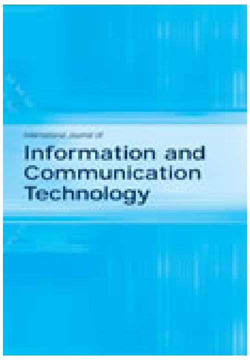

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E-commerce consumer behaviour prediction through the integration of collaborative filtering and graph neural networks

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Abstract: Due to the huge amount of information interested by users on e-commerce platforms, it is difficult to predict consumers' purchasing behaviour. To this end, this paper first forms a session graph based on consumers' session sequences. Meanwhile, inter-item multivariate relationships and inter-session cross-information are modelled through graph convolutional networks. Then, the user's intention representation is generated through comparative learning. Next, a behavioural model of user consumption based on attention network is constructed. Finally, this paper calculated the ratings of users with purchasing behaviours on the target items, and obtained several items with high ratings to generate a recommendation list to predict e-commerce consumers' behaviours. Experiments are conducted on two public datasets, and the results show that the accuracy of the proposed model is improved by at least 3.31% and 5.21% respectively, which effectively improves the accuracy of e-commerce consumer behaviour prediction.

Keywords: e-commerce consumer behaviour prediction; collaborative filtering; graph convolutional network; GCN; attention network; comparative learning.

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Biographical notes: Shuxin Wei received her PhD degree at Stamford International University in 2024 in Thailand. She is working in Guangdong University of Science and Technology since 2025. Her research interests include new quality productivity, e-commerce, digital economy, enterprise management and digital transformation.

1 Introduction

Online shopping on e-commerce platforms has many advantages, such as flexible consumption time and diversification of products, which leads to the growing scale of online shopping crowd (Baubonienė and Gulevičiūtė, 2015). For the goal of enhancing user experience and satisfaction and promote online consumption to obtain higher economic benefits, e-commerce companies need to adopt advanced and intelligent means to effectively utilise user behavioural data. Studying users' interests and preferences, accurately identifying users' needs, determining whether users have repeated shopping behaviour, and recommending products that satisfy them are the core issues that e-commerce companies need to address (Xu and Sang, 2022). Accurate prediction of users' consumption behaviour is the basic requirement for e-commerce to realise quality service. Providing personalised product recommendations to meet user preferences and needs is an effective measure to increase customer stickiness and enhance customer loyalty, and the key is to adopt effective recommendation algorithms (Patil et al., 2024). Collaborative filtering (CF) is highly applicable in e-commerce because it can accurately predict the consumption behaviour of target users based on the ratings of items by nearest-neighbour users (Cao et al., 2021).

Consumer behaviour prediction in e-commerce systems refers to the analysis of user preferences through the data of existing users on the platform, understanding the timing of possible purchases by users, and then accurately predicting the future behaviour of users. Traditional methods analyse consumer access data to explore the consumption behaviour of e-commerce platforms, and Hernandez et al. (2017) use real user online transaction data as the raw data to find out the similarity or association between the products purchased by the users, and then predict the probability of the users to make repurchase. Susanty et al. (2022) proposed a consumer behaviour prediction model based on weighted Markov chains, which predicts the behaviour of various categories by classifying consumers according to different characteristics. Qiu et al. (2015) proposed an algorithm based on the difference matrix, which can be applied to e-commerce transactions to predict the behaviour in the transaction, but the prediction error is large. Fabra et al. (2020) proposed a new algorithm for predicting users' online transaction behaviours, which uses latent factors and the utility of the behavioural sequences as the basis of analysis.

The mentioned methods only consider the shallow features of consumer consumption data without considering the consumer's behavioural preferences, which leads to poor prediction results. The CF algorithm filters a large amount of information to be recommended and sifts out the user's preference information from it, which greatly improves the efficiency of consumer behaviour prediction. Chou et al. (2022) used a large amount of consumer behaviour data as the original data, used CF technology to mine and analyse it, and then proposed a model that can analyse consumer behaviour. Li et al. (2022) proposed a CF algorithm based on radial basis function (RBF), which analyses the relationship between consumer characteristics and consumer preferences, and then predicts the preference behaviours of users using different user characteristics. He et al. (2022) focused on consumer's interest products, and through the combination of CF and neural network technology, they finally obtained a method that can effectively predict consumer's interest products. Li et al. (2019) first mined the correlation of consumers' purchased products to form consumers' preferred product sets, and then combined the hierarchical Bayesian discrete choice and support vector regression models to complete the prediction of consumer behaviour.

