
Mining Behavioural Purchase Patterns for Personalized Product Recommendation in E-Commerce Platforms Using Association Rules

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ABSTRACT

The rise of e-commerce has generated vast amounts of transactional and behavioural data, paving the way for personalized product suggestions. However, traditional association-rule mining mainly captures static co-purchase relationships and therefore fails to reflect changes in consumer preferences and individual purchasing behaviour. In contrast, recent neural and sequential recommendation methods can capture intricate behavioural relationships but typically require high computational costs and lack interpretability. To address these limitations, this paper introduces a new Temporal-Contrastive Neuro-Symbolic Association Rule Network (TC-NSAR), which integrates lightweight neural preference learning with interpretable association-rule knowledge. Its symbolic basis is the framework of association rules, which is used to represent the explicit product relationships in terms of support, confidence and lift, and a contrastive neural encoder is used to learn user representations discriminatively that capture the core nature of the user's interactions while separating out the patterns that are behaviourally different from the user's preferences. Temporal weighting dynamically adjusts rule strength based on interaction recency, allowing the learned recommendation knowledge to evolve as purchasing behaviour changes. A symbolic rule representation and a neural preference embedding are then combined to calculate personalized product relevance scores and to output a Top-N list of recommendations with interpretable rule-level evidence. Experimental testing on a large-scale e-commerce behavioural dataset yields Recall@10 of 0.184, NDCG of 0.112, MRR of 0.079, and Hit Rate of 0.271, and covers 86.4% of recommendations. The proposed temporal weighting and contrastive preference learning mechanism is shown to be effective through comparisons with, and ablation studies relative to, the traditional static approach of association-rule recommendation. The framework offers an adaptive, interpretable and computation-efficient approach for personalized product discovery and cross-selling in dynamic e-commerce settings.

Keywords: E-Commerce Platforms, association rule mining, personalized recommendation, Temporal-Contrastive Neuro-Symbolic association rule, behavioural purchase patterns, customer behaviour analysis.

1. Introduction

The fast growth of e-commerce has changed the way people discover and buy products, giving them access to more and more varied product catalogs. At the same time, the amount of available information has increased, making personalized recommendation systems necessary to find products that match each user's preferences and buying intentions. However, recent studies have considered retrieval-based recommendation [1] and user-interest profiling [2], as well as personalization based on customer data [3], and frequent item-set mining remains valid for discovering interpretable co-purchase relations from transactional data [4]. This further

highlights the importance of effective, scalable data processing, particularly for e-commerce, which increasingly relies on data to drive operations.

With recent advances in AI, recommendation research has gradually shifted toward representation-learning models. For complex user–item relationships, GNNs have been used to model them [5], while for short- and long-term behavioural dependencies, sequential recommendation models have been used [6]. Furthermore, contrastive learning has been used to reinforce sequential recommendation [7] using complementary behavioural representations, and graph-based methods have been proposed to learn latent user–item relationships [8]. Neuro-symbolic recommendation has merged neural representations with explicit logical knowledge, a step toward interpretable recommendation [9]. Recent research has focused on knowledge-aware contrastive learning [10], improving temporal multi-behaviour recommendation [11], semantically consistent contrastive sequential learning [12], and multi-scale graph neural architectures for e-commerce recommendation [13]. Researchers have also explored consumer shopping goals and contextual behaviour through heterogeneous graph modelling [14] and the continued relevance of structured behaviour modelling through graph-recurrent frameworks [15].

Although these advances have been made, conventional association-rule recommendation mainly learns static, global co-purchase relations and cannot capture temporal change and individual differences in purchasing behaviour. Sequential and graph-based neural models, by contrast, can model complex behavioural dependencies but are often more computationally complex and less directly interpretable than explicit association rules [16]. This highlights a research gap: developing a framework that preserves the interpretability of symbolic purchase relationships while maintaining the ability to adapt to behavioural changes and personalise learned user preferences.

