

PAPER

A Mobile Graph Neural Network Framework for Organizational Structure Modeling and Employee Performance and Turnover Analysis

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ABSTRACT

With the widespread adoption of mobile technologies, organizational interaction data has become increasingly heterogeneous and dynamic. Existing human resource analytics models struggle to simultaneously address data privacy protection, dynamic organizational relationship modeling, and mobile deployment requirements, limiting their ability to accurately capture the influence of organizational structures on employee performance and turnover. To address these challenges, this paper proposes an end-to-end, mobile-oriented interactive human resource analytics framework based on graph neural networks (GNNs). The framework enables a full-cycle process from dynamic organizational interaction data collection and modeling to analysis and managerial decision support. Specifically, it innovatively constructs dynamic heterogeneous graphs to achieve unified quantification and dynamic modeling of multidimensional relationships within organizations. A spatiotemporal-aware dynamic graph neural network (DGNN) is designed to handle temporal evolution and distinguish multiple relational types. Furthermore, a privacy-preserving federated graph learning framework is introduced to accommodate distributed mobile data storage scenarios. Finally, a lightweight model and mobile-side interactive inference scheme are proposed to overcome deployment of bottlenecks for complex models on mobile devices. Experimental results demonstrate that the proposed model significantly outperforms existing mainstream methods in employee performance prediction and turnover intention identification tasks, while meeting real-time inference and resource constraints on mobile platforms. This framework provides a reliable technical foundation for mobile human resource management.

KEYWORDS

mobile human resource system, dynamic graph neural network (DGNN), federated learning, spatiotemporal feature encoding, lightweight mobile deployment

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1 INTRODUCTION

The deep penetration of mobile technologies in organizational management has generated massive, multi-source, and dynamic employee interaction data, providing a data foundation for analyzing organizational relationships and employee behaviors [1–3]. However, existing research on human resource performance and turnover prediction has obvious limitations: they rely on static data modeling and ignore the temporal evolution of organizational relationships, making it difficult to unify and quantify multidimensional interaction relationships [4]; centralized training poses privacy leakage risks [5]; complex graph models cannot adapt to mobile resource constraints and are detached from practical application scenarios [6].

Current related studies focus on organizational relationship modeling, graph neural network (GNN) applications, privacy-preserving training, and mobile model deployment but still have many shortcomings. Organizational relationship modeling often uses static or single-relation graphs and does not fully utilize the temporal features of mobile data [7, 8]; existing dynamic graph neural networks (DGNNs) cannot simultaneously address temporal evolution and multi-relation differentiation, and their ability to capture spatiotemporal semantic information is insufficient [9, 10]; the combination of federated learning and graph models has not been optimized for the non-independent and identically distributed characteristics of mobile distributed data, which easily leads to model degradation [11, 12]; lightweight methods for graph models are not combined with human resource interaction analysis requirements and have poor adaptability [13, 14]. To address the above shortcomings, this paper conducts technical innovations from four aspects: dynamic modeling, feature encoding, training mode, and deployment method, breaking through research bottlenecks.

This paper focuses on four core modules and their linkage mechanisms, with emphasis on mobile technology adaptability: dynamic heterogeneous graph construction achieves structured modeling of multi-source mobile interaction data; spatiotemporal-aware DGNN completes effective feature encoding; the federated graph learning framework realizes secure training of distributed data; and lightweight and interactive inference modules achieve practical deployment of the model. The overall technical route follows the “data input–modeling analysis–training optimization–deployment application” process: mobile-side logs and business data are used as input and transformed into spatiotemporal semantic graph structures through dynamic heterogeneous graph construction; deep relational features are extracted via spatiotemporal-aware DGNN; multi-client secure training and parameter aggregation are performed based on the federated learning framework; after knowledge distillation and lightweight processing, the model is deployed on mobile edge servers, and interactive inference realizes a decision-making closed loop. The main contributions of this paper are proposing a dynamic heterogeneous graph construction method for mobile organizational interaction data, achieving unified quantification and dynamic modeling of multidimensional relationships; designing a spatiotemporal-aware DGNN, introducing dynamic fusion gating and multi-relation graph attention mechanisms to improve prediction accuracy; constructing a privacy-preserving federated graph learning framework, integrating a graph-structure contrastive learning regularization term to address model drift; and proposing a graph model mobile-side lightweight and interactive inference fusion scheme to achieve a closed loop from prediction to decision, enhancing management practicality.