With the increasing amount of data on e-commerce platforms, the cost of feature engineering is also increasing. Deep learning algorithms convert the feature engineering process into direct input of raw data, and through a multi-layer network, features are automatically extracted to improve the prediction accuracy. Zhu et al. (2022) extracted the features of user's purchasing behaviour based on long short-term memory (LSTM) network and output the prediction results by multilayer perceptron, which improved the prediction efficiency. Azadravesh et al. (2024) proposed a user consumption behaviour prediction model based on convolutional neural network (CNN) and BiLSTM, which achieved 82.9% prediction accuracy. Xu et al. (2024) used the traditional Transformer to model the user's behavioural patterns and used the contextual information of future data to assist in training, in order to improve the model performance. Graph neural networks (GNNs) show significant advantages in the task of e-commerce consumer behaviour prediction, mainly in their ability to model complex relational data, and extract high-order interaction features. Al-Otaibi (2024) modelled users' session sequences as graph-structured data and used gated GNN to capture higher-order dependencies between consumption behaviours with a prediction accuracy of 86.3%. Turatti (2025) proposed global context-enhanced predictive model for graph convolutional network (GCN), which can achieve more accurate prediction of users' consumption behaviours.

In the field of e-commerce, accurate prediction of consumer behaviour is crucial for improving user experience, optimising marketing strategies, and enhancing platform competitiveness. Although traditional CF algorithms can utilise user-item interaction data for personalised recommendation, they have limitations in dealing with complex relationships and mining deep features. GNN, with its powerful graph-structured data modelling capability, provides a new way of thinking to solve this problem. In view of this, this paper designs an e-commerce consumer behaviour prediction model that incorporates CF and GNNs. First, a session graph is constructed based on the information of items purchased by users and the corresponding session sequences. Then, this paper encodes the sequential positions of the items and input the initialised embedding vectors of the item nodes in the graph into the GCN network, and then generate the item representations that incorporate the multiple associations among the items. Next, the item representations in the session are aggregated by GCN, and the session representation is generated. The user's intention representation is generated by comparison learning. Attention network-based construction of a consumer behaviour learning module to model the behavioural patterns of user consumption. Finally, based on the calculation of the purchase behaviour of the user's rating of the target item, the number of items with high ratings is obtained to generate a recommendation list, realising the prediction of e-commerce consumer behaviour. The experimental results on two public datasets show that the F1 of the proposed model is 0.9261 and 0.9436 respectively, which is better than the benchmark model and verifies the effectiveness of the proposed model.

2 Relevant technologies

2.1 CF algorithm

The core idea of CF algorithm is to use the behavioural data of the user group to predict the target user's preference for a specific item, and then provide personalised recommendations for the user (Zhang et al., 2016). In simple terms, the recommendation is made by finding other users with similar interests to the target user or other items similar to the target item.CF algorithms are mainly categorised into two types: user-based CF and item-based CF.

1. User-based CF (Chen et al., 2020). It will recommend items to the user that are liked by other users with similar interests to them. The core principle lies in identifying users with similar tastes by analysing their historical preferences. By utilising the user-based CF technique, the system will recommend similar items to the user's previous favourite items. By analysing all the ratings of items and information, the similarity between different items is calculated, and then based on the user's historical preference information, similar items are recommended to the user.
2. Item-based CF (Ajaegbu, 2021). It focuses on recommending other items for users that are similar to their past favourite items. This mechanism identifies the similarity between items by analysing a large amount of user evaluation data on the items. Once the similar items are identified, the system recommends items to the user that he/she may like based on his/her historical preferences. Item-based CF method is based on the historical behaviour of items and recommends by calculating the similarity, which helps to discover the potential interest of users, but needs to solve the problems of cold start and data sparsity.

2.2 Graph neural network

GNN, as a neural network that operates directly on graph structures, aims to learn the vector representation of entities and relations in graph networks and their composition rules. It stores topological relationships between structured input data and uses nodes to process the input data as a way of tracking the graph structure within the nodes (Dwivedi et al., 2023). In addition, analysing from the way of propagation, GNN can be classified into GCN, graph attention network (GAT). GCN is a deep learning model based on graph-structured data, which is capable of performing convolutional operations on graph structures. The advantage of GCN is the ability to learn a low-dimensional representation of the nodes while preserving the information about the graph structure. GAT is able to dynamically adjust the weights based on the relationships between the nodes to better capture the importance and interactions between the nodes. GAT can adaptively learn the relationships between nodes and better capture the interactions between nodes.

For each graph, each node has its own features, and the learning goal of GNN is to obtain the hidden state of each node h_v. GNN updates the hidden layer features of all nodes in an iterative manner, thereby achieving state updates. At $t + 1$ time, the hidden state of node v is updated as follows:

$$h_v^{t+1} = f\left(x_v, x_c o[v], h_n^t e[v], x_n e[v]\right) \tag{1}$$

where f is the hidden state update function and also the local transformation function, x_v is the feature of node v. $x_c o[v]$ is the features of all edges adjacent to node v, $x_n e[v]$ is the features of the neighbour nodes of node v, $h_n^t e[v]$ is the hidden state of the neighbour nodes at time t.

