Temporal Heterogeneous Graph Neural Network for User Influence Prediction in Social E-Commerce

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This study proposes a user influence propagation model based on dynamic heterogeneous network representation learning. The model combines multi-type nodes and semantic edge types, and adopts a learnable temporal embedding strategy to construct a dynamic heterogeneous graph, so as to realize the time-aware representation of nodes. In the representation learning stage, a multi-head attention mechanism is introduced to enhance context modeling and propagation path awareness. Meanwhile, structural contrastive learning is used as an auxiliary task to improve the discriminability of node representation, and a joint training strategy of node classification and edge prediction is adopted to enhance the generalization ability of the model. In the experimental evaluation, the proposed model is compared with several representative Graph Neural Network (GNN) models, including Graph Convolutional Network (GCN), Temporal Graph Attention Network (TGAT), and Heterogeneous Graph Transformer (HGT). In the overall prediction task, the proposed model achieves a Mean Squared Error (MSE) of 0.1214, a Mean Absolute Error (MAE) of 0.2398, and an R^2 of 0.701. All these metrics are significantly better than those of TGAT (MSE: 0.1597, MAE: 0.2785, R^2: 0.603) and HGT (MSE: 0.1429, MAE: 0.2652, R^2: 0.642). Within a 14-day prediction window, the model maintains an error rate of 0.1390, demonstrating superior temporal generalization capability. For identifying high-influence user groups, the model achieves an MSE of 0.1268, significantly better than HGT's 0.1456, indicating higher sensitivity in modeling strong propagation nodes. This shows that the combination of these methods enables the proposed model to demonstrate stronger temporal modeling capability and heterogeneous relationship understanding capability compared with TGAT and HGT, in terms of capturing users' historical behaviors and predicting future influence.

Povzetek: Študija predstavi model za napovedovanje vpliva uporabnika, ki z večglavo pozornostjo in kontrastnim učenjem doseže nižje napake ter boljšo časovno učinkovitost kot obstoječi GNN-ji.

1 Introduction

With the rapid development of mobile internet and the widespread adoption of content-based social platforms, social commerce has emerged as a key component of the digital economy, integrating "people, products, and scenarios" [1,2]. Within this ecosystem, users actively or passively participate in the dissemination of product information through behaviors such as posting images and videos, commenting, liking, and sharing, thereby significantly enhancing information flow and product recommendation efficiency on platforms [3]. User influence, as a critical factor driving content dissemination and consumer decision-making, has attracted increasing attention from both platform operators and academic researchers [4,5]. Accurately modeling user influence not only facilitates the identification of potential Key Opinion Consumer (KOC) and Key Opinion Leader (KOL), but also serves as a fundamental support for improving personalized recommendations, content distribution efficiency, and marketing return on investment (ROI) [6].

However, existing research on user influence modeling still faces three key limitations. First, most approaches rely on static graph structures to model user relationships, which fail to capture the dynamic evolution of user behaviors and social structures, making them inadequate for real-time information propagation scenarios [7,8]. Second, the majority of models employ homogeneous graphs, which cannot represent the heterogeneous semantic relationships among different types of nodes such as users, products, and behaviors [9]. In social commerce, influence is rarely a single-dimensional phenomenon; rather, it often arises from complex behavioral sequences. For example, "User A purchases a product and writes a review, which is liked by User B and later shared by User C". Such behavioral chains involve highly heterogeneous nodes and relations [10]. Third, traditional rule-based influence evaluation methods lack flexibility and struggle to generalize in the data-rich, behaviorally diverse contexts of social commerce platforms [11].

To address the aforementioned challenges, this study proposes a dynamic heterogeneous network -based representation learning model for modeling user influence propagation in social e-commerce. To clarify the research direction, this study proposes the following research questions: Can the introduction of heterogeneous edge types improve the accuracy of influence prediction? Can the multi-head attention mechanism enhance the propagation awareness ability of node representation in dynamic heterogeneous networks? How does the proposed model perform in identifying high-influence users compared with existing graph neural network (GNN) models? The main innovations and contributions of this study are as follows:

(1) The dynamic heterogeneous network structure is introduced into the modeling of user influence propagation in social e-commerce, realizing the joint modeling of multi-type nodes (including users, commodities, behaviors, and social relationships) and their temporal evolution.

(2) A representation learning framework integrating heterogeneous GNN and time-aware mechanism is designed, which effectively improves the deep semantic extraction ability of dynamic user representation.

(3) A propagation prediction model based on representation learning is proposed. Without relying on manual feature construction, the model can accurately estimate the propagation range and influence intensity of users, significantly enhancing the scalability and application value of the model.

2 Literature review

In recent years, numerous studies have attempted to characterize user influence in social networks by constructing propagation models [12]. Traditional models such as the Independent Cascade (IC) model and the Linear Threshold (LT) model have been widely adopted for modeling information diffusion [13]. For instance, Zhou et al. [14] suggested that both IC and LT models described the process of information spreading from one node to its neighbors through probabilistic mechanisms, offering strong theoretical interpretability. However, these models heavily relied on manually predefined propagation probability parameters, making them poorly suited to the dynamic nature of social behaviors. With the advancement of machine learning techniques, some studies have shifted toward using user behavior data for influence prediction. For example, Shao et al. [15] developed a user propagation probability model based on historical behavioral logs and improved prediction performance through supervised learning. Similarly, Sunarya et al. [16] proposed a “social influence factor” model that incorporated variables such as social structure and behavioral patterns to predict influence relationships among users. Nevertheless, these approaches are typically based on homogeneous network structures and often overlook temporal dynamics and the structural heterogeneity of multi-type interactive behaviors, limiting their applicability to the heterogeneous propagation mechanisms found in modern social e-commerce platforms.

Heterogeneous information network has been widely applied in user behavior modeling and recommendation systems due to their capability to represent multi-type entities and relations. Chen et al. [17] defined the multi-type characteristics of nodes and edges in heterogeneous graph structures and introduced meta-paths as an essential tool for capturing semantic relationships. Kumar and Krishna [18] further proposed the Metapath2Vec algorithm, which generated context sequences through meta-path-guided random walks to enhance the semantic richness of node representations. In recent years, deep HGNN has become increasingly prominent. For instance, the heterogeneous graph attention networks proposed by Mei et al. [19] and Wang et al. [20] leveraged attention mechanisms at both the node type and meta-path levels to improve recommendation accuracy and behavior prediction performance. Jia et al. [21] introduced the Heterogeneous Graph Transformer (HGT), which employed a multi-head attention mechanism aware of node and edge types to further enhance the quality of node representations in heterogeneous graphs. These methods provide a solid technical foundation for modeling the diverse entity relationships among users, products, content, and behaviors in social e-commerce scenarios. However, it is important to note that most of these approaches are based on static graph structures and fail to capture the temporal evolution of user behaviors.

