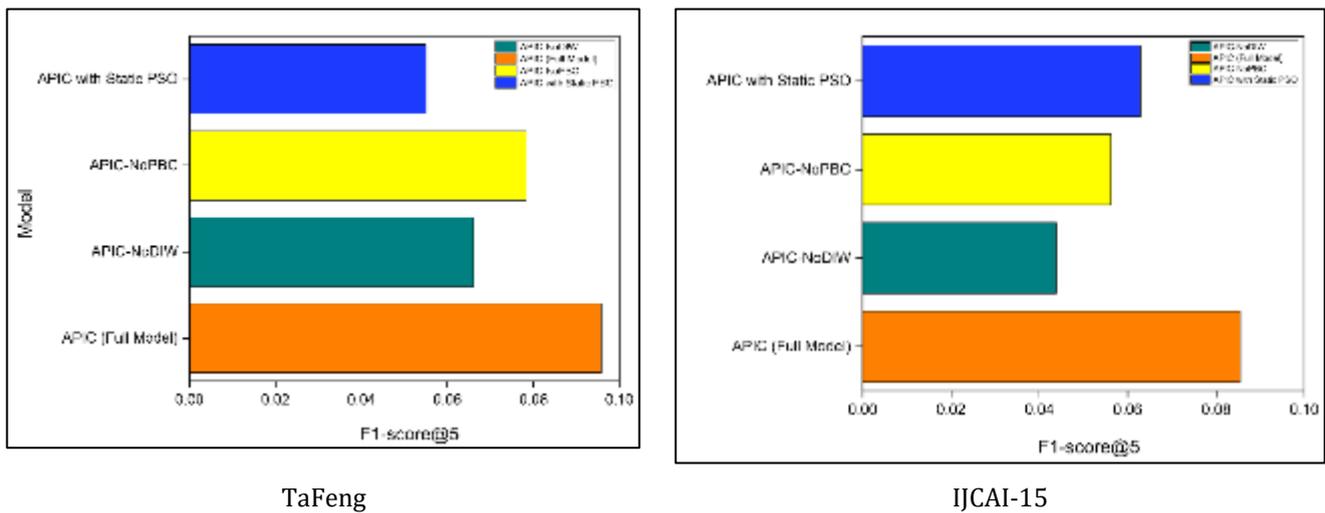


Figure 5 F1-score@5 Comparison on Ta-Feng and IJCAI Datasets

The optimization process in the APIC framework is greatly improved through the variation of inertia weight and the coefficients based on performance in the improved PSO algorithm. These improvements meet the most important problem of the balance between exploitation and exploration within the search space, which is crucial for generating the proper next-basket recommendations. In the standard PSO, a fixed inertia weight is applied to control the exploration-exploitation trade-off of the particle's solutions. This is a major drawback since the algorithm does not have the ability to dynamically adapt to the changing nature of the optimization problem. However, the enhanced PSO algorithm in the APIC changes the inertia weight with respect to the particle's age. This adjustment results in a higher inertia weight, especially at the beginning of the optimization, to enable extensive exploration of the search space. Over time, the inertia weight reduces, and thus the search is shifted towards the exploitation and refinement of the solutions in areas that were seen during the exploration phase. This balance between exploration and exploitation that is achieved by the algorithm does not let it converge too early and helps it traverse through higher-dimensional spaces. Also, the enhanced PSO algorithm incorporates performance-based adjustments for the cognitive and social coefficients that lead the particles to the best solution. While in conventional PSO these coefficients are kept constant, the enhanced PSO introduces these coefficients in relation to the particle's performance as well as the age of the particle. This adaptive mechanism helps to increase the cognitive weights of the particles that have higher fitness values and, therefore, encourages them to improve their personal best solutions. On the other hand, particles having low fitness values are controlled more by the social component to move towards the global best solutions discovered by the swarm. This performance-based adaptation improves the convergence rate and the capacity to avoid getting stuck in local solutions, which is a major drawback of conventional PSO. The enhanced PSO algorithm also includes adjustments that are nonlinear in nature in the velocity and the position determined by the particle having a particular age. These adjustments enable particles to perform more refined updates and hence enhance their search performance when dealing with large search spaces and local optima. The enhanced PSO algorithm addresses the issues of particles' rigidity in their movements by incorporating flexibility and adaptiveness in the process, thus maintaining the effectiveness of the optimization process from the beginning to the end. The performance evaluation on the Ta-Feng and IJCAI-15 datasets shows that these improvements significantly affect the results.