During the learning process, the model continuously iterates and updates the nodes, changing their embedding methods as follows. Here, t represents the tt^{th} iteration, X represents all features, H^t represents the set of embedding methods for all nodes in the t^{th} iteration.

$$H^{t+1} = F\left(H^t, X\right) \tag{2}$$

3 Session graph construction of e-commerce consumer purchase preferences

In e-commerce scenarios, a session is a collection of a series of user interactions with an e-commerce platform over a period of time. For example, a user browses multiple product pages, adds products to the shopping cart, performs searches, etc., within an hour, and these consecutive behaviours constitute a session. Conversations have temporal continuity and behavioural relevance, reflecting users' shopping intentions and interest focuses in a specific time period. By transforming consumer conversation data into graph structures and incorporating the modelling capabilities of GNN, the accuracy of capturing real-time consumer preferences can be significantly improved.

First, define the user's purchased item information and the corresponding session sequence S. Item dictionary $V = \{v_1, v_2, \ldots, v_{|V|}\}$, where $|V|$ represents the total number of non-repeating items. Given a session sequence $S = \{v_{s,1}, v_{s,2}, \ldots, v_{s,n}\}$, $v_{s,t}$ represents the item that an anonymous user interacts with at time t in the session S. Each session sequence is a hyperedge in the graph, and multiple session sequences are combined to form a session graph G.

The session graph is represented by a triplet $G = \{V_N, \varepsilon_M, W\}$, where V_N represents the set of item nodes in G, N is the number of item nodes, and ε_M is the set of M hyperedges in G. Each edge $\varepsilon_i \in \varepsilon_M$ in G connects at least two item nodes. The weight coefficient of each edge is $W_{\varepsilon_i} \in W$, and all weight coefficients form a diagonal matrix W. The graph G is represented by an incidence matrix H. For $H_{i\varepsilon} \in H$, if the item node $v_i \in V_N$ is included in the edge $\varepsilon_i \in \varepsilon_M$, the value is 1, otherwise it is 0. The degree of the item node and the degree of the edge are represented by D_v and D_e, respectively, where $D_v = \sum_{\varepsilon=1}^{M} W_\varepsilon H_{i\varepsilon}$ and $D_e = \sum_{i=1}^{N} H_{i\varepsilon}$.

In e-commerce platforms, the items purchased by users have multiple aspects, meaning they are not only related to one or a certain category of items, but also have diverse relationships such as complementarity with multiple items. The user session graph constructed in this paper has an inherent advantage in modelling multiple associations, which can capture the diverse associations between items in sessions, thereby accurately obtaining user behaviour preferences.

4 Session representation learning for e-commerce consumers based on graph CNN

4.1 Representation learning of purchased Items by consumers

Since the original e-commerce item ID cannot model the intrinsic relationships between items, this paper first maps the item ID to a one-hot encoding (Rodríguez et al., 2018), i.e., sequentially encodes the items, with the position of the target item set to 1 and other positions set to 0. Then, the one-hot encoding is transformed into a low-dimensional dense vector representation $X = [e_{v_1}, ..., e_{v_n}]$ through a projection matrix *E*, e_{v_1} for the item v_i, where *d* is the dimension of the vector. The parameters of *E* will be learned together with the parameters of other layers of the model through end-to-end training.

Based on the session graph constructed in the previous chapter, the initial embedding vectors of the item nodes in the graph are input into the GCN network to aggregate and generate item representations that integrate multiple associations between items. Inspired by literature (Gao et al., 2022), the non-linear activation of the graph network is removed and the weight of the hyperedge W_ε is set to 1. After optimisation, the matrix representation of the improved GCN is as follows.

$$X^{(l+1)} = D_v^{-1} H W D_e^{-1} H^T X^{(l)} \tag{3}$$

where D_v and D_e are the degree matrix of the node and the degree matrix of the hyperedge, respectively, $X^{(l)}$ is the embedding representation of the item node at the l^{th} layer. Similar to the GCN network, $D_v^{-1} H W D_e^{-1}$ is the Laplacian matrix, and $H^T X(l)$ is the transformation operation between features. From an essential perspective, Equation (3) is the explicit expression of the implicit transmission from node features to edge features and back to node features.

In the multi-layer GCN network adopted in this paper, the item representations captured by different layers capture different implicit semantic features of items, and as the number of network layers increases, the representations of items tend to be consistent. Therefore, compared to using the representation from only the last layer of GCN, using a weighted sum of representations from various levels can obtain a more comprehensive item representation. After aggregating through *L* layers of GCN, the item node representation e_{v_i} is generated.