For another example, Gao et al. [22] proposed a social influence prediction method based on Heterogeneous Graph Neural Network (HGNN). By utilizing historical event topic features and user interest features, they constructed an end-to-end heterogeneous neural network model to predict users’ behaviors in social networks more accurately. This method provided a reference technical foundation for modeling different types of nodes (users, commodities, behaviors) and their interaction relationships in social e-commerce platforms. Zhong & Huang [23] proposed a dynamic graph representation learning method based on temporal graph transformer. This method could effectively retain high-order neighborhood information and capture the temporal evolution characteristics of user behaviors through a time-aware mechanism, providing a new idea for the modeling of user influence propagation in social e-commerce.

However, the multi-scale attention graph transformer framework proposed by Qiu [24], although applied to computed tomography (CT) image analysis, combined the ideas of graph structure modeling and multi-head attention mechanism. It provided a technical reference for processing complex structures and multi-level contextual information, and could be used for reference in the fine-grained modeling of node features and behavioral interactions in dynamic social e-commerce networks. Zhang [25] constructed a user preference model based on GNN and multi-layer attention mechanism, which was applied to social access control management. By learning users’ social behaviors and preferences to optimize system strategies, the ideas of this model for user behavior representation and influence analysis could directly inspire the identification of high-influence users and propagation prediction in social e-commerce platforms. Table 1 summarizes these related works:

Table 1: Summary of related work on social network user influence modeling

Literature	Method	Graph Type	Dynamic/Static	Limitations
Zhou et al. [14]	IC / LT	Homogeneous	Static	Relies on manually set propagation probability and cannot handle dynamic behaviors
Shao et al. [15]	User propagation probability model	Homogeneous	Static	Ignores multi-type behaviors and temporal evolution
Sunarya et al. [16]	Social Influence Factor	Homogeneous	Static	Lacks heterogeneity and time awareness
Chen et al. [17]	Heterogeneous information network+metapath	Heterogeneous	Static	Static graph, without considering temporal evolution
Kumar & Krishna [18]	Metapath2Vec	Heterogeneous	Static	Static graph, without capturing dynamic behaviors
Mei et al. [19]/ Wang et al. [20]	Heterogeneous graph attention network	Heterogeneous	Static	Static graph, lacking time awareness
Jia et al. [21]	HGT	Heterogeneous	Static	Static graph, difficult to handle dynamic evolution
Gao et al. [22]	HGNN	Heterogeneous	Static	Static graph, without modeling temporal evolution
Zhong & Huang [23]	Time diagram converter	Heterogeneous	Dynamic	Limited handling of node type heterogeneity
Qiu [24]	Multiscale attentional diagram converter	Heterogeneous	Dynamic	Original application is image analysis, requiring migration to social e-commerce scenarios
Zhang [25]	GNN+multilayer attention mechanism	Heterogeneous	Static	Static graph, needs improvement for dynamic user influence modeling

Although existing studies have made progress in user influence modeling, heterogeneous graph representation learning, and dynamic graph analysis, several research gaps and technical challenges remain. First, there is a lack of a unified framework that integrates dynamics, heterogeneity, and behavioral diversity to comprehensively model user influence propagation. Second, most current dynamic graph models are not structurally optimized for the unique characteristics of product propagation in social e-commerce scenarios, making them inadequate for explaining user influence differences under complex behavioral paths. Third, existing models still face limitations in interpretability and deploy ability, lacking efficient mechanisms to support high-frequency propagation prediction and recommendation decision-making. To address these limitations, this study aims to construct a representation learning framework that integrates both dynamic and heterogeneous features, enabling accurate capture of influence propagation characteristics within complex and multi-faceted behavior networks. This approach seeks to bridge the gap in comprehensively modeling user influence mechanisms in social e-commerce environments and to provide more robust technical support for precision marketing and intelligent recommendation.

3 Research methodology

3.1 Overall framework of model

To address the challenge of simultaneously modeling structural heterogeneity and temporal dynamics in user influence propagation within social e-commerce scenarios, this study proposes an end-to-end framework based on dynamic heterogeneous network representation learning. The goal is to effectively capture the multi-type relationships among users, content, and products, while modeling users' propagation potential throughout temporal evolution. The proposed model takes as input multi-source behavioral logs collected from social e-commerce platforms, including user-to-user interactions (e.g., likes, comments, shares), user-product interactions (e.g., views, purchases, favorites), and the corresponding timestamps of these actions. During the preprocessing stage, these behaviors are abstracted into a heterogeneous graph consisting of multiple types of nodes (e.g., users, products, behavioral events) and multiple types of edges (e.g., social relations, product interactions, content propagation paths). The graph is then temporally segmented or constructed as an event stream based on behavioral timestamps, resulting in a sequence of dynamic heterogeneous graphs that preserve temporal evolution characteristics.

For example, within a specific time window, suppose that user A performs the following operations during this period: liking a product X (U-I edge), commenting on a product Y (U-I edge), and sharing information about a product (U-U edge). The timestamp order of these behaviors determines how to construct graph nodes and edges within this time window. Each node (e.g., user, product, behavior) is assigned a timestamp, which serves as a snapshot of the graph at that specific time point. Subsequently, the system splits the behavior data into multiple time periods (such as daily or hourly intervals), where each time period corresponds to one graph snapshot. This enables the dynamic construction of the graph from the temporal dimension.

In the representation learning module, a HGNN framework is introduced and integrated with temporal awareness mechanisms to capture both structural and behavioral representations of each node across different time periods. Specifically, the model employs type-specific transformation functions to handle semantic differences among various types of nodes and edges. Meanwhile, a temporal encoding module (such as positional encoding or time-gating mechanisms) is incorporated to model the sequential characteristics of nodes within behavioral trajectories. As a result, each user is represented by a low-dimensional embedding in the dynamic network that jointly captures their current semantic state and historical behavioral patterns. This representation not only reflects the user's interest preferences and social position, but also encodes their potential influence on information propagation within a given time window.