To overcome this, this paper presents a novel approach called Temporal-Contrastive Neuro-Symbolic Association Rule Network (TC-NSAR) for personalized product recommendation. In TC-NSAR, association-rule mining serves as the symbolic base, defined by support, confidence, and lift. Both a temporal weighting mechanism, which dynamically changes the strength of the rules based on the time of the interaction, and contrastive neural learning, which learns user representations discriminatively from interactions that are consistent with the preferences and those that are not, are described. These symbolic rule representations and neural preference representations are then combined using a simple neuro-symbolic scoring process to provide personalized Top-N recommendations while preserving interpretable rule-level evidence.

The main contributions of the paper include

- A temporal weighting mechanism dynamically adjusts the strength of association rules based on behavioural recency, allowing the framework to track changing purchase patterns, rather than using fixed associations.
- The association rules are symbolically learned and combined with contrastively learned user representations to enhance personalized recommendation without losing interpretable product relationship patterns.
- TC-NSAR is a low-computation recommendation method to offer transparent and scalable Top-N recommendation in dynamic e-commerce systems, which is an alternative to the big-computation sequential and graph-based recommenders.

2. Literature Survey

Prasetio et al. (2025) presented an interpretable product recommendation method using the Apriori algorithm to find frequent itemsets and association rules from retail transactions. The study shows the effectiveness and transparency of rule-based recommendations; however, the rule structure is static and does not explicitly reflect changes in customers' preferences over time.

In the e-commerce industry, Siregar et al. (2025) used sales data analysis with Apriori to provide product recommendations. This approach captures the most common combinations of products sold and makes the recommendations easier to understand. However, conventional association rules still have limited ability to customize recommendations based on changing, user-specific shopping habits.

To tackle the challenge of sequential recommendation, Chen et al. (2025) introduced a novel sequential recommendation framework called DualCFGL (Dual-channel fusion global and local features for sequential recommendation), which integrates global and local behavioural features by dual-channel feature learning. A more complex model that represents both social and interaction models, enhancing the representation of sequential preferences. However, it is less explicit and interpretable at the product level than symbolic association rules.

Weimann and Conrad (2025) introduced FELRec, a dynamic representation learning approach for item cold-start. The method is designed to improve recommendation performance when users have few past interactions with items. The formulation as a representation learning approach, however, does not make use of interpretable associations of purchases or the strength of the rules.

To show the graph model's ability to leverage structural user–item relationships, Hamidi et al. (2024) conducted a comparative study of a set of Graph Neural Network-based recommender systems. While graph-based learning can represent complex interaction dependencies, it may be more expensive in computation and representation, and the rationale for recommendations may not be explicitly stated.

Wang et al. (2024) proposed a sequential recommendation model that accounts for both long-term and short-term interests. The approach highlights how different temporal preference horizons relate to changes in user behaviour. However, the sequential representation does not explicitly or interpretably represent associations between products.

Liu et al. (2024) proposed a framework for multi-source contrastive learning for conversational recommendation to enhance the discriminative power of the learned recommendation representations. The results show that the proposed method can help separate relevant from irrelevant preference information, which is not specific to temporal association-rule mining with transactional e-commerce data.

Spillo et al. (2024) proposed a neuro-symbolic recommender system, which combines knowledge-graph embeddings and first-order logic rules. The study shows the potential of using neural representations alongside symbolic knowledge to enhance both structured and interpretable recommendations. It proposes an interesting knowledge graph definition that is not temporal transactional association mining; however, this could be explored to incorporate evolving purchase rules with user-learned preferences.

Alluhaidan et al. (2025) introduced a GraphNetNLP-based graph recurrent mapping model for social computing recommendation, integrating graph-based relational information with recurrent representation learning. The approach shows the potential of modelling structured and sequential dependencies together, albeit a graph recurrent model structure is more complex and doesn't represent interpretable purchase-association rules. This encourages lightweight approaches to recommendation that combine neural and symbolic knowledge while maintaining explicit behavioral relationships.