$$e_{v_i} = \frac{1}{1+L} \sum_{l=0}^{L} e_{v_i}^{(l)} \tag{4}$$

4.2 Consumer session representation learning

After the item representation learning mentioned above, the obtained representation is for a specific item in the session. Since a session sequence contains multiple items, it is necessary to aggregate the item representations in the session to generate a session representation. For a given session sequence sorted by time, the items that recently interacted with the user can better reflect the user's current interest, so modelling the positional information of items in user behaviour is particularly important. Therefore, this paper introduces a position encoding vector to represent the positional information of items to model the user's interest migration. For a session sequence *S*, the position embedding vector matrix P_s is $P_s = \{p_1, \ldots, p_i, \ldots, p_t\}$, where p_i and variable *t* is the length of *S*. Therefore, the representation of the item node incorporating positional information is as follows:

$$\overline{e}_{v_i} = \tanh\left(W_1 \left[e_{v_i} \,\|\, p_{t-i+1} \right] + b_1\right) \tag{5}$$

where W_1 is the coefficient matrix, e_{v_i} is the representation of the node v_i learned through l levels of GCN, p_{t-i+1} is the position encoding vector of the node v_i, b_1 is the bias, and || represents the concatenation function operation. To accurately model the current session representation and reduce the impact of user interest drift, this paper adopts an attention mechanism to calculate the contribution of each item node in the current session to the overall session representation.

$$\alpha_{v_i} = q_1^T \sigma\left(W_2 \overline{e}_{v_i} + W_3 e_{\overline{v}_i}^{*} + b_2\right) \tag{6}$$

where W_2, W_3 are coefficient matrices, q_1, b_2 are biases, and $e_{\overline{v}_i}^{*}$ is the average of the representations of all item nodes in the current session S.

After aggregating the item node features through GCN, the session representation S_H for session graph modelling is generated.

$$S_H = \sum_{i=1}^{t} \alpha_{v_i} \overline{e}_{v_i} \tag{7}$$

5 E-commerce consumer behaviour prediction by integrating CF and GNNs

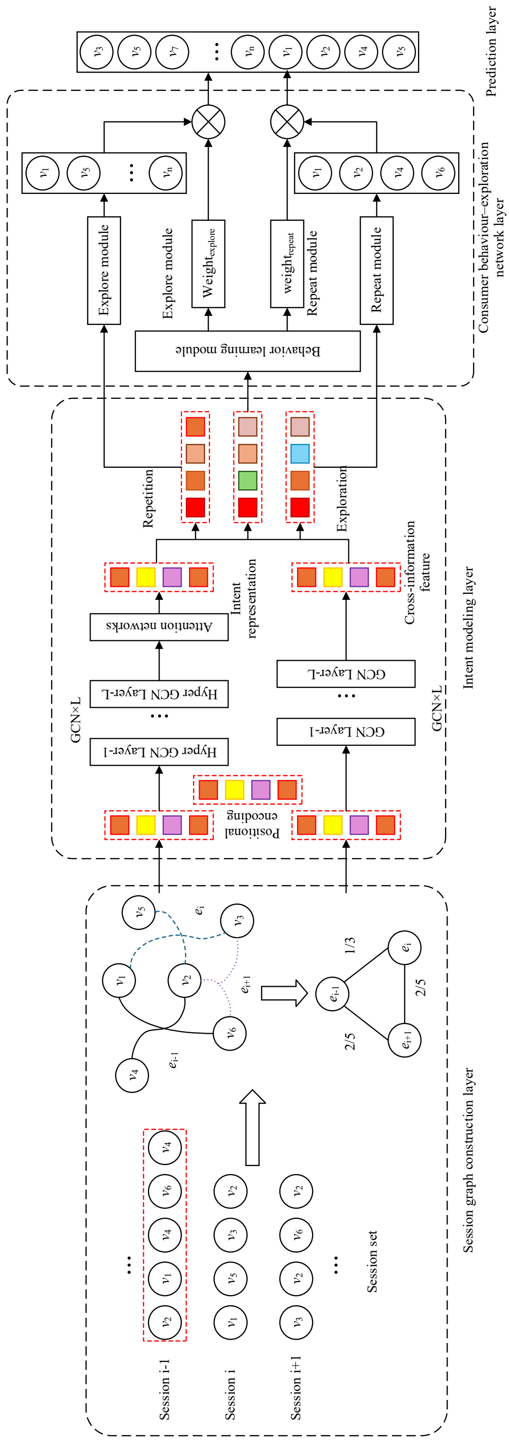
5.1 Consumer intent representation learning based on contrastive learning

Due to the strong randomness of user browsing direction on e-commerce platforms and the large amount of information of interest, it is difficult to predict user repurchase behaviour. To enhance user experience and satisfaction and improve the quality of e-commerce services, a model for e-commerce consumer behaviour prediction based on CF and GNN is constructed. The structure of the model is shown in Figure 1. First, a session graph is constructed based on consumer session data from e-commerce platforms. The GCN is used to model the multi-dimensional relationships between items in the session. The GCN is used to model the cross-information between sessions. Finally, the user's intent representation is generated through an attention network.