In the propagation modeling stage, this study constructs a prediction network based on node embeddings to regress and forecast users' influence levels within a future time window. This prediction module takes as input the users' time-aware embeddings and integrates graph structural features of their upstream and downstream propagation paths. Influence intensity is then estimated via attention-weighted aggregation or a Multi-Layer Perceptron (MLP). The output may represent the user's propagation scope, the number of influenced individuals, or the volume of conversion actions triggered, serving downstream tasks such as key node identification, personalized recommendation, or marketing optimization. The entire framework operates as a unified end-to-end architecture, enabling joint optimization of graph representation learning and propagation prediction during training to enhance embedding discriminability and forecasting accuracy. Additionally, the model offers strong scalability and interpretability, allowing for insight into influence sources through analysis of node attention weights and propagation path structures. Figure 1 illustrates the overall architecture.

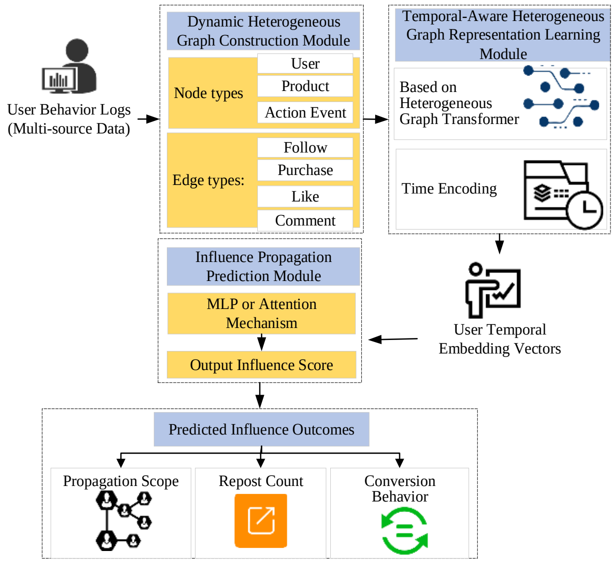

Figure 1: Model overall architecture diagram

Figure 1 shows that the first key step is to convert behavior logs into heterogeneous graphs through the data preprocessing process. Then, these graphs are divided into multiple snapshots via time slicing to form a sequence of dynamic heterogeneous graphs. Each snapshot represents the manifestation of user behaviors within a specific time window. Subsequently, the snapshots are fed into the representation learning module, which combines a time-aware mechanism to generate low-dimensional embeddings of nodes. Finally, these embeddings are used in the propagation prediction module. Figure 2 shows the algorithm pseudocode for the entire process.

```
Input:    - Multi-source user behavior logs (user-user interactions, user-item interactions, timestamps)    - Time window size Δ
Output:   - Predicted user influence scores for future time windows
# 1. Data Preprocessing
Categorize nodes as users, items, and behavior events
Construct edges: U-U, U-I, U-Action, each with timestamp
Slice behavior logs into time windows to form dynamic graphs {G_1, G_2, ..., G_T}
# 2. Dynamic Heterogeneous Graph Construction
For each time window G_t in {G_1, ..., G_T}:
   Build heterogeneous graph with multiple node and edge types
   Encode temporal information for each node using learnable position embeddings
# 3. Time-aware Representation Learning
For each node v in G_t:
   Apply heterogeneous graph neural network (HGNN)
   Integrate temporal encoding to generate time-aware node embedding h_v^t
# 4. User Influence Propagation Prediction
For each user node embedding h_v^t:
   Aggregate neighbor information via attention mechanism
   Feed aggregated representation into Multi-Layer Perceptron (MLP)
   Output predicted influence score ŷ_v^(t+Δ)
# 5. Model Training
Optimize prediction with Mean Squared Error (MSE) loss
Optionally include auxiliary tasks (node classification, edge prediction) for joint learning
Return: Predicted user influence scores for each future time window
```

Figure 2: Pseudo-code of overall algorithm flow

3.2 Dynamic heterogeneous graph construction and representation learning

Before constructing the dynamic heterogeneous graph, time slicing is first performed on user behavior logs. Based on the timestamp information of user behaviors, the behavior data is divided into multiple time windows. For example, each time window is set to 7 days. Within each time window, user behaviors are mapped to nodes and edges in the graph. Each graph slice contains the user behavior data in this time period, as well as social relationships between users, and relationships between users and products. Each edge is also attached with a timestamp to capture the temporal characteristics of information propagation. In this way, a series of dynamic graphs are constructed, where each graph represents the network state within time window t.

In social e-commerce platforms, user behaviors exhibit significant heterogeneity and temporal dynamics. Users interact with products and others through diverse actions such as likes, comments, and purchases, which evolve distinctly over different time points. To comprehensively model this structure, we construct dynamic heterogeneous graphs integrating multiple types of nodes including users, items, and action events, as well as their heterogeneous interactions. Each edge in the graph is labeled not only with semantic types (e.g., "purchase," "like," "follow") but also with precise timestamps, capturing the temporal characteristics of information propagation. The entire graph is represented as a time-evolving sequence of graphs $\{\mathcal{G}_1, \mathcal{G}_2, \ldots, \mathcal{G}_T\}$, where each graph $\mathcal{G}_t = (\mathcal{V}_t, \mathcal{E}_t)$ corresponds to a snapshot of the network structure within a specific time window.

To learn node representations with rich semantic expressiveness and temporal awareness from such graphs, this study employs HGNN as the foundational modeling approach and incorporates a temporal encoding mechanism to construct time-aware embeddings. The message passing mechanism is based on HGT. At each layer, the update of node representations considers the structural information of neighbor nodes, and performs different weighting processes according to edge types. For example, the "purchase" relationship may be more important than the "like" relationship for the spread of user influence.

