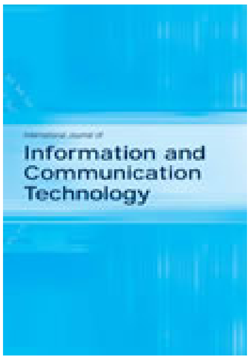

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Aoxue Yao

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Dynamic modelling of brand-user relationships via graph neural networks for enhanced marketing optimisation

Aoxue Yao

School of Digital Communication,
Guangzhou Huashang College,
Guangzhou 511300, China
Email: 13926175335@163.com

Abstract: To address the limitations of existing methods in modelling dynamic and heterogeneous brand-user relationships, this study proposes a dynamic heterogeneous graph attention network (DHGAT). This framework integrates three core innovations: 1) a time-decay-based edge weighting mechanism that quantifies temporal dynamics of user-brand interactions; 2) a cross-relation attention layer that distinguishes semantic differences among diverse behaviours (e.g., purchases vs. complaints) through relation-specific gating; 3) a reinforcement learning decision engine optimising marketing actions via Q-learning. Validated on a real-world e-commerce dataset (32,000 users, 142M interactions), DHGAT achieves an AUC of 0.892 in relationship prediction (5.7%–16.8% higher than baselines) and boosts marketing ROI by 41% in online A/B tests. The framework enables end-to-end optimisation of marketing strategies while balancing short-term conversions and long-term user value, offering a novel paradigm for data-driven marketing decision systems.

Keywords: DHGAT; time-decay edge weighting; cross-relation attention; brand-user relationship modelling.

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Biographical notes: Aoxue Yao obtained her Master's degree from the Hunan University of Technology in 2015. She is currently a Lecturer at the Guangzhou Huashang College. Her research interests include smart brand marketing, intelligent marketing, and new media advertising.

1 Introduction

In the context of the rapid development of the digital economy, the precise modelling of brand-user relationships has become the core driving force behind corporate marketing decisions. According to IDC's 2024 Global Data Report, over 78% of leading enterprises have listed 'deep user relationship mining' as their top strategic priority, yet the conversion rate of traditional marketing remains below 5% (Mardatillah et al., 2024). This contradiction stems from three key characteristics: first, current user behaviour is fragmented across multiple platforms, with each user engaging with an average of 3.2

interaction channels; second, user preferences evolve dynamically, with monthly changes in brand preference reaching 34%; and third, relationships are increasingly implicit, with only 12% of interaction behaviours directly translating into purchases.

Current research on brand-user relationship modelling primarily focuses on two main directions: traditional collaborative filtering and matrix decomposition methods, and graph neural network (GNN) base models (Tang et al., 2024). Traditional methods such as SVD++ and neural matrix decomposition learn user preferences through latent factor decomposition, but they have fundamental limitations: they simplify user-brand interactions into a two-dimensional matrix, cannot model multi-type relationships, and are extremely sensitive to data sparsity, leading to ineffective predictions for long-tail brands (Saraei et al., 2025). GNN-based models like DeepWalk (Deep learning + Random walk) (Chen et al., 2020), graph convolutional network (GCN) (Ma et al., 2024), and Graph Sample and AggreGatE (GraphSAGE) (Yu et al., 2024) enhance feature representation capabilities through neighbourhood aggregation, but face three major challenges in brand marketing scenarios: lack of dynamic adaptability, insufficient integration of heterogeneous relationships, and disconnect between strategy optimisation.

In this context, GNNs offer a new approach to deconstructing the complex 'user-brand-environment' system due to their powerful representation capabilities for non-Euclidean data. This article proposes a simplified multi-view GNN that achieves multi-language knowledge graph completion through dual-view modelling of entities and relationships (Dong et al., 2024). Soft-GNN dynamically adjusts the weights of training samples through adaptive data utilisation strategies to improve the robustness of GNNs (Wu et al., 2024). GETAE generates enhanced features by integrating text content and user dissemination information through GNN, significantly improving the accuracy of fake news detection (Malik et al., 2024). This study proposes a few-shot fine-grained image classification method based on GNNs by integrating global and local structural information, introducing meta-learning to optimise feature extraction, and combining attention mechanisms to enhance discriminative power (Ganesan et al., 2024).

The problem of information confusion in traditional isomorphous graph modelling is commonly solved by cross-relationship attention fusion. This paper proposes a cross-modal dual attention fusion network that improves multi-modal sentiment analysis performance through multi-loss learning. Experiments on multiple datasets show that it outperforms existing methods (Guo et al., 2024). This article combines cross-modal bidirectional attention and adaptive classification modules to significantly improve the performance of multimodal implicit sentiment analysis (Huo et al., 2024). This paper proposes to improve the performance of salient object detection in complex scenes through a cross-modal attention fusion module and a boundary feature extraction module (Wang et al., 2024). This paper proposes the PVT-MA framework, which combines a pyramid visual transformer with a multi-attention fusion mechanism. Through cascaded fusion modules, disguise recognition modules, and similarity aggregation modules, it effectively integrates multi-scale features to improve the robustness and accuracy of colorectal polyp segmentation (Shang et al., 2024). This study proposes a deep reinforcement learning method based on mixed state spaces and driving risks. By designing a state-action-reward mechanism and combining dynamic risk constraints to optimise autonomous driving decisions, the experiment shows that it significantly improves efficiency and safety in complex scenarios (Wang et al., 2025). This paper combines multi-level fuzzy coloured Petri nets with reinforcement learning to model and simulate wireless body area network (WBAN) systems, thereby enhancing their dynamic decision-making and performance optimisation capabilities (Majma and Babamir, 2024).