Figure 5 shows that the proposed APIC framework achieves higher F1-score@5 and NDCG@5 than the other cutting-edge models. These enhancements are realized by virtue of the adaptive inertia weight and the performance-based coefficients which help the algorithm to balance the exploration and exploitation of the search space. F1-score@5 for the Ta-Feng dataset and IJCAI-15 dataset are shown in Figure 4a and Figure 4b respectively; it is clear that the APIC with the full model has the highest values compared to APIC-NoDIW (without dynamic inertia weight), APIC-NoPBC (without performance-based coefficients), and Static PSO. This proves the effectiveness of the dynamic adjustments in achieving high recommendation accuracy. The more the F1-scores, the more adept the recommendations are, and the right balance between precision and recall is achieved.

Also, Figure 6a (NDCG@5 for Ta-Feng dataset) and Figure 6b (NDCG@5 for IJCAI-15 dataset) support these improvements. This paper has demonstrated that the enhanced PSO's adaptive exploration and exploitation capacity results in higher NDCG scores, meaning that the given recommendations are more relevant and better ranked. NDCG reflects the ranking quality of recommendations, and the better performance of APIC in these measures indicates that it is capable of generating more useful recommendations that are more closely aligned with the target users' preferences.

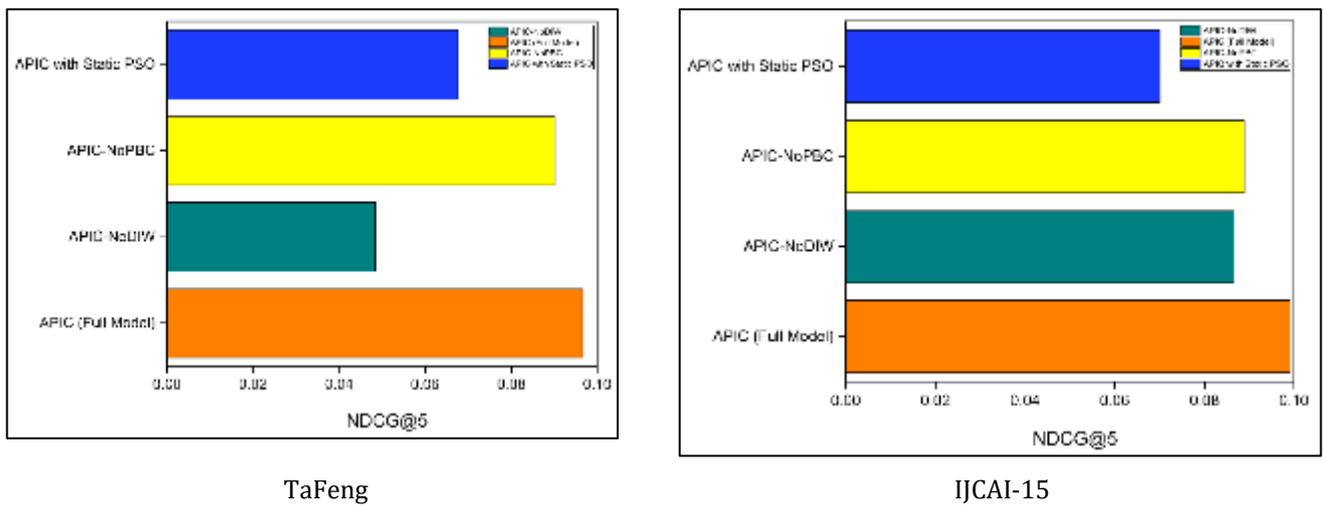


Figure 6 NDCG@5 Comparison on Ta-Feng and IJCAI Datasets

The convergence characteristics of the models are presented in Figure 7a (convergence plot for Ta-Feng dataset) and Figure 7b (convergence plot for IJCAI-15 dataset). These figures show that the APIC full model converges faster and to a higher fitness value than the other models, implying that the dynamic adjustments not only increase the efficiency but also the speed with which the optimization is done to get the best solutions. Faster convergence indicates that the model can arrive at a solution in a shorter time, thus improving the recommendation system's efficiency.