Whether the user intent is accurate affects the modelling of downstream consumer behaviour patterns. The previous chapter modelled the representation of the same session from two different levels: items and sessions. Therefore, this section uses the Agg function to aggregate the session representation S_H and item representation e_l. The user intent representation after aggregation is S_{re}.

$$S_{re} = Agg\left(S_H,\ e_l\right) \tag{8}$$

Figure 1 The proposed e-commerce consumer behaviour prediction model (see online version for colours)



Consumer behaviour data is sparse. To alleviate this problem and further accurately model user intent, this paper introduces a contrastive learning (Khosla et al., 2020) sub-task, drawing on previous research. Contrastive learning is divided into four stages: construction of positive and negative samples, data sample projection (encoder) to the latent space, training of the encoder (contrastive loss function), and downstream task optimisation. This paper combines S_H and e_l into positive sample pairs, S_H and e_l generated by randomly transforming the row and column sequences of the graph network input data into negative sample pairs. The encoder is a GCN network, and since each mini-batch contains a large number of sessions during the training process, and each given session contains a large number of negative samples, the InfoNCE loss function (Wu et al., 2023) is used as the contrastive loss function, as shown in equation (9). Among them, T is the inner product operation of the vector. The contrastive learning sub-task ultimately combines with the downstream task and is optimised together. This content will be discussed in Section 5.3.

$$L_s = -\log \sigma\left(T\left(S_H, \Theta_l\right)\right) - \log \sigma\left(1 - T\left(\overline{S}_H, \Theta_l\right)\right) \tag{9}$$

5.2 Consumer behaviour learning

For the goal of alleviating the impact of user interest drift on the model, based on the modelling of user intent representation in Section 4.2, we perform a concatenation operation on S_{re} and the average of the item representations within the current session $\overline{e}_{v_i}^*$, thereby obtaining the user's precise intent representation P_{re}. Since the user's intent representation is an implicit vector representation and cannot explicitly represent the user's behaviour pattern, the softmax function is used to normalise P_{re} into explicit probability for the consumer behaviour learning module and the behaviour exploration module, as shown below:

$$P_{re} = W_{re}\left[S_{re} \,||\, \overline{e}_{v_i}^*\right] \tag{10}$$

$$\left[P_r, P_e\right] = soft\max\left(W_n P_{re}\right) \tag{11}$$

where W_{re} is the coefficient matrix, and w_n is the transition probability matrix.

Modelling the user's repetitive consumption behaviour pattern refers to predicting the probability of the user re-clicking or repurchasing the items in the current session. Since the prediction samples of the repetitive consumption module are the item set in the current session, this paper adopts the approach of remodelling the current session representation. The modelling method is consistent with equation (6) and equation (7). Equation (12) to equation (14) respectively represents the item representation, attention weight, and final session representation of e-commerce consumer behaviour. Because the parameter matrices are different, the final generated attention weights are also different.

$$\overline{e}_{v_i}^r = \tanh\left[W_4\left[e_{v_i} \,||\, p_{t-i+1}\right] + b_3\right] \tag{12}$$

$$\alpha_{v_i}^r = q_2^T \sigma\left(W_5 \overline{e}_{v_i}^r + W_6 \overline{e}_{v_i}^* + b_4\right) \tag{13}$$

$$S_r^H = \sum_{i=1}^{t} \alpha_{v_i}^r e_{v_i}^{-r} \tag{14}$$

where W_4, W_5, W_6 are coefficient matrices, b_3, b_4 are biases. Perform aggregated operation on the session representation S_r^H and item representation e_l of the consumption behaviour module after aggregation through the GCN network, to obtain $S_r = Agg\left(S_r^H, e_l\right)$.

After generating S_r, generate a matching score for each item in the candidate set, and then normalise the score into the purchase behaviour probability of each candidate item through the softmax function.

$$\hat{y}_i^r = I\left(v_i \in I_s\right) soft\max\left(S_r^T e_{v_i}^{(0)}\right) \tag{15}$$

where the $I(v_i \in I_s)$ operation indicates that if the item to be predicted is in the current session set, it is 1, otherwise it is 0.

The modelling task of the exploration module is to predict the click probability of the user for items other than those in the current session S. The sample set is the candidate set excluding items in the current session, so the contribution of items in the current session to the entire session representation needs to be recalculated. The modelling method is consistent with equation (6) and equation (7). Equation (16)–equation (18) respectively represent the item representation of the exploration module, the contribution of each item to the entire session representation, and the final session representation. Because the parameter matrices are different, the finally generated attention weights are also different.

$$\overline{e}_{v_i}^e = \tanh\left(W_7\, e_{v_i} \,\|\, p_{t-i+1}\,] + b_5\right) \tag{16}$$

$$\alpha_{v_i}^e = q_3^T \sigma\left(W_8 e_{v_i}^e + W_9 e_{v_i}^* + b_6\right) \tag{17}$$

$$S_e^H = \sum_{i=1}^{t} \alpha_{v_i}^e e_{v_i}^e \tag{18}$$

where W_7, W_8, W_9 are coefficient matrices, b_5, b_6 are biases. Perform a aggregation operation on the session representation S_e^H and item representation e_l of the exploration module obtained through the GCN network, and the final generated session representation of the exploration module is S_e.

$$S_e = Agg\left(S_e^H, e_l\right) \tag{19}$$

After generating the session representation S_e of the exploration module, generate a matching score for each item in the candidate set, and then normalise the score into the purchase behaviour probability of each candidate item through the softmax function.

$$\hat{y}_i^e = I\left(v_i \notin I_s\right) soft\max\left(S_e^T e_{v_i}^{(0)}\right) \tag{20}$$

where the $I(v_i \in I_s)$ operation indicates that if the item to be predicted is in the current session set, it is 1, otherwise it is 0.