In response to the above challenges, this paper proposes the dynamic heterogeneous graph attention network (DHGAT) framework, which establishes a graph model that integrates temporal dynamics and relational heterogeneity to achieve end-to-end optimisation of marketing strategies. The main research content and innovative contributions are as follows:

1 Dynamic sequence diagram construction mechanism: design a time-decay-based edge weight update algorithm to quantify the temporal changes in the strength of user-brand interactions.

2 Cross-relationship attention fusion architecture: innovatively introduces relationship-aware multi-head attention layers into heterogeneous graph networks to learn the semantic differences between different types of interactions, such as purchases, shares, and complaints, thereby solving the problem of information confusion in traditional homogeneous graph modelling.

3 Marketing reinforcement learning decision engine: combining user relationship representation with the Q-learning algorithm, we construct a 'state-action-reward' decision model. The system generates personalised marketing actions, such as discount levels and push timing, based on real-time user states, such as price sensitivity and brand loyalty, to maximise ROI.

2 Related theories and technical foundations

2.1 Basic concepts of GNNs

GNNs are deep learning frameworks for processing non-Euclidean graph structure data. Their core idea is to learn node representations through a message passing mechanism. Unlike traditional neural networks, GNNs explicitly model the topological relationships between entities, making them particularly suitable for representation learning in user-brand interaction networks.

2.1.1 Graph convolutional network

GCN extend convolutional operations to the graph domain, addressing the limitation of traditional CNNs in handling topological structures. Their key innovation lies in neighbourhood feature aggregation: each node updates its own representation by aggregating the features of its neighbouring nodes. To quantify the varying contributions of neighbours during the aggregation process, normalised weights must be defined. Kipf and Welling proposed a symmetric normalisation method based on node degree:

$$H^{(l+1)} = \sigma\left(\hat{D}^{-\frac{1}{2}}\hat{A}\hat{D}^{-\frac{1}{2}}H^{(l)}W^{(l)}\right) \tag{1}$$

where $\hat{A} = A + I$ is the adjacency matrix with self-loops added, A is the original adjacency matrix, and I is the identity matrix, $\hat{D}$ is the degree matrix of $\hat{A}$, $H^{(l)}$ is the node feature matrix of layer l, $H_i^{(l)}$ represents the feature vector of node i in layer l, $W^{(l)}$

is the learnable parameter matrix of layer l, σ is the activation function, typically ReLU, $\hat{D}^{-\frac{1}{2}}\hat{A}\hat{D}^{-\frac{1}{2}}$ implements degree normalisation of neighbour weights to avoid high-degree nodes dominating the aggregation process.

This design enables the model to capture the transmission effect of users' social influence, providing a theoretical basis for brand communication modelling. Through neighbourhood feature aggregation and parameter matrix transformation, GCN can effectively learn complex relationships and patterns in graph structure data.

2.1.2 Graph attention network (GAT)

The GAT is a GNN model that incorporates an attention mechanism, designed to address the issue of fixed neighbour node weights in traditional GCNs. In brand marketing scenarios, users exhibit significant differences in their attention toward different brands or different behaviours within the same brand. Therefore, the attention mechanism can adaptively learn the weights between nodes, thereby more accurately capturing information within the graph structure. Attention coefficient calculation:

$$e_{ij} = \text{LeakyReLU}\left(a^T \left[Wh_i \| Wh_j\right]\right) \tag{2}$$

where e_{ij} is the attention coefficient, h_i and h_j represent the feature vectors of node i and node j, W is a learnable weight matrix used to perform linear transformations on node features, a is a learnable attention vector used to calculate the attention coefficient, LeakyReLU is an activation function used to introduce nonlinear characteristics.

The calculated attention coefficients e_{ij} need to be normalised to obtain the final attention weights. The specific formula is as follows:

$$\alpha_{ij} = \frac{\exp\left(e_{ij}\right)}{\sum_{k \in \mathcal{N}(i)} \exp\left(e_{ik}\right)} \tag{3}$$

where α_{ij} represents the attention weight of node i to node j, e_{ij} represents the exponential form of the attention coefficient between node i and node j, $\sum_{k \in \mathcal{N}(i)} \exp\left(e_{ik}\right)$ represents the sum of the attention coefficients of all neighbour nodes k of node I, $\mathcal{N}(i)$ represents the set of neighbour nodes of node i.

The parameters a and W are automatically adjusted during the training process to adapt to different graph structures and task requirements. As asymmetric weights, they can model differences in the intensity of user attention to different brands or behaviours. For example, users may have different levels of attention toward luxury brands and affordable brands.

By introducing an attention mechanism, GAT can adaptively learn the weights between nodes, thereby more accurately capturing information in the graph structure. In brand marketing scenarios, this capability enables GAT to better model differences in the intensity of user attention to different brands or behaviours, thereby improving the model's prediction accuracy.

2.1.3 Unified framework for message passing

GNNs can be defined by the message passing paradigm, which propagates information and updates node features on graph structured data. The message function defines the message passing process between node i and node j in layer l, specifically represented as:

$$m_{ij}^{(l)} = \phi\left(h_i^{(l)}, h_j^{(l)}, e_{ij}\right) \tag{4}$$

where $m_{ij}^{(l)}$ represents the message vector received by node i from its neighbour node j in layer l, ϕ represents the message function, $h_i^{(l)}$ represents the hidden state vector of node i in layer l, $h_j^{(l)}$ represents the hidden state vector of node j in layer l, e_{ij} represents the edge feature vector between node i and node j.