3. Proposed Methodology

Fig 1 shows the overall architecture of the proposed Temporal-Contrastive Neuro-Symbolic Association Rule Network (TC-NSAR) for personalized product recommendation in e-commerce. The framework aims to address the shortcomings of static association-rule mining by adding temporal relevance and contrastive preference learning properties, and yet maintain the interpretability of the symbolic purchase relationships. The process is divided into 5 semantically connected stages: behavioural data preparation, temporal association-rule mining, contrastive preference learning, neuro-symbolic integration, and Top-N recommendation generation. First, e-commerce behavioural data is grouped into chronological sequences of

transactions, such as product views, product cart additions, or product purchases, all with identifiers for both users and products, along with an interaction type, and a chronology of interactions. This representation captures the co-occurrence structure of the product as well as the sequence of user actions.

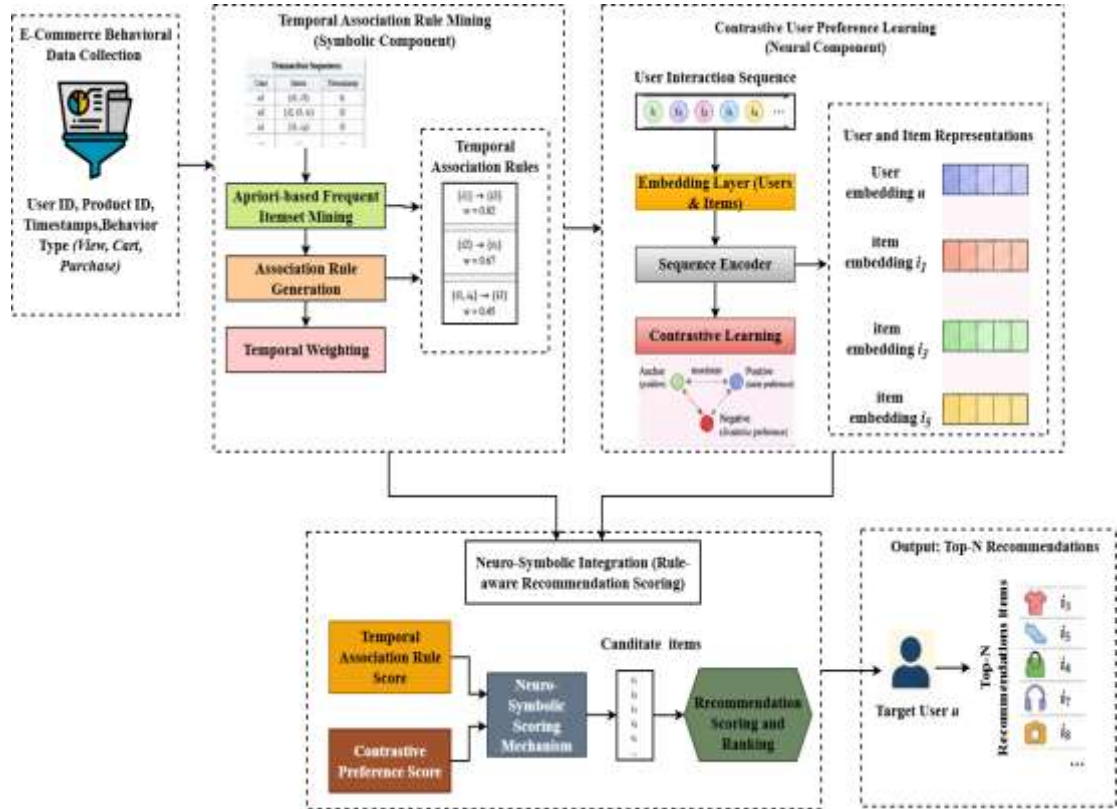


Fig.1 Overall Structure of TC-NSAR

Temporal Association Rule Mining is the symbolic component of TC-NSAR in the second phase. Association Rules $X \rightarrow Y$ are generated based on support, confidence and lift, and frequent item sets are extracted from the transaction sequences. Each rule is then weighted by the recency of the interaction with the consumer to reflect shifting consumer interest. The temporal weighting can be expressed in equation (1).