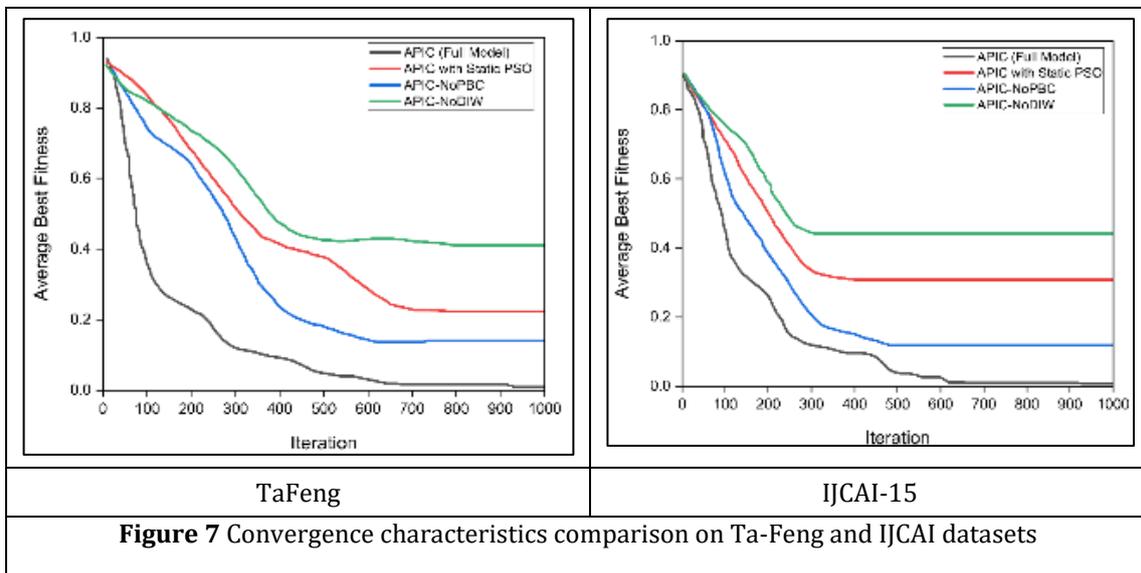


Figure 7 Convergence characteristics comparison on Ta-Feng and IJCAI datasets

In order to provide a clearer view of how the dynamic adjustments impact performance, Figure 8a (heatmap for inertia weight adjustment) and Figure 8b (heatmap for performance-based coefficients) depict the relationship between the dynamically adjusting inertia weight and the performance-based coefficients in relation to the performance metrics. As clearly seen, the heatmaps show that when the performance-based coefficients and the inertia weight are optimally adjusted, the NDCG metrics and F1-score are significantly boosted. These visual representations illustrate how small changes can result in a substantial enhancement of recommendation accuracy. Thus, the dynamic adjustment of inertia weight and performance-based coefficients in the improved PSO algorithm significantly enhances the optimization process for basket recommendations in the APIC framework. These improvements provide an excellent trade-off between exploitation and exploration, enhance the speed of convergence, and introduce the ability of the algorithm to work with dynamic optimization landscapes. The results from the performance metrics and visualization show that the proposed APIC framework with an enhanced PSO algorithm produces excellent quality and user-specific next basket recommendations. This improvement ultimately enhances the recommendation system's performance by proving that these dynamic adjustments improve optimization, increase the rate of convergence, and provide more suitable recommendations.