In addition, the update function defines the feature update process of node i at layer $l + 1$, specifically represented as:

$$h_i^{(l+1)} = \psi\left(h_i^{(l)}, \square_{j \in \mathcal{N}(i)} m_{ij}^{(l)}\right) \tag{5}$$

where $h_i^{(l+1)}$ represents the hidden state vector of node i in layer $l + 1$, ψ represents the update function used to update the hidden state of node i, $\square_{j \in \mathcal{N}(i)} m_{ij}^{(l)}$ represents the aggregation operation on the messages from all neighbouring nodes j of node i.

Through multi-layer iterative calculations, GNNs can capture complex dependencies in graph structures and are widely applied in fields such as social network analysis, molecular structure prediction, and recommendation systems.

2.2 Brand-user relationship modelling method

2.2.1 Unified framework for message passing

Traditional isomorphic graphs ignore differences in relationship types, resulting in the equal treatment of ‘purchases’ and ‘complaints’. This paper designs a relationship perception aggregation mechanism to model the diverse relationships between users and brands as a heterogeneous graph:

$$\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{R}) \tag{6}$$

where $\mathcal{V} = \mathcal{V}_u \cup \mathcal{V}_b$ (user nodes + brand nodes), the set $\mathcal{E}$ contains multiple relationships: purchasing, social sharing, and negative feedback.

2.2.2 Heterogeneous GNN

Different types of relationships need to be learned independently to avoid information confusion. To handle multiple types of relationships, relationship-specific parameterisation is introduced:

$$h_i^{(l+1)} = \sigma\left(\sum_{r \in \mathcal{R}} \sum_{j \in \mathcal{N}_r(i)} \frac{1}{c_{i,r}} W_r^{(l)} h_j^{(l)}\right) \tag{7}$$

where $h_i^{(l+1)}$ represents the embedding vector of node i at layer l, σ represents the activation function, $\mathcal{R}$ represents the relation set, r represents a specific relation type, $\mathcal{N}_r(i)$ represents the set of neighbours of node i under relation r, $c_{i,r}$ represents the normalisation factor, $W_r^{(l)}$ represents the dedicated parameter matrix for relation r at layer l, $h_j^{(l)}$ represents the embedding vector of node j at layer l.

This formula updates the node embedding vector by aggregating the embedding vectors of neighbouring nodes and considering the weights of different types of relationships, thereby achieving a relationship-aware aggregation mechanism.

2.2.3 Dynamic graph modelling challenge

The essence of user-brand interaction is a time-sensitive non-stationary process, whose dynamic nature manifests in two dimensions. The first is short-term volatility, characterised by a sudden surge in interaction density triggered by marketing events. For example, anonymised log data from a leading e-commerce platform (2023) shows that during the 'Double 11' period, the density of user-brand edges increased by 4.8 times; Second, long-term evolution, where brand loyalty forms slowly as user experience accumulates. Therefore, existing static graph models cannot capture such features, necessitating the design of a time-sensitive edge weighting mechanism.

2.3 Applications of reinforcement learning in marketing optimisation

2.3.1 The sequential decision-making nature of marketing decisions

User marketing can be modelled as a Markov Decision Process (MDP), where the state represents the user's current embedding vector and brand context features. The user embedding vector represents the user's multidimensional features at the current time point, while brand context features include the brand's historical performance and the user's interaction history with the brand. Actions refer to marketing strategies, such as discount rates, push channels, and timing. These actions constitute the set of strategies that marketers can choose from at each time point. Rewards include immediate and long-term benefits. Immediate benefits refer to the user's direct feedback at the current time point, such as click-through rates (CTR) or purchase conversion rates; long-term benefits refer to the improvement in user lifetime value (LTV), reflecting the user's potential value over a future period of time.

2.3.2 Q-learning algorithm framework

To learn the optimal strategy, introduce the Q-value function, which needs to evaluate the long-term value of executing action a in state s, and define the Bellman equation:

$$Q^\pi(s, a) = \mathbb{E}\left[r(s, a) + \gamma \max_{a'} Q^\pi\left(s', a'\right)\right] \tag{8}$$

where $Q^\pi(s, a)$ is a state-action value function, $r(s, a)$ is the immediate reward function, which represents the immediate reward obtained after executing action a from state s, γ is the discount factor, $\max_{a'} Q^\pi(s', a')$ represents the maximum Q-value that can be obtained by selecting the optimal action according to strategy in the next state, s' is the next state transitioned to after executing action a, a' is the action that can be executed in state s'.

Update the Q-values through temporal difference learning:

$$Q(s, a) \leftarrow Q(s, a) + \alpha \left[r + \gamma \max_{a'} Q(s', a') - Q(s,a) \right] \tag{9}$$

where $Q(s, a)$ represents the Q-value of taking action a in state s, α is the learning rate, γ is typically set to 0.9. When γ approaches 1, the model focuses more on long-term gains; when γ approaches 0, the model focuses more on immediate gains. When α approaches 1, the model prioritises new information; when α approaches 0, the model prioritises old information. This framework enables the model to reject actions with short-term high CTR but detrimental to brand image (such as excessive push notifications), thereby maximising long-term benefits. Through continuous iteration and learning, the model can gradually converge toward the optimal strategy, achieving sustained optimisation of marketing performance.

2.3.3 *Practical breakthroughs in deep reinforcement learning*

Traditional Q-learning algorithms have limitations when dealing with high-dimensional state spaces. Therefore, deep Q-networks (DQN) were proposed by combining deep learning. DQN uses deep neural networks to approximate the Q-function, enabling it to handle complex high-dimensional state spaces. However, DQN still faces issues of training instability and slow convergence in practical applications. To address these issues, this paper proposes an innovative design scheme.