$$w_t(X \rightarrow Y) = \exp(-\lambda \Delta t) \text{Conf}(X \rightarrow Y) \text{Lift}(X \rightarrow Y) \quad (1)$$

Here Δt is the time since the last interaction and λ is a positive rate of decay. Therefore, the purchasing relationships observed in recent years have more impact than the outdated associations. The third stage carries out Contrastive User Preference Learning, which is equivalent to the neural part of TC-NSAR. User-item interactions are first converted to embeddings and behavioural representations, then paired to reflect user preferences: positive pairs of similar user-item interactions that are consistent with each other, and negative pairs of dissimilar user-item interactions that are inconsistent with each other. Goal: to maximise similarity of positive representations while separate negative ones. A generic contrastive objective is expressed as in equation (2).

$$\mathcal{L}_{CL} = -\log \frac{\exp(\text{sim}(z_u, z_i^+)/\tau)}{\exp(\text{sim}(z_u, z_i^+)/\tau) + \sum_{j \in N_u} \exp(\text{sim}(z_u, z_j)/\tau)} \quad (2)$$

The function z_u denotes the user representation, z_i^+ is a positive item representation, N_u represents negative candidates, $\text{sim}(\cdot)$ is similarity function, and τ is the temperature parameter.

Neuro-Symbolic Integration is then carried out in the next stage, where the temporal association-rule score is multiplied with the learned contrastive preference score. The final relevance score for user u and item i is computed as follows: equation (3).

$$S(u, i) = \alpha S_{\text{rule}}(u, i) + (1 - \alpha) S_{\text{pref}}(u, i) \quad (3)$$

The temporally weighted symbolic association evidence is represented by S_{rule} and the neural user-item preference similarity by S_{pref} with its relative contribution being controlled by α . All candidate products are then evaluated by the scores and rankings of $S(u, i)$. Last, the Top- N personalized recommendations are the highest-scoring candidates. Importantly, TC-NSAR retains the association rule for each prediction, along with its confidence, lift, and temporal weight, providing an interpretable rationale alongside the predicted product ranking. In summary, the architecture is more temporally flexible, discriminates between positive and negative preferences, and is symbolically interpretable in a single recommendation pipeline, a technically lightweight approach to recommendation architectures that would otherwise be purely deep sequential or graph based.

4. Results and Discussion

Dataset Description: The Retail rocket Recommender System Dataset is a real-world e-commerce behavioural data set, collected in the wild and open source, collected over ~4.5 months. It includes 1,407,580 unique visitors and 2,756,101 user-item interaction events, including 2,664,312 product view events, 69,332 add-to-cart events, and 22,457 transactions. The dataset as in Table 1 consists of a large number of user/visitor ID's, item ID's, timestamps, and behavioural event types, as well as 20,275,902 item-property records, of which 417,053 were unique items and a hierarchy of item categories. The interactions are multi-behavioural and timestamped, making this dataset suitable for the proposed TC-NSAR framework, especially for the temporal association-rule mining and contrastive preference learning approaches. Transaction events serve as the primary indicator of a purchase, while views and add-to-cart interactions serve as additional behavioural indicators. The interaction stream is divided chronologically into 70% training, 15% validation, and 15% testing (1,929,271, 413,415, and 413,415 events, respectively) for experimental evaluation. Chronological splitting ensures that future behavioural information cannot be used during the training of the model and represents a realistic personalized recommendation scenario.