5.3 E-commerce consumer behaviour prediction based on CF algorithm

The model prediction layer merges the two parts of the item purchase behaviour scores from the consumption behaviour modelling module and the exploration module, and finally normalises the scores using the softmax function.

$$L_r = -\sum_{i=1}^{m} y_i \log \hat{y}_i + (1 - y_i) \log (1 - \hat{y}_i) \tag{21}$$

where P_r and P_e are the transition probabilities of the consumption behaviour modelling module and the exploration module, $\hat{y}_i^r$ and $\hat{y}_i^e$ are the consumption behaviour scores of the candidate set items calculated by equation (15) and equation (20), respectively. This paper trains the model by optimising the cross-entropy between the maximum probability item purchase behaviour and the actual next interaction item purchase behaviour, as calculated below.

$$L_r = -\sum_{i=1}^{m} y_i \log \hat{y}_i + (1 - y_i) \log (1 - \hat{y}_i) \tag{22}$$

where y_i is the real behaviour of the user purchasing items in the training data, and $\hat{y}_i$ is the model predicted behaviour.

Finally, combined with the discussion of the contrastive learning sub-task in Section 5.1, the user intention representation obtained through contrastive learning is for consumption behaviour modelling, so this paper adopts an end-to-end training method, training the contrastive learning sub-task and the final recommendation task together. The joint training loss function of multi-task learning is as follows.

$$L = L_r + \beta L_s \tag{23}$$

where β is the hyperparameter, L_r is the cross-entropy loss function, and L_s is the loss function of the auxiliary task.

6 Experimental results and analyses

This paper conducts experiments on public datasets in two e-commerce scenarios, namely the Yelp dataset (Qiu et al., 2020) and the Amazon dataset (Sun et al., 2021). The Yelp dataset contains a large amount of data such as user reviews, ratings, user information, and business information, consisting of 6,489 nodes and 127,366 edges. The Amazon dataset is composed of Amazon transaction data, including product information, user reviews, and sales rankings. This dataset consists of 4,039 nodes and 88,234 edges. The experimental environment is the Windows 10 operating system, 16 G memory, 3.6 GHz octa-core processor, and software is Python 3.7. In the experiment, the batch size is 100, the item embedding vector is 100, the optimiser is Adam, and the initial learning rate is 0.001. To avoid overfitting, the model training adopts L2 regularisation, and the regularisation coefficient is set to 1e-5.

For easy analysis, this paper selects CF-ANN (He et al., 2022), LSTM-MLP (Zhu et al., 2022), CNN-BiLSTM (Azadravesh et al., 2024), GRU-GNN (Al-Otaibi, 2024), and

AM-GCN (Turatti, 2025) as comparison models, and the evaluation metrics select Accuracy, F1, and AUC values. The comparison of prediction performance indicators of different models on the two datasets is shown in Table 1. On the Yelp dataset, the Accuracy and F1 of CF-GNN are 0.9539 and 0.9627, respectively, which are at least 3.31% and 5.21% higher than those of the comparison models. On the Amazon dataset, the Accuracy and F1 of CF-GNN are 0.9261 and 0.9436, respectively, which are at least 4.09% and 3.78% higher than those of the comparison models. The AUC value R is the area under the ROC curve. On the two datasets, the AUC of CF-GNN are 0.9805 and 0.9593, respectively, which are at least 9.37% and 3.58% higher than those of the comparison models.

CF-ANN only uses the CF algorithm for consumer behaviour prediction, without further considering the characteristics of the items purchased by consumers, leading to low prediction accuracy. LSTM-MLP's core advantage is capturing local spatial features, but user behaviour data is usually non-spatially structured and may not conform to the local correlation assumption. CNN-BiLSTM has built a CNN-BiLSTM prediction model, but has not fully considered user preference information. GRU-GNN models the user's session sequence into graph structure data and processes the graph data through GNN, but does not learn the representation of purchasing behaviour. AM-GCN models user consumption behaviour through GCN, but does not consider the characteristics of items, so its prediction accuracy is lower than that of CF-GNN. Comprehensive analysis above shows that CF-GNN achieves the best prediction accuracy.