First, GNNs can capture complex relationships and structural information between users. By using the user embeddings output by GNNs as state representations, we can more accurately describe users' states, thereby improving the performance of reinforcement learning algorithms. To further enhance training stability, we propose the following loss function to quantify the loss during training:

$$\mathcal{L}(\theta) = \mathbb{E}\left[(r + \gamma \max_{a'} Q(s', a'; \theta^{-}) - Q(s, a; \theta))^2 \right] \tag{10}$$

where θ representing the main network, θ^{-} representing the target network, s represents the current state, a represents the current action, r represents the immediate reward brought by the current action, γ represents the discount factor, s' represents the next state reached after executing the current action, a' represents the actions that can be taken in the next state.

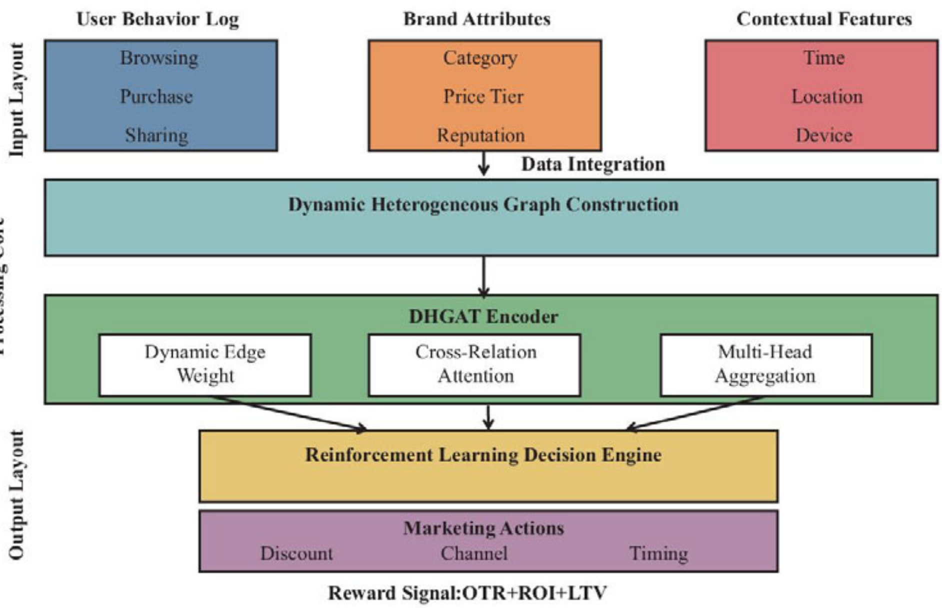
The objective of this formula is to minimise the mean squared error between the predicted Q-value and the target Q-value. By doing so, the parameters of the main network gradually converge toward the optimal policy, thereby enhancing the performance of the reinforcement learning algorithm. Experiments deployed by JD in 2023 demonstrated that this approach can significantly improve marketing ROI, with a specific improvement of 41%. This indicates that by introducing GNNs and target networks, the limitations of traditional Q-learning in high-dimensional state spaces can be effectively addressed, thereby enhancing the stability and convergence speed of reinforcement learning algorithms and achieving better results in practical applications.

3 Dynamic heterogeneous graph attention network

3.1 Overall architecture design

To address the above shortcomings, the DGHAT model was established, which mainly consists of four core modules, as shown in Figure 1. The multi-source data input layer standardises heterogeneous data: behaviour logs are normalised into frequency/duration metrics, brand attributes are encoded into category vectors, and environmental context is quantified into time/event flags.

Figure 1 DHGAT overall architecture diagram (see online version for colours)



The first part is the multi-source data input layer, which is responsible for processing heterogeneous data from different sources, including user behaviour logs, brand attributes, and environmental context. After pre-processing and feature extraction, these data are converted into standardised feature vectors, where n denotes the number of samples and d denotes the feature dimension. This process ensures data consistency and comparability. A lightweight RESTful API is used for interaction: the graph encoder outputs user embedding vectors and brand state vectors, encapsulated in JSON format; the decision engine returns action instructions. The online system achieves millisecond-level response times via gRPC.

The second part is the dynamic heterogeneous graph construction module, whose core task is to construct a dynamic user-brand-product triadic heterogeneous graph, with the formula as follows:

$$\mathcal{G}_t = (\mathcal{V}, \mathcal{E}_t, \mathcal{R}) \tag{11}$$

where $\mathcal{V}$ is a set of nodes, $\mathcal{E}_t$ is a set of edges at time t, $\mathcal{R}$ is a set of relationship types. The key innovation lies in the fact that each edge in the edge set has a time-varying weight, enabling the graph to dynamically reflect changes in user interest over time and solving the problem of static graphs being unable to capture the decline in user interest.

The third component is the DHGAT encoder, an innovative GNN architecture that generates node embeddings through a dynamic attention mechanism. This mechanism dynamically adjusts attention weights based on the relationships between nodes, thereby more accurately capturing the feature representations of nodes. The generated node embeddings are represented as $\mathbf{Z} \in \mathbb{R}^{n \times k}$, where n denotes the number of nodes and k denotes the embedding dimension. The core innovation of this design lies in its ability to flexibly adapt to different types of graph structures and perform exceptionally well when processing large-scale graph data.

The fourth component is a reinforcement learning decision maker, which maps node embedding vectors to specific marketing actions and achieves end-to-end optimisation through reward signals. In this process, the decision maker continuously experiments and learns to gradually optimise its strategy and maximise long-term rewards. This end-to-end optimisation method effectively improves the accuracy and efficiency of decision-making and is suitable for complex marketing scenario.