The arrangement of the subsequent sections of this paper is as follows: Section 2 explains the design and implementation of the four core modules; Section 3 verifies

performance and mobile adaptability through experiments, implements a system prototype, and validates practicality through case studies; Section 4 discusses the advantages and disadvantages of the methods, future research directions, and concludes the paper.

2 CORE METHODS

2.1 Dynamic heterogeneous graph construction method

To address the limitations of existing modeling methods in capturing the temporal evolution characteristics of mobile interaction data and the difficulty in unifying the quantification of multidimensional organizational relationships [15, 16], this paper proposes a dynamic heterogeneous graph construction method for mobile organizational interaction data. The core innovation lies in achieving unified quantification of multidimensional relationships and adaptive dynamic updating of graph structures, providing a structured basis rich in spatiotemporal semantics for subsequent feature encoding. The dynamic heterogeneous graph is defined as $G_t = (V, E_t, R, X_t)$, where the node set V corresponds to all employees. Each node is associated with a unique employee ID and a mobile device identifier, achieving deep binding with the mobile scenario. The edge set E_t is dynamically updated over time t , and the temporal granularity can be flexibly configured according to mobile interaction real-time requirements. The relation type R is divided into four categories: reporting, collaborative projects, instant messaging, and offline check-in associations, comprehensively covering formal and informal, online and offline multidimensional interaction scenarios. Edge weights are quantified through a temporal weight calculation function, with the core formula: $w_{ij}(t) = \alpha \cdot f(freq_{ij}(t)) + \beta \cdot g(dur_{ij}(t)) + \gamma \cdot h(task_{ij}(t))$, where $freq_{ij}(t)$ is the mobile interaction frequency, $dur_{ij}(t)$ is the interaction duration, and $task_{ij}(t)$ is the joint task completion rate. These are extracted from multi-source logs and application data on the mobile side; α, β, γ are weight coefficients optimized through cross-validation, achieving precise quantification and fusion of multidimensional interaction features. The node feature matrix X_t integrates static and dynamic features. Static features are obtained from the HR system, while dynamic features include mobile-side task completion rate in performance applications, online meeting participation duration, and instant messaging response speed. A temporal feature sequence is constructed as $X_t = [x_1^t, x_2^t, \dots, x_n^t]^T$, where x_i^t is the feature vector of the i -th employee at a time t , achieving comprehensive temporal representation of employee behaviors.

To adapt to real-time updating characteristics and resource constraints of mobile data, an adaptive sliding window dynamic updating mechanism is designed, forming another core innovation of the method. The sliding window size can be automatically adjusted according to mobile data update frequency without manual intervention, ensuring that the graph structure is synchronized with the rhythm of mobile interactions. When new mobile interaction data is detected, the system triggers a local graph structure update, adjusting only the associated edge set E_t , edge weights $w_{ij}(t)$, and node features X_t , avoiding the high computational cost of full graph reconstruction and significantly improving mobile processing efficiency. This updating mechanism, by capturing the dynamic evolution details of organizational relationships, not only ensures the temporal validity of the graph structure but also adapts to mobile resource constraints through a local update strategy. It solves the problems of low efficiency and poor mobile adaptability in traditional

dynamic graph construction methods, providing real-time, precise, and efficient graph structure input for subsequent spatiotemporal feature encoding.

