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Modeling leadership influence propagation in cross-departmental collaboration with graph neural networks

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Abstract: To address the issue that traditional methods cannot accurately model non Euclidean structured data in cross departmental collaboration networks or effectively capture the propagation patterns of leadership influence, this study constructs graph convolutional network (GCN) and graph attention network (GAT) models, and proposes a GCN plus GAT fusion model to explore the propagation of leadership influence in cross departmental collaboration. Experimental results on a real enterprise dataset show that the GCN plus GAT fusion model achieves an AUC of 84.72%, which is 9.04% higher than logistic regression (LR), 7.79% higher than support vector machine (SVM), 4.29% higher than the graph structured CNN (PSCN), 3.47% higher than the single GCN, 2.36% higher than the single GAT, and 2.85% higher than GraphSAGE. The model also achieves an F1 score of 61.95%, which is 2.71% higher than the single GAT. The model shows a performance drop of only 0.97% on a simulated dataset, demonstrating stronger generalization ability and noise resistance. These results provide theoretical support for quantitative modeling of leadership influence propagation in cross departmental collaboration and offer new ideas for improving leadership effectiveness in a digital environment.

Keywords: graph neural networks; cross-departmental collaboration; leadership influence propagation; graph convolution; graph attention

1. Introduction

In the context of digital intelligence, enterprises are accelerating their transformation from traditional organizational forms toward digitalization, networking, and intelligence. Cross-departmental collaboration, as an important pathway for breaking departmental barriers and achieving resource integration and value creation, is playing an increasingly prominent role (Sunnemark et al., 2024). Whether in government departments advancing digital governance reforms or enterprises facing process reengineering during digital transformation, cross-departmental collaboration is essential for resolving issues such as fragmented processes and information silos (Mishler & Hazen, 2023). However, differing objectives across departments, resource conflicts, and the absence of effective communication mechanisms often hinder the full realization of collaborative effectiveness (Jiang & Cheng, 2024). Leaders serve as the core driving force for enterprise growth, and whether their influence can transcend departmental boundaries and transmit effectively within collaborative networks plays a decisive role in the success or failure of cross-departmental collaboration (Vu & Le, 2025).

Cross-departmental collaboration refers to two or more independent yet interdependent departments that share information, resources, and actions through internal communication to achieve overall effects that single departments could hardly

accomplish alone (Anwar & Saraih, 2024; Peng, 2022). In the research field of leadership within cross-departmental collaboration, traditional deep learning methods have proven inadequate for handling node disorder and sample correlation issues in graph-structured data (Jarzabkowski et al., 2022). These methods either heavily rely on basic diffusion models or employ complex hand-crafted features that are difficult to generalize across different types of propagation cascade scenarios. Even the latest generative models, while enabling some understanding of propagation, still yield unsatisfactory prediction accuracy. Therefore, a deep learning approach capable of directly processing graph-structured data is urgently needed. This study addresses this demand by introducing graph neural networks into leadership influence prediction in cross-departmental collaboration. From the dual perspectives of node feature extraction and graph structure feature learning, it reveals the hidden parameters of leadership influence models, thereby gaining a more comprehensive understanding of leadership propagation patterns in cross-departmental collaboration and effectively predicting influence magnitude (Ezeanyika et al., 2025).

Graph Neural Networks (GNN) represent a class of deep learning methods specifically designed for graph-structured data proposed in recent years. In non-native domains such as social network analysis, knowledge graph reasoning, and molecular structure prediction, GNN has achieved remarkable progress. It can transform non-Euclidean spatial data into Euclidean space representations through representation learning while preserving topological information from the original graph. It also defines graph convolution operations through graph signal processing techniques to automatically extract hierarchical features. Employing convolution operations for feature extraction on non-Euclidean structured data has been proven to significantly enhance prediction accuracy and model generalization capability. Inspired by these successful applications, this study introduces graph neural network methods into the research of leadership influence propagation in cross-departmental collaboration, aiming to address the modeling difficulties that traditional methods face in non-Euclidean collaborative networks.

To tackle the challenge of quantifying and modeling leadership influence propagation in cross-departmental collaboration, this study employs graph neural network methods and constructs a hybrid model combining Graph Convolutional Network (GCN) and Graph Attention Network (GAT). This model optimizes the adaptability of convolution operations from traditional CNNs and information exchange from RNNs on non-Euclidean data, enabling leader features to simultaneously account for node attributes and subgraph structural characteristics while effectively handling both directed and undirected collaborative relationships, significantly improving prediction accuracy for leadership influence propagation in cross-departmental collaboration (Silva & Silver, 2025). The core contributions of this study include: (1) pioneering the application of graph neural networks to quantitative research on leadership propagation in cross-departmental collaboration, filling the gap left by traditional methods in graph-structured data modeling; (2) proposing a GCN+GAT fusion model that enhances feature extraction capability for heterogeneous collaborative relationships through multi-head attention mechanisms; (3) constructing a dual-dataset validation strategy with both simulated and real data to systematically evaluate model robustness under varying collaboration intensities and

noise levels. The research results demonstrate broad prospects for applying graph neural networks in cross-departmental collaboration leadership analysis and lay preliminary methodological foundations for exploring the dynamic evolution of leadership influence.

2. Literature review

Against the backdrop of digital transformation and increasingly fierce market competition, corporate operational models are rapidly shifting from traditional approaches toward greater collaboration. Cross-departmental collaboration has become a key enabler for companies to enhance agility, creativity, and resilience. In an industrial environment deeply permeated by technologies such as artificial intelligence, where multiple departments engage in deep interconnection and coordinated action, Peng M et al. noted that cross-departmental collaboration faces various challenges when addressing common issues. Through a study involving data from 452 cases, their model analysis revealed a correlation between the level of leadership commitment and cross-departmental collaboration. The study evaluated departmental coordination throughout the entire process and contributes to the theoretical understanding of cross-departmental collaboration (Peng et al., 2025). Yang, B. and Shen, Z. proposed a hybrid model that integrates Graph Convolutional Networks (GCN), Reinforcement Learning (RL), and Deep Collaborative Filtering (DCF). The GCN module captures the complex multi-relationship structure between jobs and candidates; the RL module dynamically optimizes recommendation strategies based on feedback; and the DCF module enhances personalized recommendation capabilities (Yang & Shen, 2025). Biswas S et al. addressed the problem of predicting collaborative networks for critical infrastructure enterprises in cloud environments. To quantify how technical and organizational factors influence the effectiveness of graph neural network (GNN) models in predicting cyberattacks, They proposed a framework encompassing network topology visibility, security data quality and integrity, analytical and AI capability maturity, governance and policy alignment, organizational readiness for AI-based security measures, and the perceived effectiveness of GNN-based predictive models. The results indicate that the successful implementation of GNN-based cyber defense strategies in critical infrastructure relies on accurate graph visibility, high-quality telemetry data, mature analytical pipelines, and institutionalized governance mechanisms—not merely the model architecture itself (Tian et al., 2023). He, Q. and Yang, Z developed a five-stage GenAI-enhanced knowledge management framework comprising acquisition, sharing, integration, application, and optimization. Empirical validation demonstrates that this model facilitates the construction of a logical model and proposes an operational architecture for intelligent knowledge management within such enterprises (He & Yang, 2025). Nour, S and Arbussa A pointed out that leaders should reduce formalization and hierarchical structures, empower teams, and adopt digital tools that integrate internal and external stakeholders into collaborative environments. Depending on the organization's established goals, leadership may decide to create a new digital entity that operates in parallel with other business departments, or establish new digital teams for each business unit to coordinate organization-wide digital initiatives (Nour &