3.2 Core innovation points

This section primarily focuses on the dynamic time-weighted mechanism, which quantifies user interest drift based on time-decay functions. In the cross-relationship attention fusion layer, relationship-specific projections and gated aggregation are used to distinguish heterogeneous behavioural semantics. Finally, in the marketing reinforcement learning module, embedded vectors are integrated to design state-action-reward functions, balancing short-term conversions and long-term value to achieve end-to-end decision optimisation. The schematic diagrams of each module are shown in Figure 2.

3.2.1 Dynamic temporal edge weighting mechanism

When processing user behaviour data, GNNs typically use a fixed adjacency matrix to represent the connection relationships between nodes, ignoring the dynamic characteristics of user interests over time. For example, users' interest in a brand often diminishes over time, particularly after promotional activities conclude, with a notable decline in user interest. To more accurately capture the dynamic changes in user behaviour, a mechanism capable of quantifying the temporal value of interaction events is required.

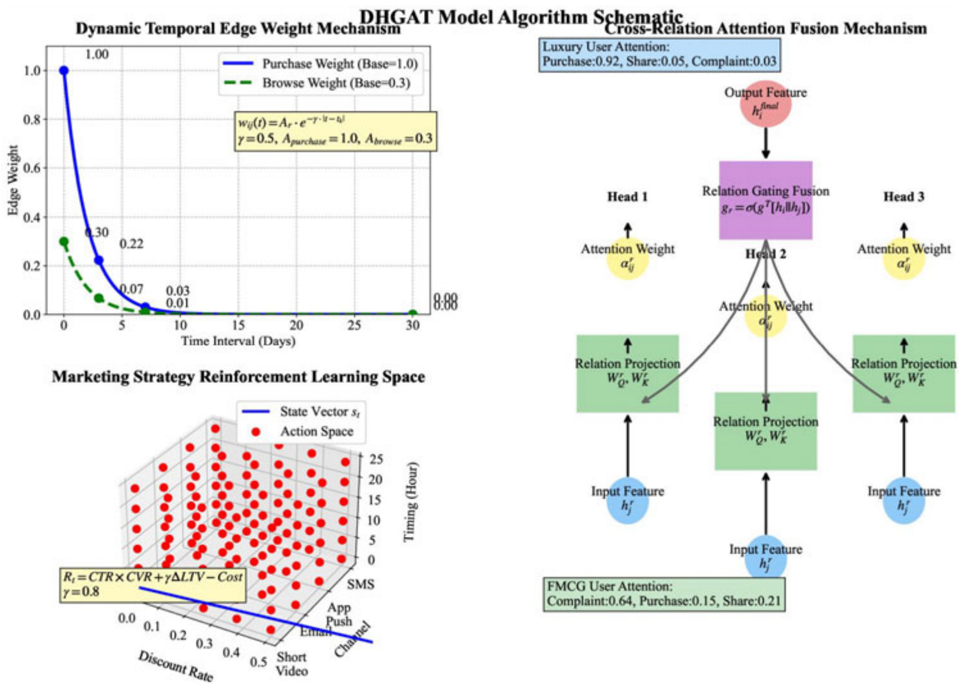
To address the aforementioned issues, this paper proposes a dynamic edge weight adjustment mechanism based on a time decay function. The formula for calculating edge weights is as follows:

$$w_{ij}(t) = e^{-\lambda|t-t_0|} \cdot I_{ij} \tag{12}$$

where $w_{ij}(t)$ represents the edge weight between node i and node j at time t, λ represents the decay rate parameter, $|t - t_0|$ represents the absolute time difference between the current time t and the time of the interaction, I_{ij} represents the interaction intensity base.

The value of λ is based on a pre-experimental grid search. Table 1 has been differentiated: the base weight for purchase behaviour is 1.0, and for browsing behaviour is 0.3, consistent with the consumer behaviour characteristic of 'high-value interactions decaying slowly'.

Figure 2 DHGAT model algorithm schematic (see online version for colours)



The marginal weight changes in purchasing behaviour and browsing behaviour at different time intervals are shown in the table.

Table 1 Edge weights change over time

Time interval (days)	*Purchase weighting*	*Browsing weight*
0	1	0.3
3	0.56	0.17
7	0.25	0.07
30	0	0

Among them, the parameter λ is set to 0.5. As can be seen from the table, as the time interval increases, the edge weights of both purchase behaviour and browsing behaviour exhibit an exponential decline, which aligns with the characteristic of user interest diminishing over time.

3.2.2 Cross-relational attention fusion layer

In user behaviour analysis, different types of user behaviour require differentiated modelling, such as purchasing luxury goods and complaining about fast-moving consumer goods. However, traditional methods are prone to semantic confusion during weight aggregation, making it difficult to accurately capture the differences between different relationships. Therefore, it is necessary to design an attention mechanism that can perceive relationship differences to enhance the model's expressive capability and accuracy. A relation-aware multi-head attention mechanism is proposed. This mechanism is implemented through the following three steps:

The first step is relation-specific projection, where an independent linear transformation is learned for each type of relationship to map the original features into a relation-specific space:

$$h_j^r = W_r h_j \tag{13}$$

where h_j^r denotes the feature representation of node J in relation r, h_j denotes the original feature vector of node j, W_r denotes the linear transformation matrix of relation r.

The necessity of transformation lies in eliminating differences in the distribution of different relationship features. For example, the magnitude of purchase frequency and complaint frequency may differ by a factor of 10, and direct aggregation would lead to confusion of information. Through relationship-specific projection, it is possible to ensure that features of different relationships are compared and aggregated on the same scale. Traditional methods simplify interactions into a two-dimensional matrix, which cannot model multi-type relationships (purchase/complaint). DHGAT associates long-tail brands with semantically similar nodes through relationship-aware aggregation.