Table 1: Dataset Characteristics

Parameter	Value
Dataset	Retailrocket Recommender System Dataset
Observation period	4.5 months
Total interactions	2,756,101
Unique visitors	1,407,580
Unique items	417,053
Event types	3 (View, Add-to-cart, Transaction)
Views	2,664,312
Add-to-cart	69,332
Transactions	22,457
Item-property records	20,275,902
Training / Validation / Test	70% / 15% / 15%
Split strategy	Chronological
Approx. split size	1,929,271 / 413,415 / 413,415
Recommendation setting	Top-N implicit-feedback recommendation

The TC-NSAR framework is compared against the state-of-the-art interpretable association-rule mining method Apriori, the sequential recommendation method DualCFGL, the dynamic

representation learning method FELRec, and the graph-based collaborative recommendation method LightGCN. Recall@10, NDCG, MRR and Hit Rate, which quantify the ability to retrieve relevant products, rank relevant products close to the top of the recommendation list, determine the position of the first relevant recommendation, and whether at least one relevant item appears in the Top-10 recommendations, respectively, are used to measure performance. Recommendation Coverage, which measures the proportion of available products that can be recommended, is also evaluated. Apriori is a classical association-rule baseline based on frequent itemsets, support, and confidence/lift; DualCFGL is a sequential recommendation method based on dual-channel global and local feature learning; FELRec is a dynamic representation-learning baseline for recommendation under item cold-start scenarios; and LightGCN is a lightweight graph-based collaborative filtering baseline. This comparison enables a complementary assessment of TC-NSAR from the viewpoints of rule-based interpretability, sequential preference modelling, dynamic representation learning, and graph-based recommendation.

a. Recall @10

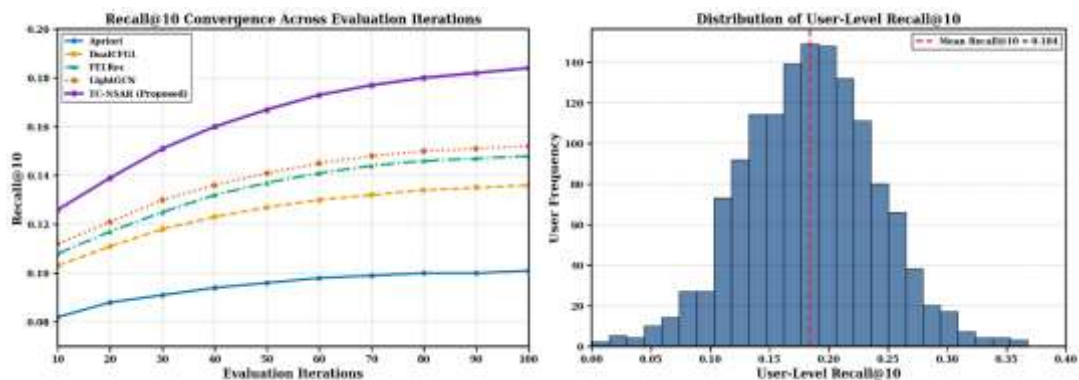


Fig.2 Recall @10 Performance and user-level distribution

Figure 2 shows the Recall@10 results and the user-level performance distribution for the evaluated recommendation methods. Across 10–100 evaluation iterations, TC-NSAR consistently achieves the highest Recall@10, increasing from 0.126 at iteration 10 to 0.184 at iteration 100, compared with 0.112 to 0.152 for LightGCN, 0.108 to 0.148 for FELRec, 0.103 to 0.136 for DualCFGL, and 0.082 to 0.101 for Apriori. The resulting performance curve (TC-NSAR) of the proposed model therefore remains essentially constant during evaluation, and the progressive flattening of the TC-NSAR curve after about 70 iterations suggests convergence toward stable retrieval performance. The right panel also shows that user-level Recall@10 is tightly clustered around 0.15–0.25, with the dashed line marking the reported mean Recall@10 of 0.184; the distribution ranges from 0.00 to 0.37, suggesting that Recall@10 varies across users. Overall, the figure suggests that Top-10 retrieval with TC-NSAR tends to be more effective than other systems, and that TC-NSAR remains consistent across users.