Each edge type is associated with a corresponding weight matrix to handle information transmission. In addition, an attention mechanism is introduced, enabling the model to automatically learn the importance of different neighbor nodes, thereby effectively improving the accuracy of propagation prediction. The representation of each node is updated by weighted aggregation of its neighbors' representations, where the weights are dynamically calculated by the attention mechanism. By introducing time-aware encoding and the time difference of neighbors' behaviors on the basis of HGT, the attention parameters consider node types and edge types, and adjust the propagation characteristics of time series. This enhances the dynamic adaptability of node representations. Additionally, a temporal difference function is introduced to encode the temporal features of neighboring nodes' behaviors. At each network layer, the node representation update can be formally defined as:

$$\mathrm{h}_v^{(l+1)} = \sigma\left(\sum_{r\in\mathcal{R}} \sum_{u\in\mathcal{N}_r(v)} \alpha_{uv}^{(r)} \cdot W_r^{(l)} \mathrm{h}_u^{(l)}\right) \quad (1)$$

$\mathcal{R}$ represents the set of all edge types. $\mathcal{N}_r(v)$ represents the set of neighbor nodes adjacent to node v through relationship type r. $W_r^{(l)}$ is the weight matrix of the corresponding edge type at the l-th layer. σ is the activation function. $\alpha_{uv}^{(r)}$ is the attention weight of edge (u,v), which combines the neighbor representation and edge type.

To improve the time modeling ability of the model, the timestamp difference Δt_{uv} is introduced into the attention weight calculation. This study adopts a learnable positional encoding technique. For each discrete timestamp t, a vector with a fixed dimension is learned as the embedding representation of the temporal position. For each time slice, the corresponding temporal vector is a trainable parameter of the model, and its dimension is consistent with that of the node embedding. Different from the fixed sine/cosine positional encoding in Transformer, this vector is optimized through backpropagation during the training process, thereby enabling adaptive capture of the patterns of user behaviors changing over time.

In the calculation of node attention, the node's own representation h_v, the neighbor node's representation h_u, and the temporal encoding vector $\phi(\Delta t_{uv})$ are concatenated first. The concatenated result is then input into the linear transformation matrices W_q and W_k. Combined with the attention parameter a_r, the attention score $\alpha_{uv}^{(r)}$ is calculated. Through this process, structural semantic information and temporal information are integrated into the node representation simultaneously, enabling time-aware modeling of neighbor relationships in the dynamic heterogeneous graph. The multi-head attention mechanism acts on both node types and edge types simultaneously, performing independent calculations for different types of neighbors within each graph layer. Time awareness is integrated into the attention calculation of each edge through learnable positional encoding, rather than using multi-head attention independently directly on time slices.

The learnable positional encoding can flexibly reflect behavior patterns under non-uniform time intervals. For scenarios where user behaviors on social e-commerce platforms are sparse or high-frequency, it provides more accurate temporal feature representation, thereby improving the discriminative ability of node representation and the accuracy of subsequent propagation prediction tasks. The time-aware attention mechanism is expressed as:

$$\alpha_{uv}^{(r)} = \frac{\exp\left(\mathrm{LeakyReLU}\left(\mathbf{a}_r^{\top}\left[W_q\mathbf{h}_v \| W_k\mathbf{h}_u \| \mathrm{LearnablePE}(\Delta t_{uv})\right]\right)\right)}{\sum_{u'\in\mathcal{N}_r(v)} \exp(\cdot)} \quad (2)$$

$\mathrm{LearnablePE}(\Delta t_{uv})$ represents a learnable time position coding vector, ‖·‖ indicates the vector stitching operation, and a_r is the attention parameter under the edge type r. The above mechanism makes the representation of nodes at each time point not only integrate the structural semantics of multi-type neighbors, but also include the time influence of propagation behavior. It provides more discriminating input features for subsequent propagation prediction tasks.

During training, structural contrastive learning (SCL) is employed as an auxiliary objective to enhance the stability and discriminative power of representation learning. Specifically, positive neighbor pairs are sampled from the graph, representing nodes connected by real edges, while negative pairs are randomly selected node pairs with no direct connection. The goal is to maximize the similarity between positive pairs and minimize the overlap between negative pairs. The objective function is defined as:

$$\mathcal{L}_{\text{contrast}} = -\log \frac{\exp\left(\frac{\sin(\mathrm{h}_v, \mathrm{h}_u^+)}{\tau}\right)}{\exp\left(\frac{\sin(\mathrm{h}_v, \mathrm{h}_u^+)}{\tau}\right) + \sum_{u^-} \exp\left(\frac{\sin(\mathrm{h}_v, \mathrm{h}_{u^-})}{\tau}\right)} \tag{3}$$

sim (·) represents cosine similarity, τ is temperature coefficient, and u^+ and u^- are positive sample and negative sample neighbors respectively. Finally, the time-aware embedded representation of nodes will be used as the input of the communication prediction module to realize the quantitative modeling of users' future influence. Figure 3 shows the whole dynamic graph representation learning process.

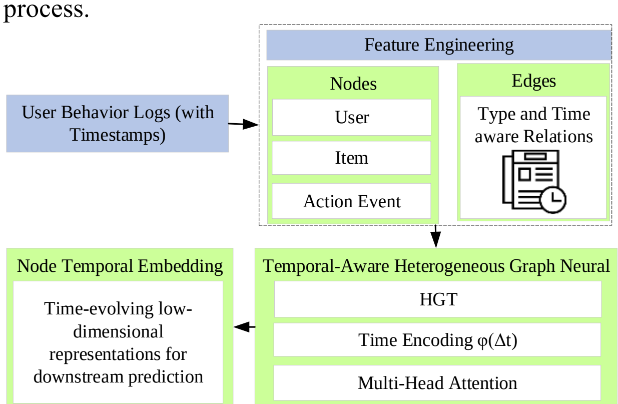

Figure 3: Construction of dynamic heterogeneous graph and learning flow chart of time-aware representation

3.3 Modeling of user influence communication

After obtaining the time-aware representation of user nodes in the dynamic heterogeneous graph, this study further constructs a user influence propagation modeling module to estimate information propagation potential in the future time window. User influence is defined as the sum of the number or weight of secondary communication behaviors (such as likes, comments, forwarding, etc.) caused by their behaviors or contents within a specific time range. The modeling task can be reduced to a time-sensitive regression prediction problem, and the goal is to estimate the possible propagation influence score $\hat{y}_v^{t+\Delta}$ in the future time period [t, t+Δ] based on the embedded vector h_v^t of the user node at a given time point.

To achieve this goal, this study designs a communication prediction module that integrates structural perception and historical behavior aggregation. Firstly, the module takes h_v^t as the basic input, and combines its neighbor node representation on the propagation path in the previous time period, and integrates the neighbor propagation contribution by weight through the attention mechanism to generate a representation vector with contextual propagation awareness. Then, the vector is input to an MLP, and the estimated influence of users in the future time period is output, as Figure 4 illustrates. MLP consists of two layers. Each layer uses the ReLU activation function, and the dropout rate is set to 0.2.