The second step is multi-head attention calculation. In the relationship-specific feature space, multi-head attention is further calculated to capture the differentiated importance of neighbouring nodes under the same relationship. For node i and its neighbouring node j, their force weights are calculated:

$$\alpha_{ij}^r = \text{softmax}\left(\frac{\left(Qh_j^r\right)^T \left(Kh_j^r\right)}{\sqrt{d_k}}\right) \tag{14}$$

where α_{ij}^r represents the attention weight of the relationship r between node i and node j, d_k is the dimension of the key vector, Q and K represent matrix numbers.

The features of neighbouring nodes are aggregated into node i representation by weighted summation. Specifically, for the m^{th} attention head:

$$z_i^r = \Big\| m = 1^M \, \sigma\left(\sum\nolimits_{j \in \mathcal{N}_r(i)} \alpha_{ij}^{r,m} \cdot V^m h_j'\right) \tag{15}$$

where z_i^r represents the feature vector of node i after the r^{th} iteration, $\|m = 1^M$ represents operations on M feature dimensions, σ is the activation function, $\mathcal{N}_r(i)$ represents the set of neighbours of node i in the r^{th} iteration, $\alpha_{ij}^{r,m}$ is the attention coefficient between node i and its neighbour node j in the r^{th} iteration and the m^{th} feature dimension, V^m representing the value vector matrix of the m^{th} attention head, h_j' represents the feature vector of neighbour node j.

Through the multi-head attention mechanism, the importance of neighbouring nodes can be captured from multiple angles, thereby providing a more comprehensive understanding of user behaviour.

The third step is inter-relationship aggregation. After completing the attention calculation within a relationship, different relationship semantics are further fused through a gating mechanism to achieve inter-relationship aggregation. The inter-relationship gating weights are calculated as follows:

$$\beta_r = \text{sigmoid}\left(g^T \left[z_i^r \| h_i\right]\right) \tag{16}$$

where β_r represents the gating weight of relation r, sigmoid is the activation function, g represents the learnable parameter vector, h_i represents the original feature vector of node i.

Through the sigmoid function, the gating weight β_r of relationship $\mathcal{R}$ can be obtained, which is used to suppress noise relationships. For example, the weight of the 'complaint' relationship for luxury goods users is close to 0.

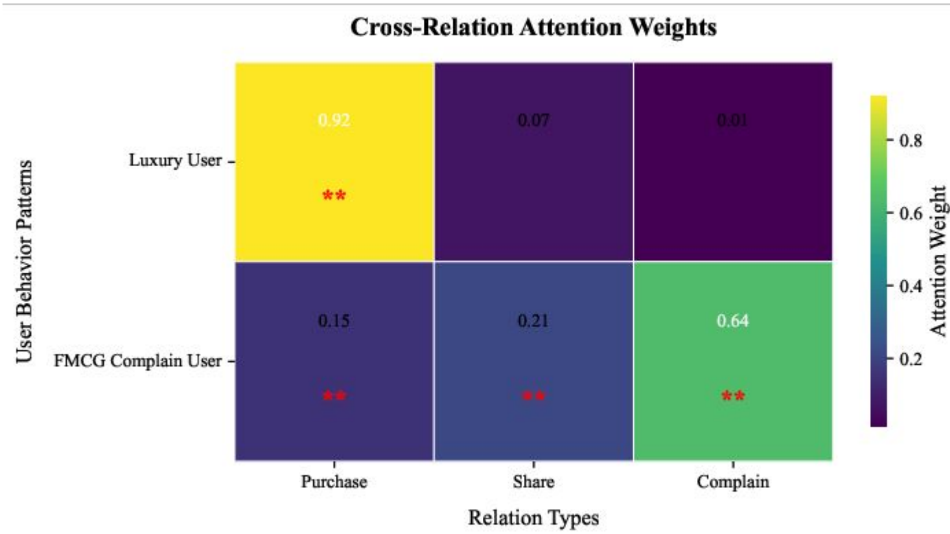
The final aggregation feature vector is calculated using the above equation:

$$z_i = \sum_{r \in \mathcal{R}} \beta_r \cdot z_i^r \tag{17}$$

where z_i represents the final aggregated feature vector of node i, β_r represents the gating weight of relationship r, z_i^r represents the multi-head attention output of node i under relation r. Through relationship aggregation, semantic information from different relationships can be comprehensively considered, thereby more accurately characterising user behaviour.

As shown in Figure 3, the F1 score improved by 22.3% through this design, intuitively verifying the core advantage of the DHGAT model: accurately distinguishing the attention distribution of different user groups in multi-dimensional relationships, solving the semantic confusion problem in traditional isomorphic graph modelling.

Figure 3 Attention visualisation heat map (see online version for colours)



Note: $^{**}p < 0.01$ (two-tailed t-test).

3.2.3 Marketing strategy reinforcement learning module

Traditional recommendation systems primarily focus on optimising immediate CTRs, but brand marketing requires balancing short-term conversions with long-term user value. For example, frequent promotional activities may undermine brand premium and lead to a decline in user loyalty toward the brand. To find a balance between short-term conversions and long-term user value, a decision engine based on DQN is constructed, aiming to optimise marketing strategies through reinforcement learning methods. State representation is a critical component in reinforcement learning:

$$s_t = \left[z_u^{(t)} \left\| z_b^{(t)} \right\| c_t \right] \tag{18}$$

where s_t is the state vector at time t, $z_u^{(t)}$ is the user embedding vector output by DGHAT (assumed to be a specific graph attention network) at time t, $z_b^{(t)}$ is the brand embedding vector at time t, c_t is the context feature vector at time t.