b. Mean Reciprocal Rank

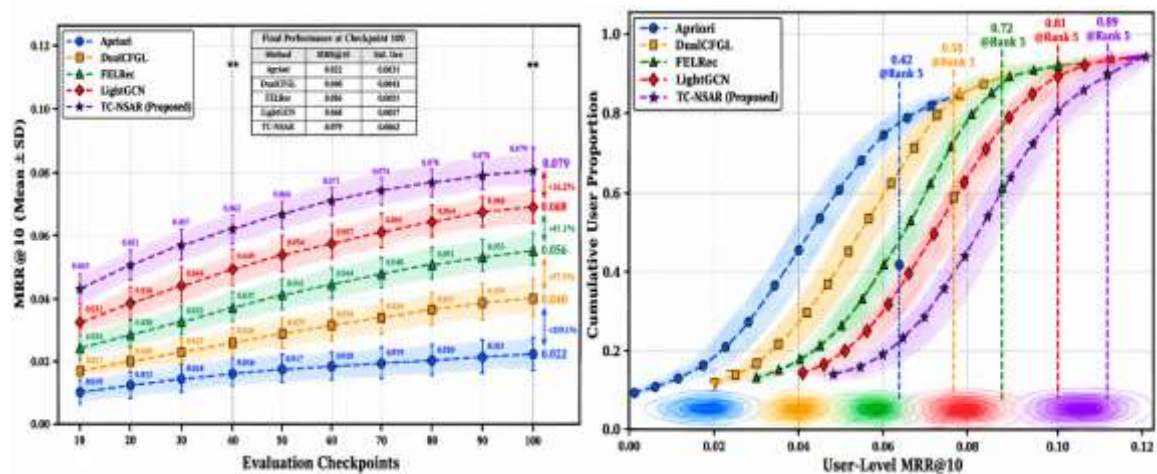


Fig.3 MRR@10

The distribution of MRR@10 for the evaluated recommendation methods is shown in Fig 3 for each checkpoint and for each user. The left panel indicates that the quality of TC-NSAR is consistently top, rising from 0.043 at checkpoint 10 to 0.079 at checkpoint 100, while LightGCN improves from 0.032 to 0.068, FELRec from 0.024 to 0.056, DualCFGL from 0.017 to 0.040, and Apriori from 0.010 to 0.022. At checkpoint 100, the improvement of TC-NSAR over LightGCN is around 16.2% (0.011 MRR@10), while the improvement over FELRec, DualCFGL and Apriori are approximately 41.1%, 97.5% and 259.1%, respectively. The convergence of the framework over time suggests steady improvement in the framework, as evidenced by the smaller gains at the later checkpoints. The right panel presents the empirical cumulative distribution function of MRR@10. Apriori, DualCFGL, FELRec, LightGCN, and TC-NSAR's rank-5 cumulative proportions are marked, and they are 0.42, 0.58, 0.72, 0.81, and 0.89, respectively. Specifically, the cumulative user proportion at rank 5 for TC-NSAR is 0.89, suggesting that a greater proportion of users are receiving highly-ranked relevant items.