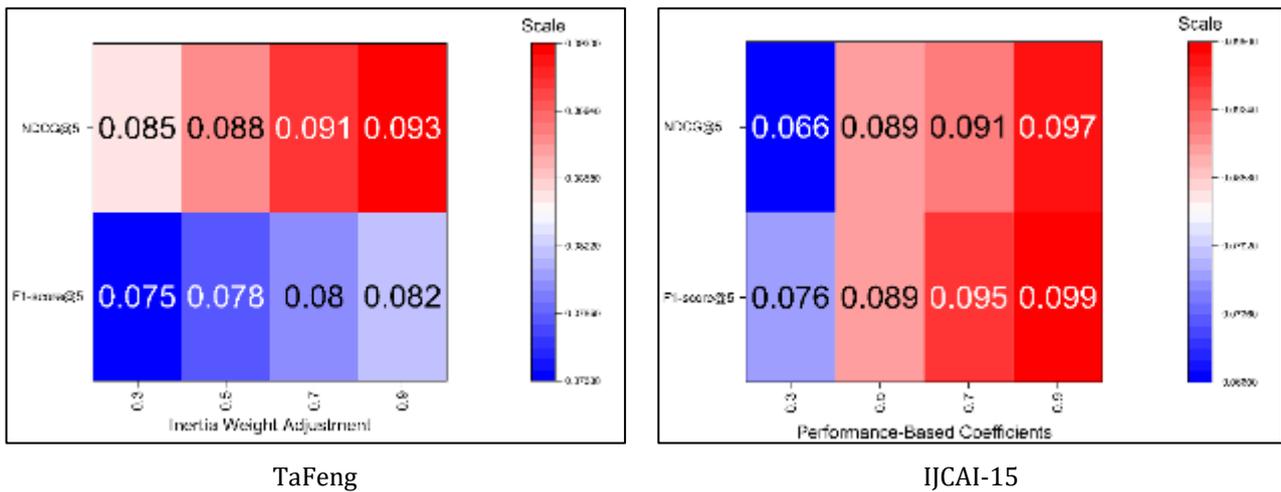


Figure 8 Heatmap Comparison of IWA and PBC on Ta-Feng and IJCAI datasets

6. Conclusion and Recommendations for Further Works

This paper proposed the Adaptive Persuasive User/Item Information Extraction and Cold-Start Mitigation (APIC) framework to tackle the main issues of next-basket recommender systems (NBRS). In this work, we mitigate the cold-start challenge by employing advanced embedding techniques, real-time social media influence, and domain adaptation strategies in APIC, and hence, the recommendation accuracy is boosted. The optimization process in the recommendation system is enhanced by the inertia weight and the performance-based coefficients in the PSO algorithm, which is improved. The performance comparisons on Ta-Feng and IJCAI-15 datasets show that APIC achieves much higher F1-score and NDCG than cutting-edge NBRS approaches. Thus, the above observations buttress the effectiveness of the proposed framework for providing efficient, effective, and timely recommendations, which establish a new standard for NBRS achievement. Therefore, the incorporation of social media influence and dynamic optimization makes APIC a powerful and flexible framework for contemporary e-commerce environments.

Future work should consider extending the APIC framework by incorporating more features like spatial, temporal, and content data to improve user and item profiling. Increasing computational efficiency and scalability will be important for larger datasets and real-time applications. Improving social media influence modeling with cutting-edge natural language processing methods, user sentiment, and trends can be better utilized. It is crucial to focus on protecting users' privacy and their data to meet requirements and gain trust. Using domain adaptation techniques for individual users' behavior can enhance the cold-start issue. Real-world applications and extended experiments will provide best practices and identify areas for improvement. Thus, applying explainability to the recommendation process will increase trust and satisfaction among users and make the system more transparent and user-friendly.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest