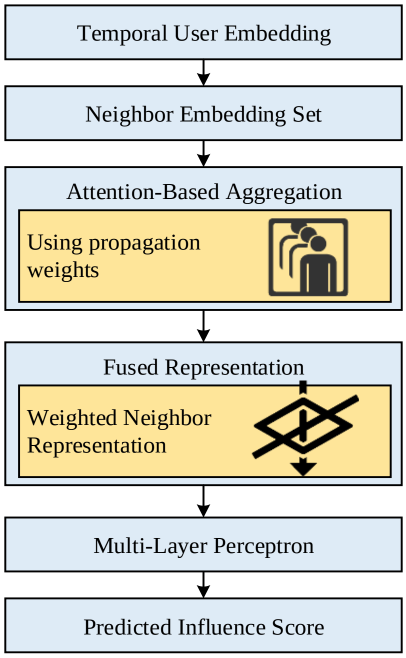

Figure 4: Structure diagram of user influence propagation modeling

The whole process can be formally expressed as follows:

$$\hat{y}_v^{t+\Delta} = \mathrm{MLP}\left(\mathrm{h}_v^t + \sum_{u\in\mathcal{N}_v^t} \beta_{uv} \cdot \mathrm{h}_u^t\right) \tag{4}$$

$\mathcal{N}_v^t$ represents the neighbor set connected with the user v by the propagation path at time t. β_{uv} is the importance weight of the neighbor node u for the propagation contribution, which is given by the following equation:

$$\beta_{uv} = \frac{\exp\left(\mathrm{q}^\top \cdot \tanh\left(W_1 \mathrm{h}_v^t + W_2 \mathrm{h}_u^t\right)\right)}{\sum_{u'\in\mathcal{N}_v^t} \exp(\cdot)} \tag{5}$$

W_1 and W_2 are the learnable weight matrices, and q is the attention projection vector. The dimension of q is 128. This mechanism not only allows the model to dynamically pay attention to the key propagation paths in the prediction, but also has certain interpretability, that is, it can trace back to which neighbor behaviors the influence comes from. In the regression task, the Mean Squared Error (MSE) is defined as the average of the squared differences between the predicted values and the true values, which is shown in equation (6).

$$\mathcal{L}_{\text{pred}} = \frac{1}{|\mathcal{V}|} \sum_{v\in\mathcal{V}} \left(\hat{y}_v^{t+\Delta} - y_v^{t+\Delta}\right)^2 \tag{6}$$

$\mathcal{L}_{\text{pred}}$ represents the loss function value of the model in the prediction task, i.e., the mean square of prediction errors, which is used to optimize model parameters. V denotes the set of nodes, representing all user nodes in the graph. $|\mathcal{V}|$ indicates the size of the node set, i.e., the total number of users, which is used to normalize the error. v$\in$ V represents the current user node being indexed. $\hat{y}_v^{t+\Delta}$ denotes the propagation influence score of user v in the future time window [t, t+Δ] predicted by the model. $y_v^{t+\Delta}$ represents the actual observed propagation influence value of user v in the same time window. $\hat{y}_v^{t+\Delta} - y_v^{t+\Delta}$ indicates the error between the predicted value and the true value. $(\hat{y}_v^{t+\Delta} - y_v^{t+\Delta})^2$ represents the squared error, which is used to penalize predictions with larger deviations and ensure that the loss function is sensitive to large errors. $\frac{1}{|\mathcal{V}|}\sum_{v\in\mathcal{V}}(\cdot)$ denotes the average of squared errors over all nodes, obtaining the mean squared error of the entire network.

In addition, to further improve generalization ability, the model incorporates auxiliary tasks (such as node classification or edge prediction) during the propagation prediction training process as joint learning objectives. This enables the user embeddings to retain propagation semantics while gaining broader task adaptability. Through this modeling approach, the framework effectively integrates structural semantics, behavioral history, and temporal information into a unified prediction architecture, providing a reliable technical foundation for subsequent user selection, targeted marketing, and propagation path control.

3.4 Experimental design

The data used in this study is derived from user behavior logs of a large-scale social e-commerce platform, including user-user interactions (such as likes, comments, and follows), user-product behaviors (such as views, purchases, and favorites), and corresponding timestamp information. To protect privacy, all users and products have undergone anonymization processing. The data covers the time range from January 2024 to June 2024, including approximately 500,000 active users, 300,000 products, and 12 million behavior records. For the construction of dynamic heterogeneous graphs, the data preprocessing process includes the following steps:

1) Node type division: Map users, commodities, and behavior events to different types of nodes.

2) Edge type division: Establish edges according to behavior types, including user-user (U–U), user-commodity (U–I), and user-behavior event (U–Action), with timestamps of behaviors attached. Edge weights are assigned based on interaction types and frequencies to reflect the contribution of each behavior to propagation. For example, likes, comments, shares, and purchases are weighted differently to capture their respective influence intensities.

3) Time slicing: The behavior logs are segmented according to a fixed time window (7 days) to generate a time-series graph $\{G_1, G_2, \ldots, G_T\}$, where each graph G_t corresponds to a network snapshot of a time period.

4) Graph construction: Within each time window, nodes and edges are combined to form a heterogeneous graph, with node types, edge types, and temporal attributes retained. This graph serves as input for subsequent time-aware heterogeneous graph representation learning.

For missing or noisy behavior events, smoothing processing is performed through time window aggregation and neighbor weighted average strategies to ensure the stability and integrity of input node features. Figure 5 shows the pseudocode for this process:

```
# Input: user behavior logs (logs), time window length (window_size)
# Output: dynamic heterogeneous graph sequence (graphs)

graphs = []  # initialize list to store graph sequence

# Map logs to node types: user, item, action event
nodes = map_nodes(logs)

# Map logs to edge types: U-U, U-I, U-Action, with timestamp
edges = map_edges(logs)

# Slice logs into time windows
for t in range(start_time, end_time, window_size):
    G_t = build_heterogeneous_graph(nodes, edges, time_window=t)
    graphs.append(G_t)

return graphs
```

Figure 5: Pseudo-codes of data preprocessing process

For model comparison, three representative baseline models are selected: Graph Convolutional Network (GCN), Temporal Graph Attention Network (TGAT), and HGT. In terms of evaluation metrics, to quantify the model's ability to predict users' future influence in information propagation, MSE, Mean Absolute Error (MAE), and the coefficient of determination (R^2) are adopted as the primary regression performance indicators. In addition, for the auxiliary evaluation of influence estimation, continuous propagation scores are divided into three intensity categories (high, medium, and low) according to preset thresholds. Then, F1-score and AUC are calculated on these categories to evaluate the model's discriminative ability at different propagation intensity levels. Meanwhile, the category distribution and threshold division strategy are explicitly reported to ensure the transparency and reproducibility of the results.