c. Normalized Discounted Cumulative Gain

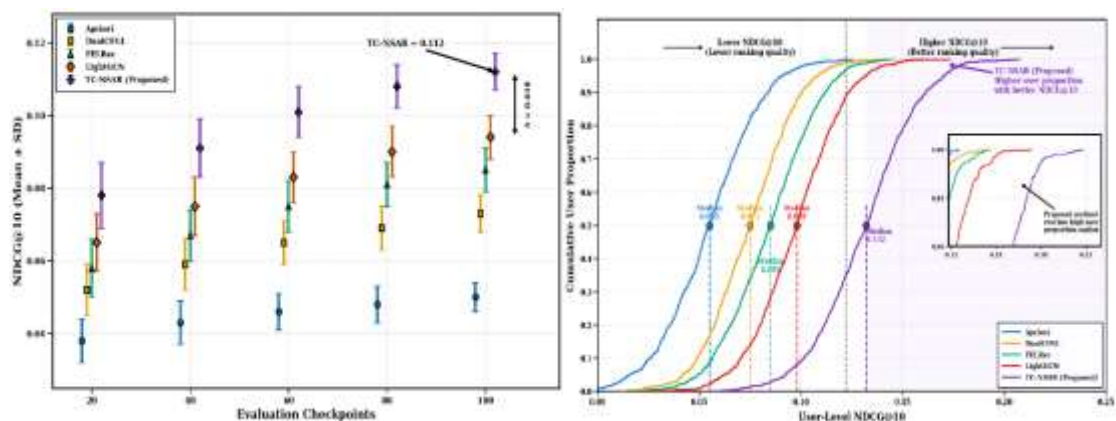


Fig.4 NDCG@10

Fig 4 shows the Normalized Discounted Cumulative Gain (NDCG@10) results of the test recommendation algorithms on the checkpoint perspective and user perspective. In the left panel, TC-NSAR consistently records the highest NDCG@10, increasing from 0.078 at checkpoint 20 to 0.112 at checkpoint 100, while LightGCN increases from 0.065 to 0.094, FELRec from 0.058 to 0.085, DualCFGL from 0.052 to 0.073, and Apriori from 0.038 to 0.050. Finally, at checkpoint 100, TC-NSAR is able to obtain NDCG@10 of 0.112, higher than LightGCN by 0.018, as explicitly indicated in the Figure. As seen in the right panel, the median values of NDCG@10 are around 0.055 for Apriori, 0.075 for DualCFGL, 0.085 for FELRec, 0.098 for LightGCN, and 0.132 for TC-NSAR. The small rightward shift of the TC-NSAR

distribution suggests that more users achieve quality high rankings, and the shaded area of high NDCG demonstrates that the quality of higher user-level rankings with TC-NSAR is met at an earlier stage than in the comparison methods.