Arbussà 2025). Jain L et al. propose a dedicated GNN for Opinion Leader Identification (GOLI) model that leverages GNN capabilities to classify opinion leaders and their influence on online social networks. Experiments utilizing graph neural networks across six different online social networks demonstrate that after training, each dataset can identify opinion leaders. Analysis of these leaders' influence in information propagation reveals that GNN models perform excellently in terms of accuracy and precision (Jain et al., 2023). To address this, we use graph neural networks (GNNs) to learn representations of nodes and edges in cross departmental collaboration networks and construct a leadership influence propagation model, thereby overcoming the limitations of existing methods in modeling structured propagation.

3. Graph neural network-based influence prediction model

3.1. Basic method and problem description

3.1.1. Definition of cross-departmental collaboration network

Cross-Departmental Collaboration Network Given a directed graph $G=(V,E,X,W)$, where $V=\{v_1,v_2,\dots,v_N\}$ represents the set of nodes, and each node v_i represents a participating entity (department or individual) in cross-departmental collaboration. $E\subseteq V\times V$ represents the set of edges, where edge $(v_i,v_j)\in E$ indicates the existence of a collaborative relationship between node v_i and node v_j , and the direction of the edge indicates the direction of influence propagation. $X=\{x_1,x_2,\dots,x_N\}$ denotes the node feature matrix, where v_i represents the feature vector of node F , including leadership features (value leadership, strategic insight, etc.) and department attribute features (department size, business type, etc.), and H denotes the feature dimension. $W=\{w_{ij}\}$ represents the edge weight matrix, where w_{ij} indicates the collaboration strength between node v_i and node v_j , determined by factors such as communication frequency, number of collaborative projects, and scale of resource exchange (Kumar et al., 2022).

For node v_i in the cross-departmental collaboration network, its r -hop neighborhood defines as $\Gamma_{v_i}^r=\{v_j \mid d(v_i,v_j)\leq r\}$, where $d(v_i,v_j)$ represents the shortest path length between node v_i and node v_j . The r -ego network of node v_i defines as the subgraph $G_{v_i}^r$ induced by vertex set $\Gamma_{v_i}^r$ in graph G . At a certain moment t , observing node v_i in the cross-departmental collaboration network, we introduce state variable $s_{v_i}^t$, where $s_{v_i}^t=1$ indicates that node v_i has already received leadership

influence and exhibited corresponding collaborative behavior at or before moment t ; $s_{v_i}^t = 0$ indicates that node v_i has not yet received leadership influence at moment t .

3.1.2. Problem description

Given cross-departmental collaboration network G , node v_i 's r -ego network $G_{v_i}^r$, and behavior state set $S_{v_i}^t = \{s_{v_j}^t \mid v_j \in \Gamma_{v_i}^r \setminus \{v_i\}\}$ of r -hop neighbors, calculate the probability that node v_i receives leadership influence and exhibits collaborative behavior after time interval Δt :

$$P(s_{v_i}^{t+\Delta t} = 1 \mid G_{v_i}^r, S_{v_i}^t, X) \quad (1)$$

In practical applications, assume the existence of M cross-departmental collaboration instance, where each instance represents with a triple (v_i, a_i, t_i) , with a_i indicating the corresponding collaborative behavior and t_i indicating the timestamp. For each instance node v_i , given its r -ego network $G_{v_i}^r$, behavior state set $S_{v_i}^t$ of r -hop neighbors, and behavior state $s_{v_i}^{t_i+\Delta t}$ after time interval Δt , the cross-departmental leadership influence propagation prediction problem transforms into a binary graph classification problem, by constructing a graph neural network model to learn the mapping relationship between node features and network structure features, achieving prediction of the node's future behavior state.

3.2. Model method

3.2.1. Graph embedding technique

For cross-departmental collaboration network G , we first sample the ego network of each node through the Random Walk with Restart (RWR) algorithm to generate fixed-length node sequences. The core idea of the RWR algorithm works as follows: starting from the initial node, at each step we visit a neighbor node with probability α and return to the initial node with probability $1-\alpha$, ensuring that the sampled sequence focuses on the local network structure of the node (Jing et al., 2024).

Let the sampled node sequence denote as $W = [w_1, w_2, \dots, w_T]$, where T represents the sequence length, and the Inf2vec algorithm learns the node embedding vectors by maximizing the following objective function:

$$J(\theta) = \frac{1}{T} \sum_{t=1}^T \sum_{\substack{-c \leq j \leq c, \\ j \neq 0}} \log P(w_{t+j} \mid w_t; \theta) \quad (2)$$

where C represents the window size, $P(w_{t+j} | w_t; \theta)$ denotes the conditional probability of node w_{t+j} appearing given the presence of node w_t , calculated through the Softmax function:

$$P(w_{t+j} | w_t; \theta) = \frac{\exp(z_{w_{t+j}}^T u_{w_t})}{\sum_{v \in V} \exp(z_v^T u_{w_t})} \quad (3)$$

where $u_{w_t} \in R^D$ represents the input embedding vector of node w_t , $z_v \in R^D$ denotes the output embedding vector of node v , $\theta = \{u_v, z_v | v \in V\}$ indicates the embedding vector dimension, and F represents the model parameters.

After completing training through the Inf2vec algorithm, each node v_i obtains a D -dimensional embedding vector $x_{v_i}^e \in R^D$, which we concatenate with the node's original feature $x_{v_i}^o \in R^F$ to obtain the node's comprehensive feature vector:

$$x_{v_i} = [x_{v_i}^o \oplus x_{v_i}^e] \in R^{F+D} \quad (4)$$

where $\oplus$ represents the vector concatenation operation.