In terms of training parameter settings, all models are evaluated under the same data partition and graph structure. The time window is set to seven days, and a sliding window approach is used to generate training and testing graph sequences. The length of the time window Δ is set to 7 days, mainly based on statistical analysis of user behavior activity. Through the analysis of user behavior logs in the dataset, it is found that the vast majority of users have at least one interaction behavior (such as liking, commenting, purchasing, etc.) within 7 consecutive days. This setting can ensure the relative completeness of node and edge information in graph snapshots, while also balancing computational efficiency. Specifically, the first 70% of the time slices are used for training, while the remaining 30% are used for validation and testing. Details are shown in Table 2.

Table 2: Model parameter settings

Parameter category	Parameter name	Parameter value
Training parameter	Optimizer	Adam (β_1=0.9, β_2=0.999, ϵ=10^{-8})
	Initial learning rate	0.001
	Batch size	512
	Maximum number of training rounds	100
Model parameter	Embedded dimension	128
	Time window length	7 days
	Time coding mode	Learnable position embedding
Attention mechanism parameter	Number of multi-headed attention heads	4
	Attention vector dimension q	128
	Attention matrix	128×128
MLP parameter	Hidden layer number	2
	Activation function	ReLU
	Dropout rate	0.2

4 Result and discussion

4.1 Comparison of overall prediction performance of models

First, the overall regression performance of each model in predicting users' future influence scores is evaluated, using MSE, MAE, and R^2 as the primary evaluation metrics. Figure 6 presents the results.

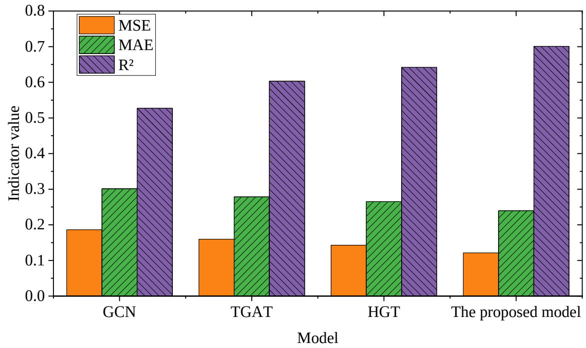

Figure 6: Overall regression performance of different models in influence prediction task

Figure 6 shows that the proposed model achieves the best performance across all evaluation metrics in the user influence propagation prediction task. Compared to the traditional static GNN model GCN, the proposed model reduces MSE and MAE by 34.8% and 20.4%, respectively, while increasing R^2 by approximately 17.4 percentage points. This indicates that the model not only provides more accurate numerical predictions but also demonstrates stronger fitting capability. Compared with the time-aware GNN TGAT, the proposed model still shows significant improvements in both MSE and MAE, suggesting that incorporating temporal factors alone is insufficient to fully capture the dynamic evolution of user influence. Although HGT, with its strong heterogeneous graph modeling capability, improves prediction performance to some extent, its disregard for temporal dynamics results in a delayed response to propagation trends. Consequently, its performance in terms of R^2 and error metrics lags behind the proposed approach. Overall, by integrating both heterogeneous structure and temporal evolution, the proposed model effectively captures complex propagation relationships between users and between users and items. This leads to more expressive node embeddings and significantly improves the accuracy of future influence prediction.

To verify the statistical significance of these performance improvements, 5 repeated experiments are conducted for each model, and a paired t-test is used to examine the differences in MSE, MAE, and R^2 among different models. The results show that the performance differences between the proposed model and GCN, TGAT, and HGT are all significant at the level of $p < 0.05$, which supports the conclusion of "significant improvement".

4.2 Prediction robustness evaluation under different time spans

To further evaluate the model's robustness across prediction tasks of varying durations, this study sets three prediction windows (Δ = 3 days, 7 days, and 14 days) and recorded the performance of each model in terms of MSE. Figure 7 presents the results.

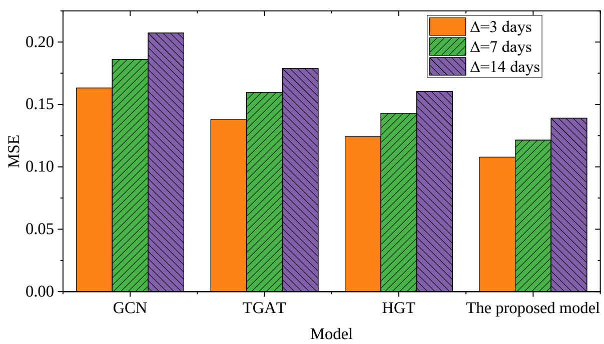

Figure 7: MSE performance under different prediction time spans

The data in Figure 7 further validate the model's robustness across different prediction horizons. As the prediction window extends from Δ = 3 days to Δ = 14 days, all models experience an increase in error, reflecting the growing uncertainty and modeling difficulty of propagation behaviors over longer time spans. However, the proposed model consistently achieves the lowest MSE across all time intervals, with the smallest error increase, demonstrating superior temporal generalization and trend extrapolation capabilities. Compared to GCN, the proposed model reduces error by 33% in the long-term prediction scenario (Δ = 14 days), and outperforms TGAT and HGT with error reductions of 22.3% and 13.3%, respectively. This advantage stems primarily from the model's dynamic temporal modeling and precise capture of user behavior patterns within heterogeneous structures, enabling user representations to reflect both current behavior states and the cumulative effect of historical actions on future propagation potential. Therefore, in evolving social e-commerce propagation scenarios, the proposed model exhibits stronger robustness and generalization in prediction stability and temporal adaptability, making it well-suited for deployment in real-world marketing monitoring and propagation effectiveness analysis systems.