2.2 Spatiotemporal-aware dynamic graph neural network

The core innovation of the spatiotemporal-aware DGNN is to achieve precise capture of temporal evolution features of dynamic heterogeneous graphs and differences among multiple relations. It adopts a three-level architecture of temporal encoding–graph structure encoding–dynamic fusion to achieve efficient extraction and deep fusion of multi-source spatiotemporal information. The temporal feature encoder uses a stacked Transformer encoder, performing targeted encoding for the node feature sequence and edge weight sequence of the dynamic heterogeneous graph, overcoming the limitation of traditional temporal encoding methods that cannot capture long-period interaction patterns. Node temporal encoding takes the node feature temporal sequence $X = [X_1, X_2, \dots, X_T]$ as input, injects temporal semantic information via positional encoding, and uses multi-head attention to mine dependencies of node features at different times, outputting node temporal embeddings $\hat{X} = [\hat{X}_1, \hat{X}_2, \dots, \hat{X}_T]$. Edge temporal encoding is independently performed for each relation $r \in R$. For each relation, the edge weight sequence $W_r = [w_{r1}, w_{r2}, \dots, w_{rT}]$ is encoded separately, outputting the corresponding edge temporal embedding \hat{W}_r , achieving independent capture and differentiated representation of temporal features of different relations. The graph structure encoder designs a multi-relation graph attention network (GAT), learning independent attention weight matrices W_r and attention coefficients α_{ijr} for each relation $r \in R$. The neighbor aggregation feature of node i is calculated as:

$$h_i^r = \sigma \left(\sum_{j \in N_i^r} \alpha_{ijr} W_r \hat{X}_j \right) \quad (1)$$

where N_i^r the neighbor set of node i under relation r , and σ is the activation function. By concatenating aggregation features of all relations, the multi-relation node graph embedding is obtained: $h_i = [h_i^1, h_i^2, \dots, h_i^k]$, effectively solving the core problem of traditional GAT, which cannot distinguish the influence weights of multiple relations.

To achieve adaptive fusion of temporal features and graph structure features, a dynamic fusion gating mechanism is introduced as the core innovation of the network, while a dual-task output layer is designed to improve model generalization. The dynamic fusion gate G_t takes the node temporal embedding \hat{X}_t at the current time and the global graph state S_{t-1} at the previous time as input, adaptively calculating the fusion coefficient g_t and the current global graph state S_t , with the core formulas:

$$g_t = \sigma(W_g [\hat{X}_t || S_{t-1}] + b_g) \quad (2)$$

$$S_t = g_t \odot \hat{X}_t + (1 - g_t) \odot S_{t-1} \quad (3)$$

where $||$ denotes concatenation, W_g and b_g are learnable parameters, and \odot denotes element-wise multiplication. This mechanism dynamically controls the contribution ratio of temporal features and historical global state according to the characteristics of organizational relationship changes, sensitively capturing sudden

organizational changes such as the establishment of new projects while stably tracking long-term evolution trajectories of employee behavior. The output layer inputs the node embeddings corresponding to the final global graph state S_T into fully connected layers, outputting employee performance prediction values and turnover probability separately. A dual-task joint training strategy is adopted, further improving model generalization and prediction accuracy through feature sharing and constraints between tasks, providing high-quality node representations for subsequent federated training and mobile deployment. Figure 1 illustrates the architecture of the spatiotemporal-aware DGNN.