3.2.2. Graph convolutional neural network

CNN constitutes a classic deep learning framework, with core characteristics including local connection, weight sharing, and multi-layer stacking. In graph problems, these characteristics remain applicable because graph structure represents a typical local connection structure, and shared weights can reduce computational cost. Additionally, multi-layer stacking serves as the key to processing hierarchical patterns. However, CNN applies only to Euclidean space data, such as two-dimensional images. **Figure 1** shows the CNN network structure. For general graph structures, the convolution and pooling operations in CNN prove difficult to transfer to graphs, which include both Euclidean space data and non-Euclidean space data.

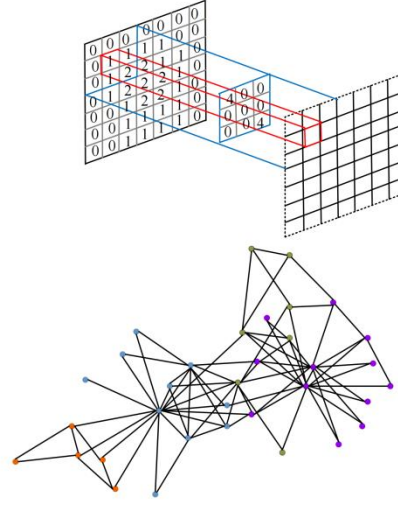


Figure 1. CNN Network Structure.

Graph Convolutional Neural Network generalizes the convolution operation from Euclidean space to non-Euclidean space through the graph Laplacian matrix, achieving feature extraction for graph-structured data (Jing et al., 2024). For cross-departmental collaboration network G , we first construct its adjacency matrix $A \in R^{N \times N}$, where, $A_{ij} = w_{ij}$ if $(v_i, v_j) \in E$, otherwise $A_{ij} = 0$. To avoid gradient vanishing and eigenvalue explosion, we perform normalization processing on the adjacency matrix:

$$\tilde{A} = \hat{D}^{-1/2} (\hat{A}) \hat{D}^{-1/2} \quad (5)$$

where $\hat{A} = A + I_N$ (I_N denotes the identity matrix for preserving node self-features),

$\hat{D}$ represents the degree matrix of $\hat{A}$, satisfying $\hat{D}_{ii} = \sum_j \hat{A}_{ij}$.

The inter-layer propagation formula of GCN works as follows:

$$H^{(l+1)} = \sigma(\tilde{A}H^{(l)}W^{(l)} + b^{(l)}) \quad (6)$$

where $H^{(l)} \in R^{N \times F^{(l)}}$ represents the feature matrix of layer l , $F^{(l)}$ denotes the feature dimension of layer l , $W^{(l)} \in R^{F^{(l)} \times F^{(l+1)}}$ indicates the weight matrix of layer l , $b^{(l)} \in R^{F^{(l+1)}}$ represents the bias vector of layer l , $\sigma(\cdot)$ denotes the nonlinear activation function, and this paper adopts the Exponential Linear Unit (ELU):

$$\sigma(x) = \begin{cases} x & x > 0 \\ e^x - 1 & x \leq 0 \end{cases} \quad (7)$$

3.2.3. Graph attention network

This paper proposes a Graph Attention Network (GAT) model to establish the leadership influence propagation in cross-departmental collaboration, introducing the

attention mechanism into the information propagation step, calculating the hidden state of nodes by adding attention to the neighbor nodes of each node, defining a graph attention layer and building arbitrary graph attention networks through multi-layer stacking, with the graph attention layer shown in **Figure 2**.

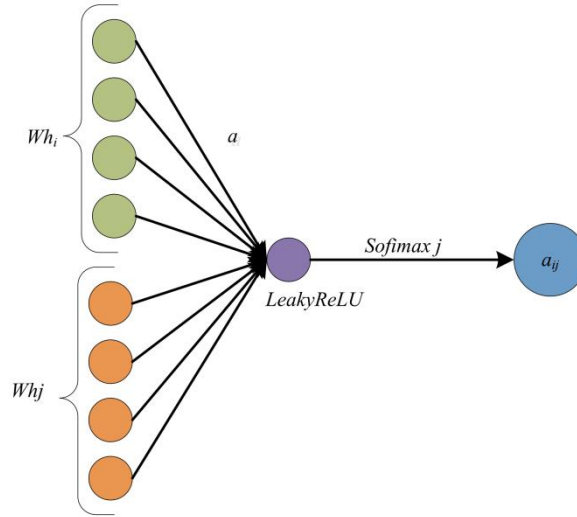


Figure 2. Graph Attention Layer.

The function of this layer works as calculating the attention coefficient of node pair A, with the calculation formula as follows:

$$e_{ij} = a\left(\left[Wh_i \parallel Wh_j\right]\right), k \in N_i \quad (8)$$

$$\alpha_{ij} = \frac{\exp\left(\text{LeakyReLU}\left(e_{ij}\right)\right)}{\sum_{k \in N_i} \exp\left(\text{LeakyReLU}\left(e_{ik}\right)\right)} \quad (9)$$

where e_{ij} represents the similarity coefficient between node pairs, α_{ij} denotes the attention coefficient of node j to node i , and N_i indicates the neighbor node set of node i in the graph. The input set of node features $h = \{h_1, h_2, h_3, \dots, h_N\}$ ($h_i \in R^F$), where N represents the number of nodes, and F denotes the feature dimension of each node. This layer generates a new set of node features with feature dimension $F' h' = \{h'_1, h'_2, h'_3, \dots, h'_N\}$. $W \in R^{F' \times F}$ represents the shared linear transformation weight matrix, whose function works as increasing the dimension of vertex features. $a \in R^{2F'}$ represents the weight vector of a single-layer feedforward neural network, whose function works as mapping the concatenated high-dimensional features to a real number. We normalize the similarity coefficients through the Softmax function, then obtain the attention coefficients using the LeakyReLU nonlinear function. Finally, we acquire the output features of each node, where σ denotes the activation function:

$$h'_i = \sigma \left(\sum_{j \in N_i} \alpha_{ij} W h_j \right) \quad (10)$$

Finally, based on the normalized attention coefficients, we perform weighted summation of the neighbor node features to obtain the output feature of node v_i at layer $l+1$:

$$h_i^{(l+1)} = \sigma \left(\sum_{j \in N_i} \alpha_{ij} h_j^{(l+1)'} \right) \quad (11)$$

To enhance model stability and expressive capability, this paper adopts the multi-head attention mechanism, calculating and concatenating output features through K independent attention heads:

$$h_i^{(l+1)} = \oplus_{k=1}^K \sigma \left(\sum_{j \in N_i} \alpha_{ij}^k W^k h_j^{(l)} \right) \quad (12)$$

where α_{ij}^k represents the attention coefficient of the W^k -th attention head, and k denotes the weight matrix of the D-th attention head.