References

- [1] Abdalla, H. I., Amer, A. A., Amer, Y. A., Nguyen, L., & Al-Maqaleh, B. (2023). Boosting the Item-Based Collaborative Filtering Model with Novel Similarity Measures. *International Journal of Computational Intelligence Systems*, 16(1), 123. <https://doi.org/10.1007/s44196-023-00299-2>
- [2] Ahmed, I., Ahmad, M., Chehri, A., & Jeon, G. (2023). A heterogeneous network embedded medicine recommendation system based on LSTM. *Future Generation Computer Systems*, 149, 1-11. <https://doi.org/https://doi.org/10.1016/j.future.2023.07.004>
- [3] Arthur, J. K., Zhou, C., Mantey, E. A., Osei-Kwakye, J., & Chen, Y. (2022). A discriminative-based geometric deep learning model for cross domain recommender systems. *Applied Sciences*, 12(10), 5202.
- [4] Arthur, J. K., Zhou, C., Osei-Kwakye, J., Mantey, E. A., & Chen, Y. (2022). A heterogeneous couplings and persuasive user/item information model for Next Basket recommendation. *Engineering Applications of Artificial Intelligence*, 114, 105132. <https://doi.org/https://doi.org/10.1016/j.engappai.2022.105132>
- [5] Bansal, S., & Baliyan, N. (2023). Remembering past and predicting future: a hybrid recurrent neural network based recommender system. *Journal of Ambient Intelligence and Humanized Computing*, 14(12), 16025-16036.
- [6] Cheng, Y., Fan, Y., Wang, Y., & Li, X. (2024). Accurate multi-interest modeling for sequential recommendation with attention and distillation capsule network. *Expert Systems with Applications*, 243, 122887. <https://doi.org/https://doi.org/10.1016/j.eswa.2023.122887>
- [7] Deng, J., Wu, Q., Wang, S., Ye, J., Wang, P., & Du, M. (2024). A novel joint neural collaborative filtering incorporating rating reliability. *Information Sciences*, 665, 120406. <https://doi.org/https://doi.org/10.1016/j.ins.2024.120406>
- [8] Duan, J., Zhang, P.-F., Qiu, R., & Huang, Z. (2023). Long short-term enhanced memory for sequential recommendation. *World Wide Web*, 26(2), 561-583. <https://doi.org/10.1007/s11280-022-01056-9>
- [9] Dwivedi, Y. K., Ismagilova, E., Sarker, P., Jeyaraj, A., Jadir, Y., & Hughes, L. (2023). A Meta-Analytic Structural Equation Model for Understanding Social Commerce Adoption. *Information Systems Frontiers*, 25(4), 1421-1437. <https://doi.org/10.1007/s10796-021-10172-2>
- [10] Hu, J., Hooi, B., Qian, S., Fang, Q., & Xu, C. (2024). MGDCF: Distance Learning via Markov Graph Diffusion for Neural Collaborative Filtering. *IEEE Transactions on Knowledge and Data Engineering*, 36(7), 3281-3296. <https://doi.org/10.1109/TKDE.2023.3348537>
- [11] Jiang, L.-C., Liu, R.-R., & Jia, C.-X. (2022). User-location distribution serves as a useful feature in item-based collaborative filtering. *Physica A: Statistical Mechanics and its Applications*, 586, 126491. <https://doi.org/https://doi.org/10.1016/j.physa.2021.126491>
- [12] Li, M., Jullien, S., Ariannezhad, M., & de Rijke, M. (2023). A next basket recommendation reality check. *ACM Transactions on Information Systems*, 41(4), 1-29.
- [13] Liu, L. (2024). Dynamic time-aware collaborative sequential recommendation with attention-based network. *Knowledge and Information Systems*, 66(3), 1639-1655. <https://doi.org/10.1007/s10115-023-01996-2>
- [14] Liu, Y., Achananuparp, P., & Lim, E.-P. (2024). Non-binary evaluation of next-basket food recommendation. *User Modeling and User-Adapted Interaction*, 34(1), 183-227. <https://doi.org/10.1007/s11257-023-09369-8>
- [15] Ma, L.-C. (2023). Novel next-group recommendation approach based on sequential market basket information. *Electronic Commerce Research*, 23(4), 2399-2418. <https://doi.org/10.1007/s10660-022-09543-x>
- [16] Mao, H., Mao, M., & Mao, F. (2024). Ranking on user-item heterogeneous graph for Ecommerce next basket recommendations. *Knowledge-Based Systems*, 296, 111863. <https://doi.org/https://doi.org/10.1016/j.knosys.2024.111863>