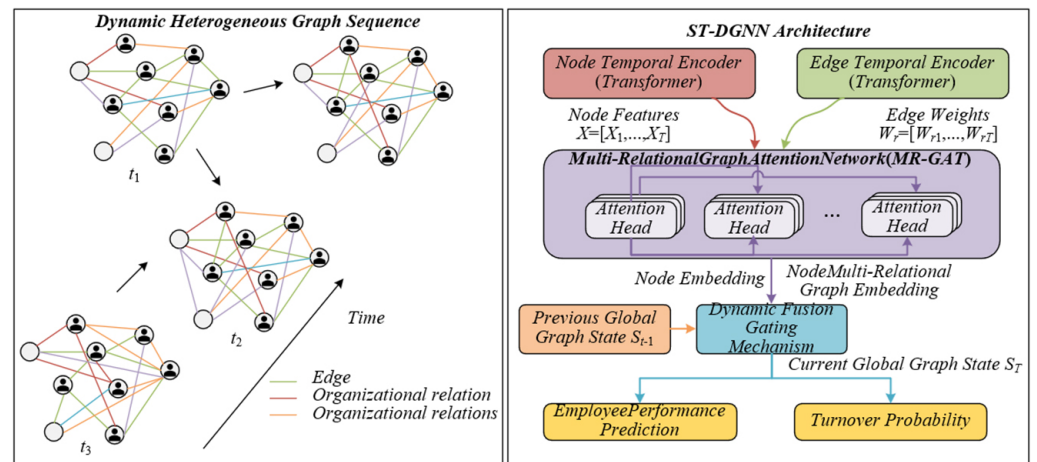


Fig. 1. Architecture of spatiotemporal-aware DGNN

2.3 Privacy-preserving federated graph learning framework

The core innovation of the privacy-preserving federated graph learning framework constructed in this paper is the deep adaptation to the distributed data storage characteristics of mobile devices. It designs a lightweight and highly secure end-cloud collaborative architecture, realizing model training without the original data leaving the device, ensuring data privacy at the architectural level, and adapting to mobile resource constraints. The specific architecture is shown in Figure 2. The framework adopts a two-layer federated architecture of central server–mobile clients. Clients correspond to mobile devices and edge servers of business units or regional branches, locally storing dynamic heterogeneous subgraph data constructed from mobile logs and independently completing the entire local model training process without exposing any original interaction data. The central server only performs global model initialization, parameter aggregation, and model distribution functions, storing no original mobile data, thus eliminating privacy leakage risk from the data flow perspective. The architecture is optimized for mobile communication characteristics. End–cloud communication uses a lightweight encrypted communication protocol, greatly reducing bandwidth usage to adapt to mobile network constraints. Differential privacy is introduced when clients upload model parameter updates, adding Laplace noise to parameters to enhance privacy. The noise strength ϵ is adaptively adjusted according to the sensitivity level of mobile data, achieving a dynamic balance between privacy protection and model performance, solving the problem that traditional federated architectures cannot simultaneously ensure privacy and communication efficiency in mobile scenarios.