3.3. Model overall structure

Figure 3 shows the structure of the cross-departmental leadership influence propagation prediction model. The graph neural network-based cross-departmental leadership influence propagation prediction model constructed in this paper mainly includes five parts: input layer, graph embedding layer, regularization layer, graph neural network layer (GCN+GAT), and output layer.

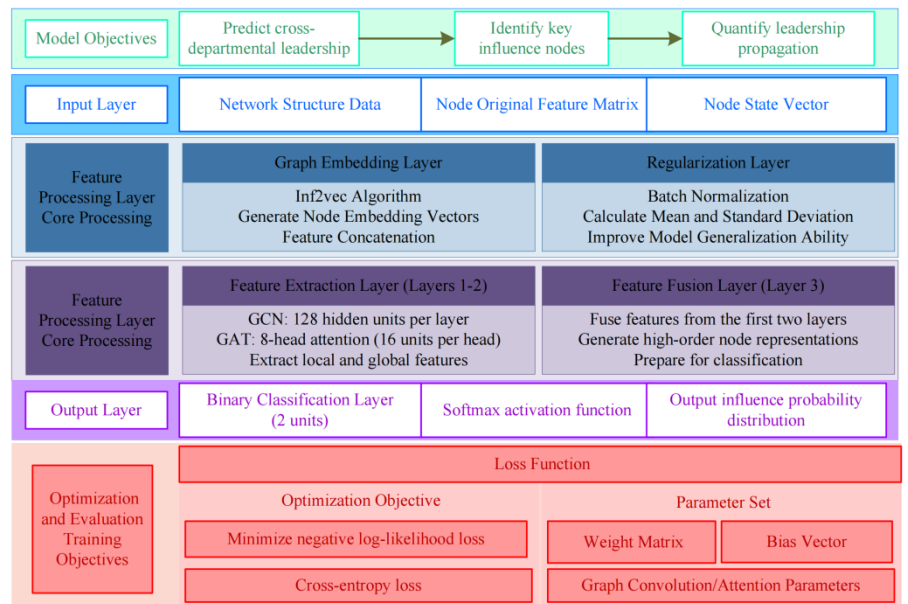


Figure 3. Cross-Departmental Leadership Influence Propagation Prediction Model Structure.

3.3.1. Input layer

The input layer receives raw data from the cross-departmental collaboration network, including network structure data (adjacency matrix A), node feature data (original feature matrix X^o), and node state data (state vector S^t) (Tamraparani, 2021; Zhang et al., 2024). The node original feature matrix X^o contains leadership features, department attribute features, etc., and the state vector E indicates the behavior state of the node at moment F .

3.3.2. Graph embedding layer

We adopt the Inf2vec algorithm to perform graph embedding learning on the cross-departmental collaboration network, mapping each node to a low-dimensional embedding space to obtain the node embedding vector matrix X^e (Cao et al., 2024; Makarov et al., 2021). We concatenate the embedding vectors with the original feature vectors to obtain the node comprehensive feature matrix $X = [X^o \oplus X^e]$, providing a foundation for subsequent feature extraction (Ji et al., 2022; Su et al., 2025; Yuan et al., 2024).

3.3.3. Regularization layer

To prevent model overfitting and enhance model generalization capability, we perform batch normalization processing on the node comprehensive feature matrix. For each feature dimension d in feature matrix X , we calculate its mean value μ_d and standard deviation σ_d , and perform the following normalization operation:

$$y_{id} = \frac{x_{id} - \mu_d}{\sqrt{\sigma_d^2 + \epsilon}} \quad (13)$$

where x_{id} represents the feature value of node v_i at dimension d , y_{id} denotes the normalized feature value, and $\epsilon = 10^{-5}$ indicates a constant value for maintaining numerical stability.

3.3.4. Graph neural network layer

The graph neural network layer adopts a three-layer structure, with the first two layers as feature extraction layers and the third layer as feature fusion layer. For the GCN model, the first two layers each contain 128 hidden units, extracting local and global features of nodes through graph convolution operations; for the GAT model, the first two layers adopt the multi-head attention mechanism ($K = 8$ attention heads), with each attention head containing 16 hidden units, totaling $8 \times 16 = 128$ hidden units, adaptively extracting key features of nodes through the attention mechanism.

3.3.5. Output layer

The output layer serves as a binary classification layer, containing 2 hidden units, and adopts the Softmax activation function to output the probability distribution of nodes being influenced by leadership:

$$\hat{y}_i = \text{Soft max} \left(h_i^{(3)} W^{(3)} + b^{(3)} \right) \quad (14)$$

where $h_i^{(3)}$ represents the output feature vector of the graph neural network layer, $W^{(3)} \in R^{128 \times 2}$ denotes the output layer weight matrix, and $b^{(3)} \in R^2$ indicates the output layer bias vector. The optimization objective of the model works as minimizing the negative log-likelihood loss function:

$$\mathcal{L}(\theta) = -\frac{1}{M} \sum_{i=1}^M \sum_{c=0}^1 y_{ic} \log \hat{y}_{ic} \quad (15)$$

where y_{ic} represents the true label of node v_i , $y_{i1} = 1$ indicates being influenced, $y_{i0} = 1$ indicates not being influenced, $\hat{y}_{ic}$ denotes the probability predicted by the model, and θ represents the set of all model parameters.

4. Model data processing and construction

4.1. Data source

This study adopts a dual-dataset validation strategy, constructing both a simulated cross-departmental collaboration network dataset (Sim-Collab) and a real organizational cross-departmental collaboration dataset (Real-Collab), ensuring data validity and comparability.

Simulated Dataset (Sim-Collab): Generated based on the Independent Cascade (IC) model, a classic probabilistic model in leadership influence propagation research for cross-departmental collaboration, with core mechanism of active nodes activating neighbor nodes through specific success probabilities. This study generates 5 cross-departmental collaboration networks of different scales by setting different leadership influence propagation probabilities ranging from 0.1 to 0.9, with each network containing 1000 nodes (simulating organizational departments), node feature dimension of 32, including 6 leadership features, 10 department attribute features, and 16 collaboration history features. Edge weights randomly generate from collaboration frequency [0,1], simulating dynamic association relationships in cross-departmental collaboration.