Table 1 Comparison of prediction accuracy

Model	*Yelp dataset*			*Amazon dataset*		
	Accuracy/%	*F1/%*	*AUC*	*Accuracy/%*	*F1/%*	*AUC*
CF-ANN	0.8209	0.8158	0.8432	0.7946	0.8019	0.8267
LSTM-MLP	0.8537	0.8369	0.8854	0.8042	0.8283	0.8539
CNN-BiLSTM	0.8692	0.8623	0.9181	0.8367	0.8461	0.8725
GRU-GNN	0.8841	0.8917	0.9338	0.8698	0.8794	0.9007
AM-GCN	0.9208	0.9106	0.9714	0.8852	0.9058	0.9261
CF-GNN	0.9539	0.9627	0.9805	0.9261	0.9436	0.9593

Next, this paper visualises the item representations under the browsing and purchasing behaviours of the e-commerce platform to observe whether CF-GNN has learned the semantic information of different types of behaviours. In the experiment, the dimension of the item representation is 64, so this paper uses T-SNE for dimensionality reduction and visualisation of the representation. The item representation visualisation results of AM-GCN and CF-GNN on two datasets are shown in Figure 2 and Figure 3. The figure on the left is AM-GCN and the figure on the right is CF-GCN. For comparison, this paper also shows the visualisation cases of AM-GCN, because it is the best comparison method in our experiment. In the visualisation of AM-GCN no obvious pattern was observed, and we can see that there is overlap between the representations of the same item under browsing and purchasing behaviours. This is because AM-GCN does not model different behaviours separately. However, it can be found that in the visualisation results of CF-GNN, the item representations under browsing behaviours gradually converge toward the target item, which is reasonable. Because users often browse similar items before purchasing a certain item to compare, browsing behaviour is more related to the final purchase. Compared with the relatively tightly distributed item representations under browsing behaviours, the item representations under purchasing behaviours show a more scattered state, which corresponds to the relatively diverse purchasing preferences and purchasing intentions of users, and also reflects the semantic differences between browsing and purchasing behaviours.

Figure 2 Visualising consumer behavioural representations on the Yelp dataset (see online version for colours)

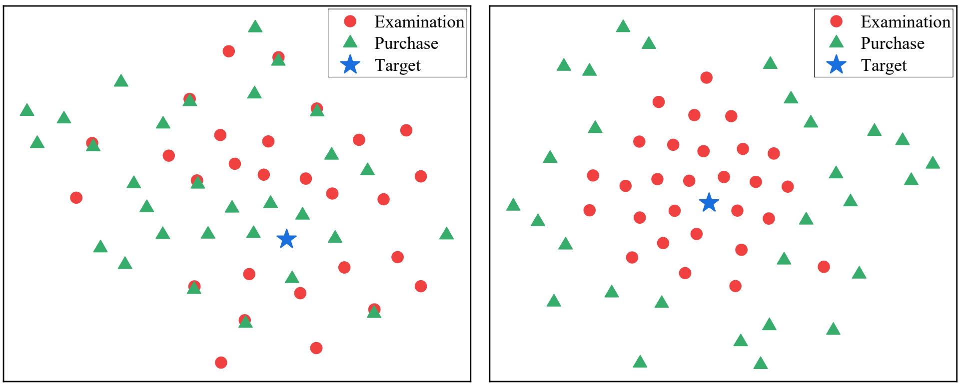
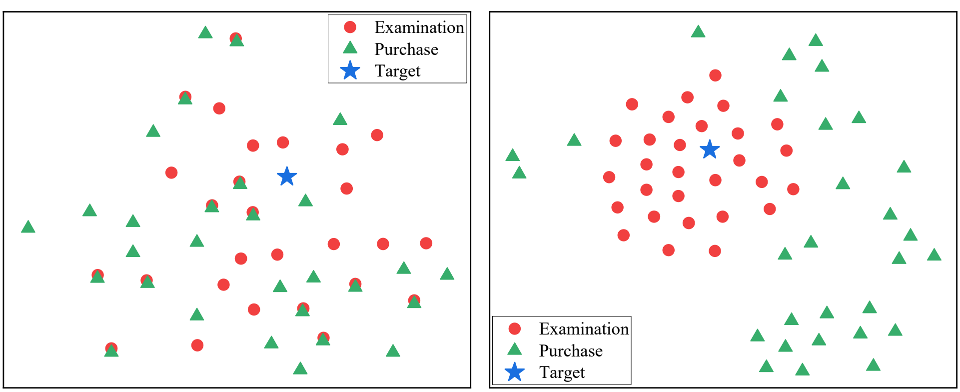


Figure 3 Visualising consumer behavioural representations on the Amazon dataset (see online version for colours)



To verify the effectiveness of each component in the CF-GNN model, this paper designs further ablation experiments and makes corresponding analyses. Now, the necessity of each component is verified through the following methods.

1 w/o GCN: Remove the GCN module and use a regular GNN for embedding learning of the session graph.