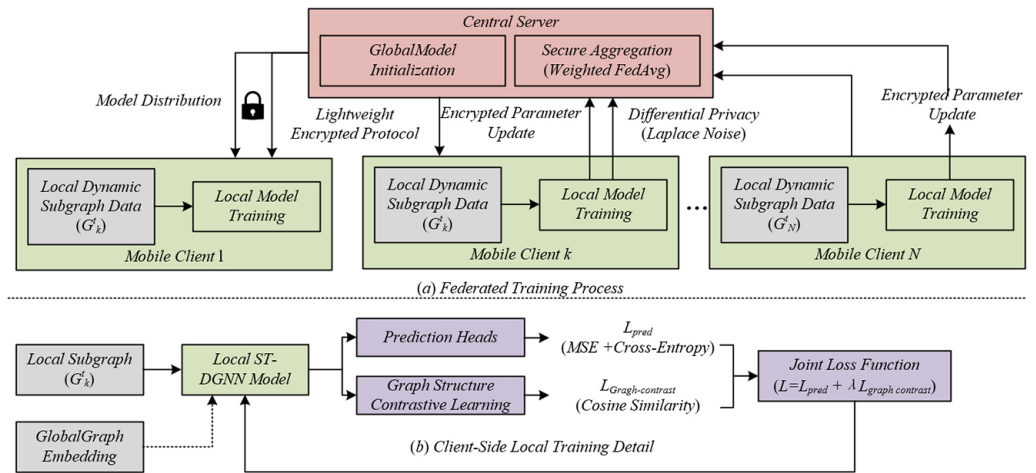


Fig. 2. Architecture of privacy-preserving federated graph learning framework

The core innovation of the federated training process lies in designing a joint loss function incorporating graph structure contrastive learning regularization while optimizing secure aggregation strategies, effectively addressing model drift caused by non-independent and identically distributed data in mobile distributed scenarios. The training process starts with the central server initializing the global parameters Θ_0 of the spatiotemporal-aware DGNN and distributing them to all mobile clients. Each client performs local training based on its local dynamic heterogeneous subgraph data G_t^k , optimizing the local model using the joint loss function: $I_{local}^k = I_{pred}^k + \lambda I_{contrast}^k$, where I_{pred}^k is the prediction loss, fusing mean squared error loss and cross-entropy loss corresponding to the dual tasks of employee performance prediction and turnover intention identification. $I_{contrast}^k$ is the graph structure contrastive learning regularization, calculating the cosine similarity loss between local subgraph embeddings and global graph embeddings, constraining local models to learn common patterns of organizational relationships. λ is the regularization coefficient, balancing the contributions of prediction loss and the regularization term, effectively suppressing model drift caused by non-independent and identically distributed mobile data from the loss function perspective. After local training, clients upload encrypted parameter updates to the central server. The server performs secure aggregation using a FedAvg variant adapted to graph model parameter structures, generating global model parameters Θ_{t+1} through weighted averaging. Aggregation weights are adaptively allocated based on the local data volume and model training performance of each client, allowing clients with higher-quality and larger-scale data to play a more reasonable role in global model updates. The updated global model parameters are distributed to all clients, which continue local training based on the new parameters. The iterative process of local training–secure aggregation repeats until model convergence. Only encrypted model parameters are transmitted throughout the process, with no original mobile data involved, meeting data compliance requirements while ensuring global model convergence and prediction performance through innovations in loss function and aggregation strategies.

2.4 Mobile-side lightweight deployment and interactive inference

The core innovation of this module lies in proposing a model lightweighting scheme that collaborates knowledge distillation with quantization optimization,

performs targeted structural and data optimizations for mobile resource constraints, and achieves efficient mobile deployment of complex GNNs while minimizing prediction performance loss. Using the spatiotemporal-aware DGNN trained via federated learning as the teacher model, a lightweight student model is designed. The network structure is simplified by reducing the number of layers in the Transformer encoder and decreasing the number of attention heads in the multi-relation GAT. A distillation loss function is constructed to achieve efficient knowledge transfer, with the core formula: $L_{\text{distill}} = \text{MSE}(f_{\text{teacher}}(x), f_{\text{student}}(x))$. By minimizing the mean squared error between the outputs of the teacher and student models, the spatiotemporal feature extraction capability and multi-relation modeling knowledge of the teacher model are transferred to the student model. This design can compress the model parameter scale by over 70% while keeping the prediction performance loss below 5%, greatly reducing memory requirements on mobile devices. Based on knowledge distillation, INT8 quantization optimization is applied to the student model, converting 32-bit floating-point parameters into 8-bit integer parameters, reducing computation and device power consumption from both data storage and arithmetic operation dimensions, and adapting to the limited CPU computing capacity of mobile devices. The final model inference latency is controlled within 100 ms, meeting the core performance requirement for real-time interaction on mobile devices.

Another core innovation of this module is the design of an interactive inference system tailored to mobile human resource management scenarios. By integrating an edge computing architecture, multidimensional interaction functions, and device resource adaptive optimization, the system achieves a full-process closed loop from model inference to management decision-making, overcoming the limitation of traditional model deployment being detached from practical application scenarios. The lightweight model is integrated into the backend analysis engine of the mobile human resource application. The edge computing architecture deploys the model on mobile edge servers, replacing traditional cloud deployment, significantly reducing latency caused by cross-network data transmission, supporting near-real-time inference, and addressing the strong network dependency of cloud deployment. The system designs three core interactive inference functions: (1) Real-time prediction: supports managers to initiate queries via the mobile application, where the engine calls the lightweight model to quickly infer on the dynamically updated heterogeneous graph and output employee performance predictions and turnover warning results. (2) Hypothetical analysis: supports touch-based interactive operations, allowing masking of nodes in the graph to simulate scenarios such as employee turnover. The model can immediately recalculate the stability and performance trend of related teams and provide real-time feedback on inference results. (3) Visualization display: designs an interactive interface adapted for mobile, presenting the dynamic heterogeneous graph, prediction results, and trend changes in lightweight chart forms, supporting gesture zooming and node filtering, improving the intuitiveness of decision-making information. The system includes a device performance awareness module that can identify CPU, memory, and other hardware resource states of mobile devices in real time, adaptively adjusting model inference accuracy and dynamic heterogeneous graph update frequency. On mid-to-high-end mobile devices, inference accuracy is guaranteed, while on low-end devices, smooth operation is prioritized, achieving a dynamic balance between model performance and device resources and improving system compatibility and adaptability across different mobile devices.