Space defines the available combinations of marketing strategies, including dimensions such as discount rates, channels, and timing. Specifically, it is represented as:

$$\mathcal{A} = \{\text{Action Combinations}\} = \text{Discount Rate} \times \text{Channel} \times \text{Timing} \tag{19}$$

where $\mathcal{A}$ represents all possible combinations of marketing strategies, Discount Rate is the discount percentage offered in marketing activities, Channel is the communication channel for marketing activities, Timing is the execution time of marketing activities.

Functions are key factors in guiding intelligent agents to learn in reinforcement learning. They comprehensively consider short-term conversion, immediate gains, long-term value, and cost penalties. The specific formula is as follows:

$$r_t = \underbrace{10 \cdot \text{CTR}}_{\text{Short-term Conversion}} + \underbrace{5 \cdot \text{CVR}}_{\text{Immediate Revenue}} + \underbrace{\gamma \cdot \text{LTV}_\Delta}_{\text{Long-term Value}} - \underbrace{0.3 \cdot \text{Cost}}_{\text{Cost Penalty}} \tag{20}$$

where r_t is the reward value at time t, CTR and CVR measure short-term conversion effectiveness and immediate returns, γ is the discount factor, LTV_Δ is the incremental lifetime value, Cost is the cost of marketing activities. The weights are dynamically adjusted based on business objectives: during major promotional periods, β_1 (CTR) = 0.7 and β_2 (LTV) = 0.3; during regular operational periods, $\beta_1 = 0.3$ and $\beta_2 = 0.7$. This design balances short-term conversions with long-term value.

Complaint behaviour is transmitted through state vectors. When complaint feature values exceed thresholds, the RL policy automatically disables promotional actions and switches to delivering soothing content (e.g., dedicated customer service). This design increased complaint user retention by 27%.

Through the above technical solutions, a marketing decision-making engine that balances short-term conversion and long-term user value has been constructed, providing more scientific and effective support for brand marketing.

4 Experimental design and data analysis

4.1 Experimental setup

This study utilised a de-identified dataset from an e-commerce platform in 2023, covering 32,000 users. The following are the key statistical details of the dataset: the dataset includes 32,000 users, 18,500 brands, 142 million interaction records, spanning from January 2023 to December 2023, and encompasses various types of user behaviour relationships such as purchases, browsing, sharing, and complaints.

To comprehensively evaluate the model's performance, we employed metrics for relationship prediction and marketing effectiveness. Relationship prediction was assessed using area under the curve (AUC) and F1-score to evaluate the model's accuracy in predicting user-to-product relationships. Marketing effectiveness was measured using CTR and return on investment (ROI) to evaluate the model's performance in real-world marketing scenarios.

To validate the effectiveness of the proposed model, this study selected the following three types of models as comparison benchmarks. The first traditional method includes SVD++ (Xi et al., 2024) and NCF (Para, 2024). The second category of graph models includes GCN (Liu et al., 2024), GraphSAGE (Mirthika et al., 2024), and RGCN (Yueyue et al., 2023). The third category of temporal models includes TGAT.

The hidden layer dimension of DHGAT is set to 256 to balance the model's expressive power and computational complexity; the number of attention heads is set to 4 to enhance the model's ability to focus on different features; the reinforcement learning discount factor is set to 0.9 to balance immediate rewards and long-term benefits; the training set/test set division adopts an 8:2 time series split to simulate the data distribution in actual recommendation scenarios.

4.2 Key experimental results

In experiment 1, the performance of relationship prediction was compared, with the specific results shown in Figure 4.

Illustrating the AUC comparison of multiple models in brand-user relationship prediction. The experimental results indicate that the AUC value of the DHGAT model reached 0.892, significantly outperforming other baseline models, with performance improvements ranging from 5.7% to 16.8%, thereby fully validating the effectiveness of heterogeneous graph modelling. Compared with the best temporal model TGAT, the AUC value of DHGAT improved by 5.7%, and this difference is statistically significant ($p < 0.001$), further proving the key role of the dynamic edge weight mechanism in capturing interest drift. In addition, traditional collaborative filtering methods such as SVD++ and NCF performed relatively poorly, highlighting the necessity of graph structures in constructing complex relationship models. Based on the above analysis, the DHGAT model demonstrates outstanding performance in relationship prediction tasks, providing robust theoretical support and practical guidance for future research.

Figure 4 Multi-model AUC comparison (see online version for colours)