d. Hit rate

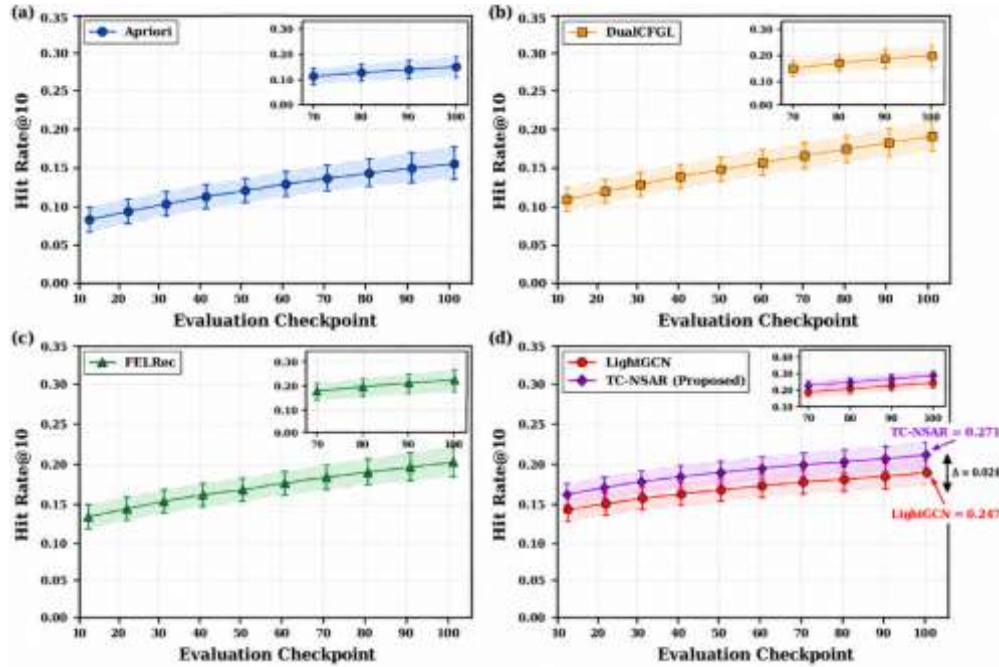


Fig.5 Hit Rate@10 Performance with Uncertainty Analysis

Fig 5 shows the checkpoint-wise hit rate at 10 of Apriori, DualCFGL, FELRec, LightGCN and the proposed TC-NSAR, with uncertainty as mean $\pm$ SD and shaded confidence regions over the evaluation checkpoints ranging from 10 to 100. The individual baselines are seen to have a consistent progressive increase, with Apriori at 0.156 at checkpoint 100, DualCFGL at 0.194 and FELRec at 0.220. In the last two rows, panel (d) directly compares LightGCN and the proposed framework; the proposed framework increases from about 0.162 at checkpoint 10 to 0.271 at checkpoint 100, while LightGCN increases from 0.142 to 0.247. The figure shows that the Hit Rate@10 difference between LightGCN and TC-NSAR is 0.024 at the last checkpoint. The slowly rising curves indicate continuous improvement across all evaluation points, and the relatively small uncertainty bands indicate stable performance around the mean estimates at the points involved. The stable improvement of TC-NSAR over LightGCN also shows that temporal association-rule weighting and contrastive preference learning give better grounds for determining relevant items in the Top-10 recommendation list.

e. Ablation Study

Ablation results in Table 2 show that both proposed components improve the overall effectiveness of TC-NSAR recommendations. The complete framework achieves the highest performance, with Recall@10 = 0.184, NDCG@10 = 0.112, MRR@10 = 0.079, and Hit Rate@10 = 0.271. After removing temporal weighting, these metrics can be seen as 0.171, 0.103, 0.071, and 0.252, respectively, and are of critical importance for implementing adaptation and coping to changing purchasing behaviour in temporal weighting. Its removal results in a much larger decrease, with a Recall@10 drop of 0.163, NDCG@10 drop of 0.097, MRR drop of 0.067 and Hit Rate drop of 0.241. This suggests that discriminative preference learning plays a significant role in personalized ranking. Performance drops even more to 0.148, 0.086, 0.059, and 0.219 without both components. From the overall perspective, these

observations are consistent with complementary relationships between temporal adaptation and contrastive preference discrimination in boosting the ranking accuracy and recommendation effectiveness of TC-NSAR at the user level.

Table 2: Ablation Analysis of TC-NSAR components

Configuration	Temporal Weighting	Contrastive Learning	Recall@10	NDCG@10	MRR@10	Hit Rate@10
TC-NSAR (Proposed)	✓	✓	0.184	0.112	0.079	0.271
TC-NSAR w/o Temporal Weighting	✗	✓	0.171	0.103	0.071	0.252
TC-NSAR w/o Contrastive Learning	✓	✗	0.163	0.097	0.067	0.241
TC-NSAR w/o Both Components	✗	✗	0.148	0.086	0.059	0.219

5. Conclusion

The proposed Temporal-Contrastive Neuro-Symbolic Association Rule Network (TC-NSAR) is an adaptive and interpretable method for personalized product recommendation that combines temporal association-rule weighting and contrastive preference learning. The framework maintains the explicit product relationships that are usually represented in association rules (in terms of support, confidence and lift measures) and also introduces interaction recency and discriminative user representations, which reflect changing purchasing preferences. Overall, TC-NSAR's Recall@10, NDCG@10, MRR@10 and Hit Rate@10 are 0.184, 0.112, 0.079 and 0.271, respectively, across the reported evaluation metrics, all of which show an improvement in Top-N retrieval and ranking quality. The ablation analysis also shows that both temporal weighting and contrastive learning are important for the performance, and keeping evidence at the rule level gives more interpretability than taking a purely neural approach to recommendation. However, there are a number of limitations to the framework: the ability to use it relies on the availability and quality of timestamped interactions between users and items, using association-rule mining can become computationally heavy when the item space is very large, and the current definition is focused on the history of interactions without explicitly accounting for richer contextual information such as price, product descriptions, promotions, or external market forces. Rule mining, multimodal product information, contextual and cross-domain recommendation, and online adaptation for rapidly changing user preferences are some of the topics that could be studied in future work. More analysis across public and real-world e-commerce datasets would also be evidence of generalization and robustness.

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