Real-world data (Real-Collab): This study selected cross-departmental collaboration data from a large-scale manufacturing enterprise over the past three years, covering 161 core departmental nodes including R&D, production, sales, and marketing, with 847 cross-departmental collaborative projects completed. Based on project cooperation documents, internal communication records, performance evaluation reports, and leadership rating scales, professionals conducted ratings using a 5-point Likert scale. Industry characteristics and collaboration history features were extracted from ERP and project management platforms to ensure data authenticity and reliability.

4.2. Data preprocessing workflow

Data preprocessing strictly adheres to the standardization requirements for graph neural network modeling. **Figure 4** illustrates the data processing workflow. Participants in cross-departmental collaboration are mapped as nodes, and

collaborative relationships are mapped as directed edges. Edge weights are calculated based on the number of collaborative projects and communication frequency. Communication frequency is normalized by the number of monthly interactions to ensure that edge weights fall within the range $[0,1]$. The Random Walk with Restarts (RWR) algorithm is used to sample the 2-nearest-neighbor ego-centric network for each node, with a return probability α set to 80% and a fixed number of sampled nodes $n = 50$. This approach ensures the integrity of local network structural information while reducing the computational complexity of the model. To address the imbalance between positive and negative examples in the dataset—which reached as high as 300:1 in the simulation—we filtered the data to maintain a ratio of approximately 3:1 between negative and positive examples. Nodes with only one active neighbor were excluded, while those with two or more active neighbors were retained, ensuring the model can effectively extract local network structural features and enhance its robustness. The processed dataset was split into training, validation, and test sets in a 75%, 12.5%, and 12.5% ratio, respectively, consistent with the original paper to ensure the comparability of the experiments.

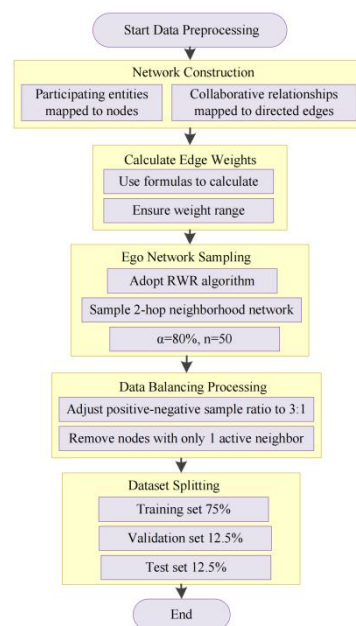


Figure 4. Data Preprocessing Workflow.

This study adopts a node-level temporal event sample construction approach, where each training sample corresponds to a “node-time window” pair. The specific procedure is as follows:

(1) Divide the observation period into 36 time windows on a monthly basis, with 3 years for the real dataset. For each node (department), record whether it “was influenced by leadership and exhibited significant collaborative behavior” within each time window.

(2) If a node meets any of the following conditions within a time window, mark it as a positive example (influenced by leadership, label = 1): the node actively initiated a cross-departmental collaboration project, and its leadership score prior to project launch (rated by experts) was in the top 30th percentile; or the node’s collaboration participation

frequency in the current time window increased by more than 50% compared to the previous window, and at least 2 of its neighbor nodes were marked as positive examples in the previous window. Otherwise mark as a negative example (label = 0).

(3) Each sample consists of a triple $(v, t, N_t(v))$, where v represents the node, t represents the current time window, and $N_t(v)$ represents the 2-hop egocentric network of node v in time window t (including features, states, and edge weights of neighbor nodes). The prediction target is the state label of node v in the next time window $t + 1$.

(4) The initial positive-to-negative ratio in the simulated dataset reached 1:300 at its highest, adjusted to 1:3 through downsampling; the real dataset maintained its original distribution with a 1:3 ratio. Samples with only 1 active neighbor were excluded, retaining samples with 2 or more active neighbors to ensure the model could learn effective local propagation structures.

4.3. Dataset feature description

Table 1 shows the characteristics of the simulated dataset (Sim-Collab). It presents the number of nodes and positive-to-negative ratios across different datasets, enabling clearer observation of the propagation probability ranges.

Table 1. Characteristics of the Simulated Dataset (Sim-Collab).

Dataset	Number of nodes (simulated departments)	Number of edges	Positive examples	Negative examples	Positive-negative ratio	Average degree	Feature dimension	Propagation probability range
Sim-1	1000	4832	856	2568	1:3	9.66	32	[0.1,0.3]
Sim-2	1000	5217	912	2736	1:3	10.43	32	[0.2,0.4]
Sim-3	1000	5643	978	2934	1:3	11.29	32	[0.3,0.5]
Sim-4	1000	6128	1054	3162	1:3	12.26	32	[0.4,0.6]
Sim-5	1000	6584	1132	3396	1:3	13.17	32	[0.5,0.9]

Table 2 lists the features of the real-world dataset (Real-Collab), while the simulated dataset covers scenarios with varying degrees of collaboration.

Table 2. Characteristics of the Real-World Dataset (Real-Collab).

Number of nodes (actual departments)	Number of edges (collaborative relationships)	Number of samples (node-time window pairs)	Positive examples	Negative examples	Positive-negative ratio	Average degree	Feature dimension	Time span	Leadership feature source
161	847	272	68	204	1:3	23.29	32	3 years	Expert ratings (5-point scale)

4.4. Model performance evaluation metrics

The precision is the proportion of samples correctly classified as positive out of all samples predicted to be positive. The formula is:

$$Precision = \frac{TP}{TP + FP} \quad (16)$$

The recall rate is actually the proportion of positive samples that were predicted to be positive, and the formula is:

$$Recall = \frac{TP}{TP + FN} \quad (17)$$

Overall Accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (18)$$

where TP , TN , FP , and FN represent the total counts of true positives, true negatives, false positives, and false negatives respectively.

The macro-averaged F1 score comprehensively considers the precision and recall of each category, with the formula as follows:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (19)$$

4.5. Experimental environment and parameter settings

The experimental setup is shown in **Table 3**. For the Inf2vec algorithm, the window size is $c = 5$, the embedding dimension is $D = 64$, and the number of negative samples is $K = 5$; the batch normalization parameter $\varepsilon = 10^{-5}$, and the dropout rate is $p = 0.2$; The first two layers have 128 hidden units, use the ELU activation function, and employ the Glorot method for weight initialization; the number of attention heads is $K = 8$, with 16 hidden units per head and a total of 128 hidden units, and the attention mechanism uses the LeakyReLU activation function; Softmax activation function; weight matrix $W \in \mathbb{R}^{128 \times 2}$, bias vector $b \in \mathbb{R}^2$; Adagrad optimizer, learning rate $\eta = 0.1$, weight decay $\lambda = 5e^{-4}$; batch size of 1024, maximum training iterations of 500, early stopping mechanism: training stops if the validation set loss does not decrease for 10 consecutive iterations.