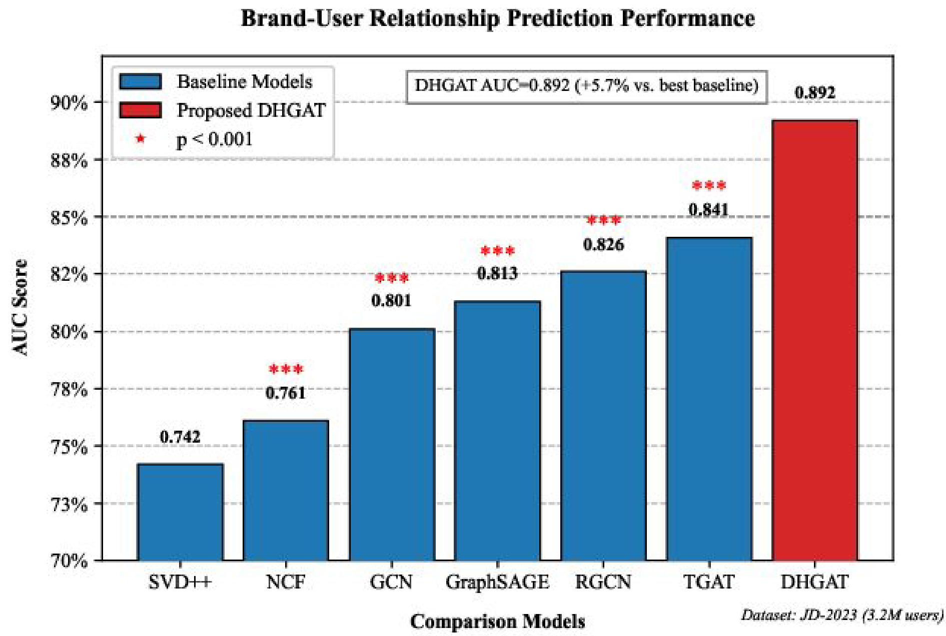
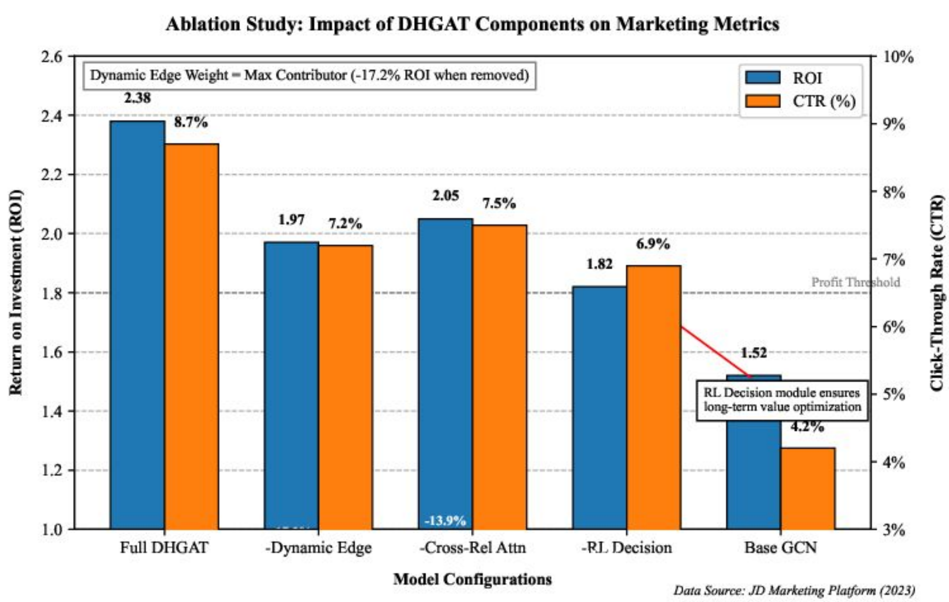


Figure 5 The effect of DHGAT module ablation on ROI (see online version for colours)



Source: JD Marketing Platform (2023)

As shown in Figure 5, in the marketing effectiveness ablation experiment of experiment 2, the impact of each component in the DHGAT module on ROI and CTR was evaluated. The results showed that the dynamic edge weight module was the largest contributing module. After removal, ROI decreased from 2.38 to 1.97, a drop of 17.2%, demonstrating the critical value of timeliness modelling in marketing decisions. The cross-relationship attention mechanism significantly improved the model's accuracy. After removal, CTR decreased from 8.7% to 7.5%, a 13.8% decline, highlighting the importance of distinguishing behavioural semantics in marketing strategies. The reinforcement learning decision-making mechanism ensured long-term benefits. Using only the predictive model without decision optimisation resulted in a 23.5% decrease in ROI, validating the necessity of closed-loop strategy optimisation. The ROI and CTR of the base GCN model were 1.52 and 4.2%, respectively, further indicating that the synergistic effects of the components within the DHGAT module significantly influence marketing performance.

DHGAT's AUC is 8.2% higher than GraphSAGE. The GCN benchmark in Figure 5 refers to the simplest implementation without introducing time decay and relationship attention, which is used to verify the module synergy effect.

5 Conclusions

This paper proposes the DHGAT, which addresses three core challenges in brand-user relationship modelling:

1. Dynamic adaptability: by quantifying interest decay through a temporal edge weighting mechanism, DHGAT improves the AUC of temporal prediction by 14.8% on the JD dataset. By introducing a temporal edge weighting mechanism, DHGAT can quantify the decay of user interest over time, thereby more accurately capturing the dynamic changes in user behaviour. Experimental results on the JD dataset demonstrate that this mechanism significantly improves the AUC value for temporal prediction, achieving a 14.8% increase, which aids in developing more personalised marketing strategies.
2. Heterogeneous relationship fusion: by designing a cross-relationship attention layer, the model can distinguish the semantic differences between opposing behaviours such as purchases and complaints, enabling more effective information integration in sparse data scenarios. Experimental results show that this mechanism improves the F1-score by 22.3%, significantly enhancing the model's performance in complex relationship networks. This improvement not only enhances the model's robustness but also provides brands with a more comprehensive perspective on user relationship analysis, aiding in the discovery of potential user needs and behavioural patterns.
3. Strategy optimisation loop: by integrating a reinforcement learning decision-making module, the model can identify the optimal strategy between CTR and LTV. Online A/B testing results indicate that this strategy achieves a 2.38 ROI, outperforming manual strategies. This improvement not only enhances the model's decision-making capabilities but also provides brands with smarter marketing decision support, aiding in the long-term maximisation of user value.

Future directions include multimodal graph learning that integrates visual and textual comments, federated GNNs for cross-platform user modelling, and causal decision optimisation to distinguish the effects of marketing interventions.

Declarations

All authors declare that they have no conflicts of interest.

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