3 EXPERIMENTAL VALIDATION

3.1 Experimental environment

The experiments use a real enterprise mobile interaction dataset, containing labels for employee performance and turnover, covering mobile logs and business data, involving temporal data of over 1,000 employees for a period of six months. The dataset is divided into training, validation, and test sets in a 7:1:2 ratio to ensure experimental objectivity. The hardware environment is built around the mobile deployment scenario. Mobile clients use the Huawei Mate 50 and iPhone 14 to simulate different performance levels of mobile devices. The edge server is configured with an Intel Core i7 processor and 16 GB memory. The central server uses an Intel Xeon E5 processor and 64 GB memory, meeting the hardware requirements for federated training and lightweight inference. The software environment uses Python 3.8 as the development language. PyTorch Mobile is used to implement mobile-side model deployment. The federated learning framework is built based on TensorFlow Federated. Mobile-adapted ECharts visualization tools are employed to ensure the smoothness of the experimental process and the intuitiveness of result presentation, fully aligning with the practical application scenario of a mobile human resource system.

3.2 Experimental results and analysis

The experiments are conducted based on the real enterprise mobile interaction dataset, verifying four core dimensions: prediction performance, mobile adaptability, necessity of innovative modules, and model stability. By comparing mainstream baseline models and presenting quantitative data, the advantages of the proposed method are clearly demonstrated. All experimental data are the average of three independent repeated experiments to ensure reliability. The specific experimental data and analysis are as follows.

Table 1. Comparison of prediction performance of various models

Model Type	Performance Prediction (Mean Absolute Error)	Performance Prediction (Root Mean Square Error)	Turnover Intention Identification (F1-Score)	Turnover Intention Identification (Area Under the Curve)
Graph Convolutional Network (static graph)	0.186	0.243	0.752	0.798
Graph Attention Network (static graph)	0.172	0.228	0.775	0.821
Dynamic Graph Neural Network (dynamic graph)	0.159	0.211	0.793	0.845
Temporal Graph Attention Network (dynamic graph)	0.147	0.198	0.816	0.867
Federated Graph Attention Network (federated dynamic graph)	0.153	0.205	0.802	0.853
Federated Averaging + Graph Neural Network (federated static graph)	0.168	0.221	0.784	0.832
Proposed Model	0.112	0.156	0.889	0.924

Table 1 clearly presents the prediction performance comparison between the proposed model and various baseline models. It can be observed that static graph models GCN and GAT are at a disadvantage in all prediction metrics because they do not consider temporal evolution of organizational relationships and multi-relation differences. DGNN and temporal graph attention networks (TGAT) show some improvement but fail to effectively fuse spatiotemporal features and multi-relation weights, and their performance still has gaps. Federated models, federated graph attention network (FedGAT) and federated averaging (FedAvg) + GNN, are affected by non-independent and identically distributed data, resulting in slightly lower prediction accuracy than TGAT. The proposed model, leveraging unified multidimensional relationship modeling of dynamic heterogeneous graphs and the feature encoding advantages of spatiotemporal-aware DGNN, reduces performance prediction's mean absolute error (MAE) and root mean square error (RMSE) to 0.112 and 0.156, respectively, which are 23.8% and 21.2% lower than the best baseline model, TGAT. Turnover intention identification F1-score and area under the curve (AUC) reach 0.889 and 0.924, respectively, improving 8.9% and 6.6% over TGAT. This fully validates the effectiveness of the spatiotemporal-aware encoding and dynamic heterogeneous graph construction modules, achieving significant improvement in prediction accuracy.