Table 3. Experimental Environment Configuration.

Environment type	Configuration item	Specific parameters
Hardware Environment	Processor	Intel Core i7-12700H(2.7 GHz)
	Memory	32 GB DDR5
	Graphics Card	NVIDIA GeForce RTX 3060 (6 GB VRAM)
	Operating System	Ubuntu 20.04 LTS
Software Environment	Deep Learning Framework	PyTorch 1.12.1
	Programming Language	Python 3.8.10
	GPU Acceleration Tool	CUDA 11.6

5. Experimental results analysis

5.1. Baseline model selection

To comprehensively validate the superiority of the GCN+GAT hybrid model proposed in this paper, we selected six benchmark models of different types, covering traditional statistical methods, classical machine learning methods, early graph neural network methods, and advanced deep learning methods, to facilitate a multi-level comparison. Logistic Regression (LR) is a classic linear classification model that manually extracts node features, including node-specific features, graph representation vectors, and local network features for training. The manual feature extraction for LR/SVM models, as shown in **Table 4**, represents traditional statistical learning methods. Support Vector Machines (SVM) are classic nonlinear classification models that use the RBF kernel function and, together with LR, constitute the traditional machine learning benchmarks. Graph-structured CNN (PSCN) transforms graph-structured data into sequence data in Euclidean space, using CNN for feature extraction and classification, representing an early graph data processing method. Graph Convolutional Networks (GCN) are single-layer graph convolutional models, adopting the three-layer structure described in the original paper, with 128 hidden units in each of the first two layers, representing a foundational graph neural network method. Graph Attention Network (GAT) is a single-layer graph attention model that employs an 8-head attention mechanism, representing an advanced graph neural network method. GraphSAGE is an inductive graph neural network model that aggregates features by sampling neighboring nodes; it is suitable for dynamic network scenarios and represents an emerging graph learning method.

Table 4. Manually Extracted Features for LR/SVM Models.

Feature category	Feature name	Feature description
Node Features	Coreness	The coreness degree of nodes in the network
	Pagerank	The importance score of nodes
	Authority score	The authority score of nodes
	Eigenvector Centrality	Node centrality based on eigenvectors
Graph Representation	Inf2vec embedding vector	64-dimensional graph embedding vector
Subgraph Features	Number of active neighbors	The count of active neighbors in the node's ego-centric network
	Subnetwork density	The ratio of actual edges to maximum possible edges in the subgraph induced by active neighbors
	Number of connected components	The count of connected components in the subgraph induced by active neighbors

5.2. Simulated dataset experimental results

The experimental results on five synthetic datasets are shown in **Table 5**. As can be seen, the GCN+GAT hybrid model proposed in this paper significantly outperforms the six baseline models on all evaluation metrics, The AUC value reaches 85.69%, which is 11.37% higher than LR, 10.01% higher than SVM, 7.04% higher than PSCN, 5.86% higher than a standalone GCN, 2.12% higher than a standalone GAT, 4.44% higher than GraphSAGE, and 2.14% higher in F1 score. Although the training time

for the hybrid model is longer than that of the standalone models, given the relatively small scale of the cross-departmental collaboration network—with 1,000 nodes in the simulated dataset—the training time remains within an acceptable range.

Table 5. Experimental Results on Simulated Dataset (Mean $\pm$ Standard Deviation).

Model	AUC (%)	Precision (%)	Recall (%)	F1 score (%)	Training time (s)
LR	74.32 $\pm$ 2.15	40.25 $\pm$ 3.26	69.87 $\pm$ 2.84	51.36 $\pm$ 2.58	10.24 $\pm$ 1.36
SVM	75.68 $\pm$ 1.98	41.58 $\pm$ 2.97	70.32 $\pm$ 2.65	52.64 $\pm$ 2.34	18.56 $\pm$ 2.17
PSCN	78.65 $\pm$ 1.87	44.83 $\pm$ 2.95	68.54 $\pm$ 3.12	54.17 $\pm$ 2.36	48.73 $\pm$ 3.58
GCN	79.83 $\pm$ 1.64	45.36 $\pm$ 2.78	71.29 $\pm$ 2.67	55.42 $\pm$ 2.14	65.38 $\pm$ 4.29
GAT	83.57 $\pm$ 1.32	48.62 $\pm$ 2.54	76.38 $\pm$ 2.43	59.75 $\pm$ 1.98	89.62 $\pm$ 5.13
GraphSAGE	81.25 $\pm$ 1.46	46.73 $\pm$ 2.68	73.15 $\pm$ 2.54	57.28 $\pm$ 2.05	96.35 $\pm$ 5.87
GCN+GAT	85.69 $\pm$ 1.18	50.36 $\pm$ 2.37	78.45 $\pm$ 2.26	61.89 $\pm$ 1.82	128.46 $\pm$ 6.34

5.3. Real-world dataset experimental results

Figure 5 shows a comparison of the performance of various models on the Real-Collab dataset, which consists of real-world cross-departmental collaboration data. On this real-world dataset, the GCN+GAT hybrid model continues to demonstrate the best performance: The AUC reached 84.72%, representing an improvement of 9.04% over LR, 7.79% over SVM, 4.29% over PSCN, 3.47% over the standalone GCN, 2.36% over the standalone GAT, and 2.85% over GraphSAGE; The F1 score reached 61.95%, an improvement of 2.71% over the standalone GAT, validating the applicability of the hybrid model in real-world scenarios.