Similarly, by repeating the experiment 5 times and conducting paired t-tests, it is verified that the MSE improvements of the proposed model under different prediction windows are all statistically significant ($p < 0.05$). This further demonstrates the model's robustness and temporal adaptability in dynamic heterogeneous scenarios, making it suitable for marketing monitoring and propagation effect analysis in real e-commerce environments.

4.3 The analysis of the influence of heterogeneous structure on prediction performance

To further investigate the impact of heterogeneous structural information on model performance, this study designs four different edge-type configurations. These configurations progressively incorporate user social edges (U–U), behavior event edges (U–Action), and item similarity edges (I–I) to construct dynamic heterogeneous graphs. Under a consistent structural design, only the number and semantic complexity of heterogeneous edge types are varied. The model's performance across multiple evaluation metrics under different configurations is compared. Figure 8 presents the specific results.

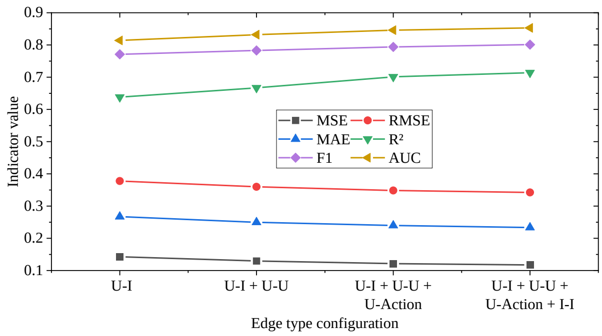

Figure 8: Influence of heterogeneous edge type configuration on model performance

Figure 8 demonstrates that incorporating heterogeneous structures significantly enhances the model's multi-dimensional performance. In the regression task, as the semantic richness of edge types increases, the model's errors measured by MSE and MAE steadily decrease, while R^2 correspondingly improves, indicating stronger fitting capability. For the auxiliary binary classification task, both the F1 score and AUC metrics for propagation event recognition show notable increases with enhanced heterogeneous structures. This suggests that the model not only achieves more accurate regression of user propagation intensity but also exhibits strong binary classification ability. Particularly, after introducing item-to-item (I–I) edges, the model captures latent user interest migration trends, resulting in higher accuracy in identifying propagation potential. These findings further confirm the importance and applicability of dynamic heterogeneous graph modeling in social e-commerce propagation scenarios.

4.4 Hierarchical analysis of user influence distribution and behavior intensity

All users in the test set are divided into three tiers based on their actual influence scores. The k-means clustering algorithm is adopted to partition the influence scores to determine the boundaries between users with high, medium, and low influence. This ensures that the tiered results can truly reflect the distribution of user influence. The MSE of each model is then calculated for these user tiers to analyze their sensitivity in recognizing varying levels of user behavior. The results are shown in Figure 9. As illustrated, the proposed model achieves the best performance across all user tiers, with particularly notable error reduction for high-influence users, where the MSE reaches 0.1268. This indicates that the model has a stronger ability to differentiate behavior intensity levels, accurately capturing propagation trends of highly influential users while reducing the risk of misclassifying extreme individual behaviors. Such capability is of significant practical importance for applications like precision marketing and user segmentation-based recommendation.

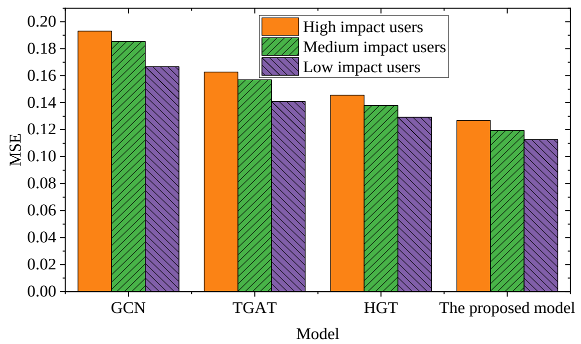

Figure 9: Prediction error under different influence levels

To enhance the model interpretability, this study further analyzes the attention weights in the propagation prediction module. For an intuitive demonstration of the mechanism's effect, the attention weights of some neighbor nodes of two high-influence users are selected as examples (Table 3).

Table 3: An example of neighbor attention weight of high-impact users

User ID	Neighbor node ID	Types of behaviors	Attention weight
U102	U87	Like	0.32
U102	U45	Comment	0.27
U102	I23	Purchase	0.21
U102	U76	Share	0.20
U215	U103	Comment	0.35
U215	I87	Purchase	0.30
U215	U112	Like	0.20
U215	U90	Share	0.15

Table 3 shows the model can dynamically adjust attention weights based on the behavior types of user neighbors and their historical propagation contributions. For instance, the neighbor nodes of the high-influence user U102 who have performed "like" and "comment" behaviors have relatively higher weights, indicating that these neighbors exert a greater impact on U102’s future propagation potential. Similarly, the key neighbor nodes of user U215 mainly contribute to influence through "comment" and "purchase" behaviors.

4.5 Analysis of ablation experiment

To verify the proposed effectiveness of each module in the dynamic heterogeneous graph representation learning framework, ablation experiments are conducted on key components in this section, including the SCL module and the joint auxiliary task module (i.e., node classification and edge prediction). By comparing the performance of the complete model with the models from which each module is removed in the propagation prediction task, the contribution of each module to the model performance can be quantified, and the innovation of the method design can be verified. The definitions of different model variants are as follows: Full Model: Includes the SCL module and joint auxiliary tasks. w/o SCL (without SCL): Retains the time-aware heterogeneous graph representation learning and propagation prediction modules unchanged, but removes the auxiliary objective of SCL. w/o Auxiliary Tasks (without Auxiliary Tasks): Keeps the SCL module and propagation prediction module unchanged, but removes the node classification and edge prediction tasks. w/o SCL & Auxiliary Tasks (baseline version): Only retains the time-aware heterogeneous graph representation learning and propagation prediction modules. The experimental results are shown in Table 4:

Table 4: Ablation experimental results

Model Version	MSE	MAE	R^2
Full Model	0.1268	0.2103	0.892
w/o SCL	0.1425	0.2271	0.871
w/o Auxiliary Tasks	0.1352	0.2184	0.882
w/o SCL & Auxiliary Tasks	0.1548	0.2397	0.861

Table 4 shows that after removing the SCL module, both MSE and MAE increase significantly, indicating that structural contrastive learning helps enhance the discriminative power and stability of node representations. When the auxiliary task module is removed, MSE and MAE also rise, suggesting that joint learning enables node representations to simultaneously consider propagation prediction and structural semantics, which is beneficial for improving generalization ability. The performance of the full model is significantly better than other ablated versions, with an R^2 of 0.892, demonstrating the obvious advantages of the multi-module joint design. It is evident that both structural contrastive learning and auxiliary tasks play a significant role in improving dynamic heterogeneous graph representation learning and user influence prediction. Specifically, SCL strengthens the distinguishability of node representations, while auxiliary tasks provide additional semantic supervision, making node embeddings more robust and generalizable in the propagation prediction task. Through this ablation analysis, the contribution of each module in the overall framework can be clearly identified, verifying the innovativeness and technical effectiveness of the model design.