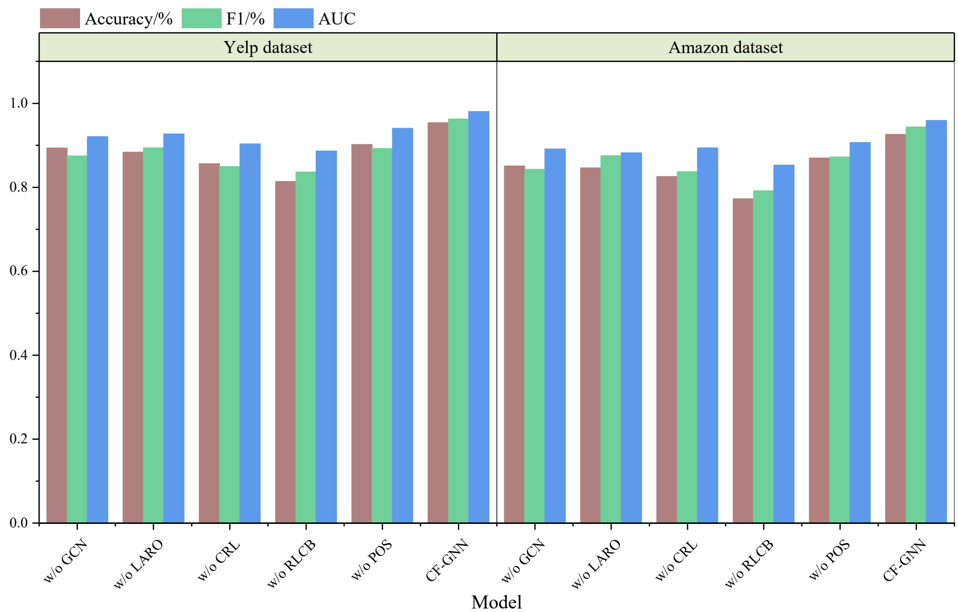
2 w/o LARO: Remove the item representation learning and only perform representation learning on the session.

3 w/o CRL: Remove the session representation learning and only perform representation learning on the item.

4 w/o RLCB: Remove the consumer behaviour representation learning and only perform representation learning on the session and the item.

5 w/o POS: Remove the modelling of the position information of the behaviour pattern as an auxiliary information in the CF-GNN model.

Figure 4 Ablation experiments with different components in CF-GNN (see online version for colours)



The experimental results are shown in Figure 4, which demonstrates the impact of different submodules of CF-GNN on the model. According to the experimental results, the following conclusions are drawn. On the two datasets, the experimental effect of w/o POS is second only to CF-GNN, and is better than w/o GCN, w/o LARO, w/o CRL, and w/o RLCB, indicating that modelling the position information of user interaction behaviour is important for distinguishing user interaction behaviour and has a positive effect on capturing user interest preferences. The experimental effect of the w/o GCN model is lower than that of CF-GNN, indicating that GCN is better than GNN in capturing the multi-dimensional relationships between items in the session. The experimental effect of the w/o RLCB model is the worst among the sub-module analysis, indicating that modelling user consumption behaviour plays an important role in improving the model performance. As can be seen from the above analysis, the CF-GNN algorithm that integrates various submodules achieves the best effect, which verifies the effectiveness of the CF-GNN model in modelling the multi-dimensional relationships between items in the session, the cross information between sessions, and the position information of interactive behaviour.

7 Conclusions

As the e-commerce platforms quickly growing, accurately predicting consumer behaviour has become key to improving personalised recommendation effectiveness. Although traditional CF algorithms can mine the latent patterns of user-item interactions, they are difficult to effectively capture the high-order complex relationships between users and items; while GNN, due to its powerful graph structure modelling capability, provides a new approach to mining deep associations in the user-item interaction graph. In view of this, this paper designs an e-commerce consumer behaviour prediction model that integrates CF and GNN. First, construct a session graph based on user purchase item information and corresponding session sequences, then perform sequential position encoding on the items, initialising the item nodes in the graph as embedding vectors. Use GCN to model the multi-dimensional relationships between items and cross information between sessions in the session graph, and aggregate to generate a session representation that integrates the multi-dimensional relationships between items. Then, aggregate the item representations in the session using GCN to generate a session representation. Generate user intent representations through contrastive learning. Construct a consumption behaviour learning module using an attention network to model user consumption behaviour patterns. Finally, calculate the scores of user purchase behaviours for target items, obtain several items with high scores, and generate a recommendation list to achieve e-commerce consumer behaviour prediction. Experimental outcome demonstrates the designed model has significantly improved in key indicators such as accuracy and F1 for consumer behaviour prediction, enabling a more accurate understanding of consumer behaviour trends and providing strong support for personalised recommendations and precise marketing on e-commerce platforms.

Although the model suggested in this paper has achieved good prediction results, the adjacency matrix in GCN is prone to overfitting. To address this issue, this paper will introduce user relationship graphs or graphs generated by K-nearest neighbours (KNN) to fix the next one or more relationship matrices that express the user's own characteristics, thereby improving the graph convolution effect.

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Declarations

All authors declare that they have no conflicts of interest.

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