- [17] Nasir, M., & Ezeife, C. I. (2023). A survey and taxonomy of sequential recommender systems for e-commerce product recommendation. *SN Computer Science*, 4(6), 708.
- [18] Osei-kwakye, J., Han, F., Amponsah, A. A., Ling, Q.-H., & Abeo, T. A. (2023). A diversity enhanced hybrid particle swarm optimization and crow search algorithm for feature selection. *Applied Intelligence*, 53(17), 20535-20560. <https://doi.org/10.1007/s10489-023-04519-2>
- [19] Osei-kwakye, J., Han, F., Amponsah, A. A., Ling, Q., & Abeo, T. A. (2022). A hybrid optimization method by incorporating adaptive response strategy for Feedforward neural network. *Connection Science*, 34(1), 578-607. <https://doi.org/10.1080/09540091.2021.2025339>
- [20] Rendle, S., Freudenthaler, C., & Schmidt-Thieme, L. (2010). Factorizing personalized markov chains for next-basket recommendation. *Proceedings of the 19th international conference on World wide web*,
- [21] Rendle, S., Krichene, W., Zhang, L., & Anderson, J. (2020). Neural collaborative filtering vs. matrix factorization revisited. *Proceedings of the 14th ACM Conference on Recommender Systems*,
- [22] Sharma, K., Lee, Y.-C., Nambi, S., Salian, A., Shah, S., Kim, S.-W., & Kumar, S. (2024). A survey of graph neural networks for social recommender systems. *ACM Computing Surveys*, 56(10), 1-34.
- [23] Singh, P. K., Sinha, S., & Choudhury, P. (2022). An improved item-based collaborative filtering using a modified Bhattacharyya coefficient and user-user similarity as weight. *Knowledge and Information Systems*, 64(3), 665-701. <https://doi.org/10.1007/s10115-021-01651-8>
- [24] Sun, W., Xie, R., Zhang, J., Zhao, W. X., Lin, L., & Wen, J.-R. (2023a). Generative Next-Basket Recommendation *Proceedings of the 17th ACM Conference on Recommender Systems*, Singapore, Singapore. <https://doi.org/10.1145/3604915.3608823>
- [25] Sun, W., Xie, R., Zhang, J., Zhao, W. X., Lin, L., & Wen, J.-R. (2023b). Generative next-basket recommendation. *Proceedings of the 17th ACM Conference on Recommender Systems*,
- [26] Tan, Q., Zhang, X., Huang, X., Chen, H., Li, J., & Hu, X. (2024). Collaborative Graph Neural Networks for Attributed Network Embedding. *IEEE Transactions on Knowledge and Data Engineering*, 36(3), 972-986. <https://doi.org/10.1109/TKDE.2023.3298002>
- [27] Tao, Y., Wang, C., Yao, L., Li, W., & Yu, Y. (2023). Item trend learning for sequential recommendation system using gated graph neural network. *Neural Computing and Applications*, 35(18), 13077-13092. <https://doi.org/10.1007/s00521-021-05723-2>
- [28] Wang, P., Guo, J., Lan, Y., Xu, J., Wan, S., & Cheng, X. (2015). Learning hierarchical representation model for nextbasket recommendation. *Proceedings of the 38th International ACM SIGIR conference on Research and Development in Information Retrieval*,
- [29] Wang, W., & Cao, L. (2021). Interactive sequential basket recommendation by learning basket couplings and positive/negative feedback. *ACM Transactions on Information Systems (TOIS)*, 39(3), 1-26.
- [30] Xu, Y., Ji, J., Ni, Q., Feng, K., Beer, M., & Chen, H. (2023). A graph-guided collaborative convolutional neural network for fault diagnosis of electromechanical systems. *Mechanical Systems and Signal Processing*, 200, 110609.
- [31] Yang, Y., Jang, H. J., & Kim, B. (2020). A Hybrid Recommender System for Sequential Recommendation: Combining Similarity Models With Markov Chains. *IEEE Access*, 8, 190136-190146. <https://doi.org/10.1109/ACCESS.2020.3027380>
- [32] Yannam, V. R., Kumar, J., Vankayala, T., & Babu, K. S. (2023). Hybrid approach for next basket recommendation system. *International Journal of Information Technology*, 15(3), 1733-1740. <https://doi.org/10.1007/s41870-023-01220-y>
- [33] Zeng, W., Liu, J., & Zhang, B. (2024). Hierarchical representation learning for next basket recommendation. *Array*, 23, 100354. <https://doi.org/https://doi.org/10.1016/j.array.2024.100354>
- [34] Zhang, Q., Lu, J., & Jin, Y. (2021). Artificial intelligence in recommender systems. *Complex & Intelligent Systems*, 7(1), 439-457. <https://doi.org/10.1007/s40747-020-00212-w>