4.6 Computational complexity analysis

To evaluate the feasibility of the proposed model in practical deployment, this study analyzes the model's time complexity and memory consumption, and compares it with existing heterogeneous graph models, namely HGT and TGAT. The analysis focuses on both the training and inference phases. In the training phase, the proposed model, like TGAT, has a time complexity of $O(h \cdot N \cdot E \cdot d)$. The computational load mainly comes from the aggregation operation of multi-head attention on neighbor nodes, thus maintaining good scalability on large-scale graph data. In contrast, HGT needs to model multiple node types and edge types, leading to an increased complexity of $O(h \cdot N \cdot E \cdot d \cdot |R| \cdot |T|)$. When the number of edge types and node types is large, the training efficiency of HGT decreases significantly. In the inference phase, the proposed model also maintains a comparable complexity to TGAT, i.e., $O(h \cdot N \cdot E \cdot d)$, ensuring efficient prediction capability. However, HGT involves an additional matrix transformation overhead of $O(N \cdot d^2)$ besides the conventional neighbor aggregation computation, which further reduces the inference efficiency when the node scale is large. Therefore, it can be concluded that the proposed model, while integrating temporal information and heterogeneous structural information, avoids excessive complexity growth, making it more suitable for the requirements of efficient inference and rapid updates in practical applications.

The results are shown in Table 5. Where: h denotes the number of heads in multi-head attention. N represents the number of nodes. E indicates the number of edges in the graph (i.e., the total number of neighbors across all nodes). d stands for the dimension of node embeddings. $|R|$ is the number of edge types. $|T|$ is the number of node types.

Table 5: Complexity comparison

Model	Training time complexity	Reasoning time complexity
The proposed model	$O(h \cdot N \cdot E \cdot d)$	$O(h \cdot N \cdot E \cdot d)$
HGT	$O(h \cdot N \cdot E \cdot d \cdot \lvert R \rvert \cdot \lvert T \rvert)$	$O(h \cdot E \cdot d + N \cdot d^2)$
TGAT	$O(h \cdot N \cdot E \cdot d)$	$O(h \cdot N \cdot E \cdot d)$

Table 5 shows that the proposed model has a complexity similar to that of TGAT. However, when dealing with multi-type nodes and edges, it is more efficient than HGT. At the same time, on the premise of ensuring prediction accuracy, its memory usage remains at a reasonable level, making it suitable for online deployment and analysis in real social e-commerce scenarios.

4.7 Discussion

In the previous experiments, the proposed user influence propagation model based on dynamic heterogeneous graph representation learning exhibited excellent performance in the overall regression task. For example, in the general prediction task, compared with TGAT's results (MSE = 0.1597, MAE = 0.2785, R^2 = 0.603), the proposed model achieved an MSE of 0.1214, an MAE of 0.2398, and an R^2 of 0.701. This represents a performance improvement of approximately 22.3% to 17.4%. The proposed model showed the smallest error growth across all time horizons. Especially in the long-term prediction scenario with Δ = 14 days, it reduced errors by 33%, 22.3%, and 13.3% compared with GCN, TGAT, and HGT respectively. This demonstrates its excellent temporal generalization ability and trend extrapolation ability. This improvement is mainly attributed to the model's simultaneous consideration of temporal dynamic evolution and heterogeneous structural information. This enables node embeddings to comprehensively reflect the current behavioral state and historical cumulative effects, thereby predicting future propagation potential more accurately. Compared with schemes in the literature that only use single temporal encoding or heterogeneous modeling (e.g., Wang et al. [26], Zhou et al. [27], and Chen et al. [28]), this study integrates neighbor node information through a multi-head attention mechanism and introduces learnable temporal encoding. This significantly enhances the model's ability to capture key nodes in propagation paths and improves its interpretability. Despite the above achievements, this study still has certain limitations. First, the model has limited ability to model multi-hop propagation paths and multi-level influence cascades, and there is room for improvement in the prediction accuracy for low-activity users. Second, due to the complex structure of the model, the computational cost of training and inference is relatively high, which may pose challenges for the deployment of large-scale online systems. Finally, user behaviors have high semantic dependence. In the future, joint modeling of text information and graph structure data can be further explored to enhance the model's interpretability and generalization ability.

5 Conclusion

5.1 Research contribution

This study addresses the dynamic propagation mechanism of user influence in social e-commerce environments by proposing a user influence propagation modeling method based on dynamic heterogeneous network representation learning. The method constructs a dynamic heterogeneous graph with a time-aware mechanism, comprehensively modeling the semantic relationships among multiple entity types such as users, products, and behavioral events. By jointly capturing structural heterogeneity and behavioral evolution, the study achieves precise characterization of users' future propagation potential. In terms of model design, this study integrates multi-head attention mechanisms with learnable temporal embedding strategies, enabling node representations to maintain structural diversity while enhancing temporal trend awareness.

5.2 Limitations and future research directions

Although preliminary achievements have been made in method development and experimental verification, there are still several limitations. The current model mainly focuses on influence prediction between static node pairs, and its ability to model multi-hop paths and multi-level influence cascades is limited. Future work can expand this by introducing a path attention mechanism or causal GNN. In addition, data sparsity may lead to insufficient information for some user or item nodes, thereby affecting prediction accuracy. The high complexity of the model may cause overfitting risks, which need to be mitigated through regularization or larger-scale data. The high computational cost during training and inference also restricts the model's real-time application on ultra-large-scale platforms. To address these limitations, future research will focus on optimizing the model's generalization ability, reducing computational costs, and exploring richer data fusion strategies to improve the model's practical usability and adaptability.

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