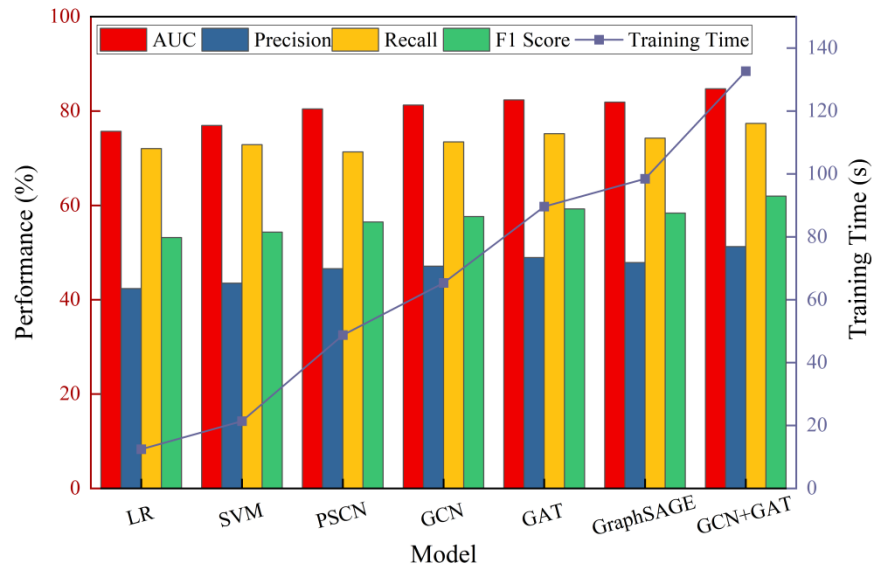


Figure 5. Performance Comparison Results Across Models.

Figure 6 compares the simulated dataset with the real-world dataset. The model in this study shows a decrease in AUC value on the real dataset from 85.7% to 84.7%, an increase in precision from 50.4% to 51.3%, a decrease in recall from 78.5% to 77.4%, and a rise in F1 value from 61.9% to 62%. These results demonstrate the precise prediction capability of the GCN+GAT model, which can be applied to predict

and analyze leadership propagation in various cross-departmental collaboration scenarios in real-world settings.

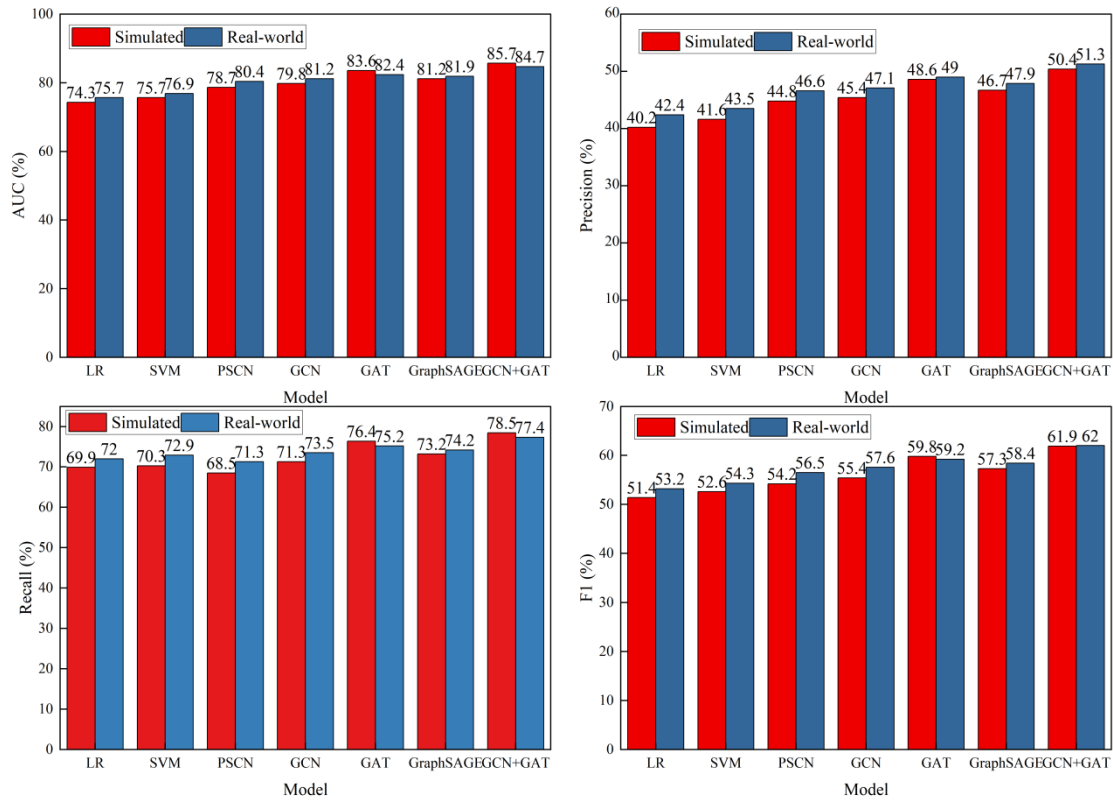


Figure 6. Comparison Between Simulated Dataset and Real-World Dataset.

5.4. Impact of different leadership dimensions on propagation effects

To analyze the impact of each dimension in the leadership model on node influence propagation effectiveness, this study conducts evaluation and training through formulas (15)–(19) mentioned above. **Table 6** shows the influence of different leadership dimensions on model performance. **Table 6** presents the impact of different leadership dimensions on model performance. Removing any leadership dimension causes model performance degradation, proving the integrity and necessity of the model. Value-leading power exerts the most significant effect on leadership influence propagation, with AUC value declining 5.47% upon removal, indicating that value-leading power serves as the core of digital and intelligent leadership and can effectively cross-departmental collaboration consensus, acting as the key driving force of influence propagation. Digital and intelligent strategic insight and cross-team goal consensus power rank second in impact, with performance decline magnitudes of 4.15% and 3.38% respectively, reflecting the importance of strategic consensus and goal alignment in cross-departmental collaboration. Digital and intelligent foundation construction power shows relatively smaller impact, with a performance decline magnitude of 1.40%, and its effect primarily manifests indirectly through supporting the of other leadership dimensions.

Table 6. Impact of Different Leadership Dimensions on Model Performance.

Removed leadership dimension	AUC (%)	Precision (%)	Recall (%)	F1 score (%)	Performance decline magnitude (AUC)
None (Complete Features)	84.72	51.28	77.36	61.95	-
Value-Leading Power	79.25	47.63	72.18	57.32	5.47%
Digital and Intelligent Strategic Insight	80.58	48.36	73.42	58.45	4.15%
Cross-Team Goal Consensus Power	81.36	49.12	74.25	59.28	3.38%
Agile Value Delivery Power	82.14	49.75	75.13	60.12	2.69%
Digital and Intelligent Resilience Evolution Power	82.87	50.23	75.89	60.76	2.07%
Digital and Intelligent Foundation Construction Power	83.54	50.76	76.58	61.34	1.40%

5.5. Parameter sensitivity analysis

Set the return probability α range from 10% to 90% with a step size of 10%. **Figure 7** shows the impact of return probability on model performance. Prediction performance shows a trend of initial increase followed by slight decline. The model achieves optimal performance when return probability reaches 80%, indicating that appropriately narrowing the egocentric network sampling range can better focus on core collaborative relationships and effectively capture hidden propagation patterns of leadership influence in cross-departmental collaboration. Excessively narrowing the sampling range beyond 80% leads to information loss and consequently reduces prediction accuracy for influence propagation.

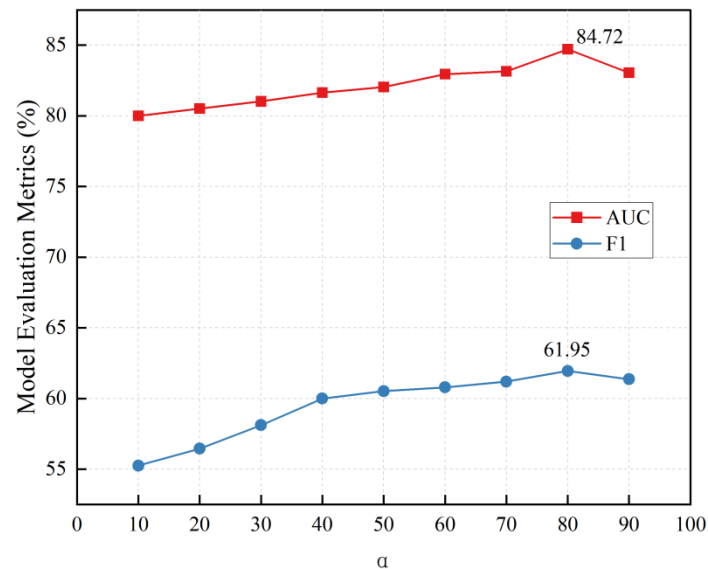
**Figure 7.** Impact of Return Probability on Model Performance.

Figure 8 shows the impact of sampling scale on model performance. As sampling scale expands, prediction performance generally shows an upward trend, but an inflection point appears when the sample size reaches 70. This occurs because increasing sampled nodes can acquire more subgraph information, yet when sampling nodes become excessive, the algorithm has to incorporate nodes farther from the center user. These nodes struggle to provide valuable structural information and user features

for the center node, and may instead become noise in the network, interfering with the model's recognition of leadership influence propagation patterns and thereby affecting final performance.

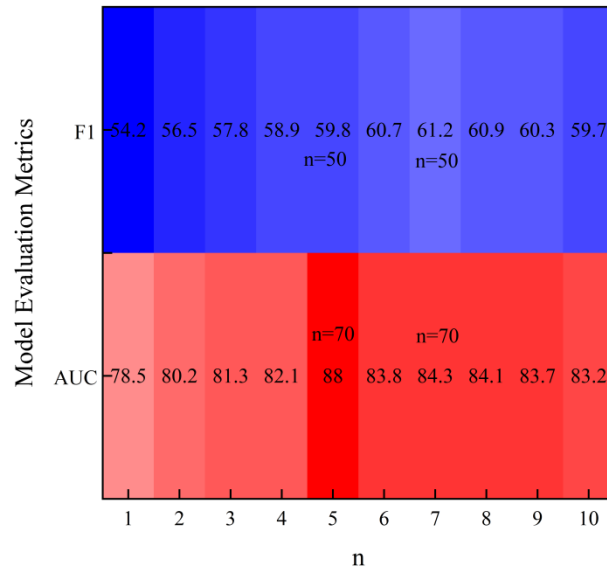


Figure 8. Impact of Sampling Scale on Model Performance.

Figure 9 shows the impact of attention head count on model performance. The GAT model learning effect first increases and then stabilizes as the number of attention heads grows. At $K = 8$, the learning effect reaches its optimum with AUC at 84.72% and F1 at 61.95%, indicating the best performance at this point. When K exceeds 8, the model learning effect does not improve significantly, yet training time increases substantially. The results demonstrate that moderately increasing attention head count enhances the model's feature representation capability, but excessive attention heads raise model complexity and increase overfitting risk, which hinders stable capture of key propagation patterns.

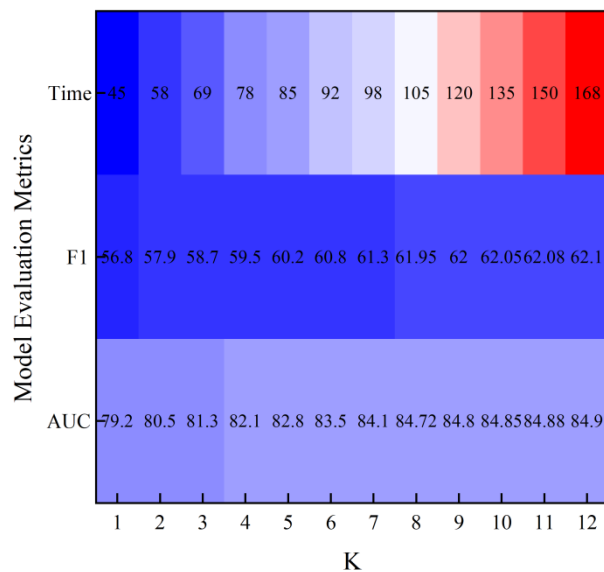


Figure 9. Impact of Attention Head Count on Model Performance.

6. Conclusion

This study systematically models leadership influence propagation in cross departmental collaboration using Graph Neural Networks. Traditional methods struggle to capture the non Euclidean structural characteristics of cross departmental collaboration networks and fail to effectively characterize the dynamic propagation paths of leadership influence. To address these limitations, we propose two modeling approaches, namely Graph Convolutional Networks and Graph Attention Networks. We further develop a GCN plus GAT fusion model to enhance the representation and prediction of leadership influence. Experimental results demonstrate that our proposed GCN plus GAT fusion model significantly outperforms multiple baseline methods on real world enterprise datasets, achieving an AUC of 84.72 percent, a precision of 51.28 percent, and a recall of 77.36 percent. Compared with logistic regression, support vector machine, graph structured CNN, single GCN, single GAT, and GraphSAGE, our model achieves consistent improvements in AUC and F1 scores. These results validate the effectiveness and superiority of graph convolution and graph attention mechanisms for modeling leadership influence propagation in cross departmental collaboration. This study provides a new technical pathway for leadership analysis in organizational behavior research. It also establishes a methodological foundation for enhancing cross departmental collaboration effectiveness and organizational resilience in digital environments, offering broad application prospects.

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