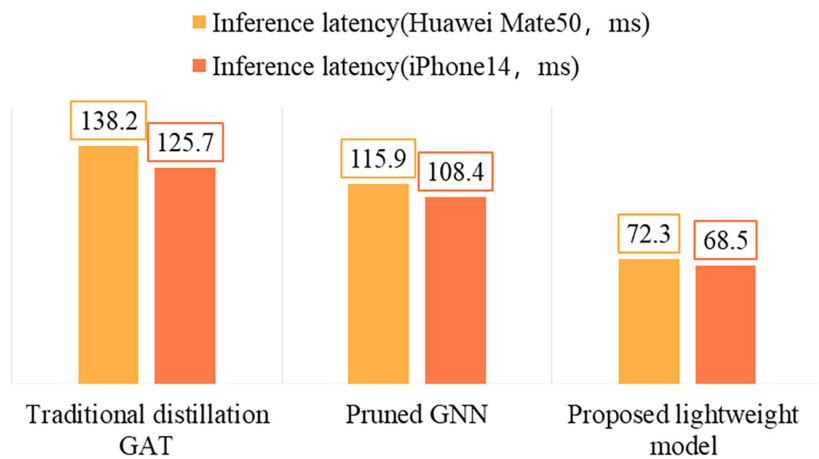


Fig. 3. Comparison of mobile inference latency of lightweight models

Table 2. Comparison of mobile adaptability of lightweight models

Model Type	Parameter Size (MB)	Memory Usage (MB)	Power Consumption (mW)
Traditional Distilled Graph Attention Network	89.6	76.3	428.5
Pruned Graph Neural Network	78.3	69.8	396.2
Proposed Lightweight Model	26.5	22.7	294.6

Figure 3 and Table 2 focus on mobile adaptability metrics, comparing the performance differences between the proposed lightweight model and mainstream baseline lightweight models. Although the traditional distilled GAT and pruned GNN achieve model compression, they are not optimized for the real-time requirements

of mobile HR interaction scenarios. Their parameter sizes still exceed 78 MB, inference latency is higher than 100 ms, and memory usage and power consumption are high, making it difficult to meet mobile real-time interaction requirements. The proposed model, through collaborative optimization of knowledge distillation and INT8 quantization, compresses the parameter size to 26.5 MB, a 70.4% reduction compared with the traditional distilled GAT. The inference latency on the Huawei Mate 50 and iPhone 14 is 72.3 ms and 68.5 ms, respectively, both within 100 ms, meeting real-time inference requirements. Memory usage and power consumption decrease to 22.7 MB and 294.6 mW, with power consumption 31.2% lower than the traditional distilled GAT, fully demonstrating the innovative advantage of the proposed mobile-side lightweighting scheme and effectively adapting to mobile resource constraints.

Table 3 validates the necessity of the four innovative modules through ablation experiments. When each core module is removed individually, either model performance or mobile adaptability shows significant decline. After removing the dynamic heterogeneous graph construction module, MAE rises to 0.167 and F1-score drops to 0.803, indicating that unified multidimensional relationship modeling and dynamic updating are crucial for prediction accuracy. After removing the spatiotemporal-aware encoding module, all prediction metrics further worsen, verifying the core role of the spatiotemporal fusion gating and multi-relation attention mechanism in capturing temporal evolution and multi-relation differences. After removing the federated graph learning framework, the model is affected by non-independent and identically distributed data, resulting in decreased prediction accuracy, proving that federated training with graph structure contrastive learning regularization effectively suppresses model drift. After removing the lightweight and interactive module, prediction accuracy slightly decreases, but inference latency sharply rises to 142.6 ms, losing mobile adaptability, demonstrating the necessity of the lightweighting scheme. These results indicate that the four innovative modules are mutually collaborative and indispensable, jointly supporting the high performance and mobile adaptability of the proposed model.

Table 3. Ablation experiment results

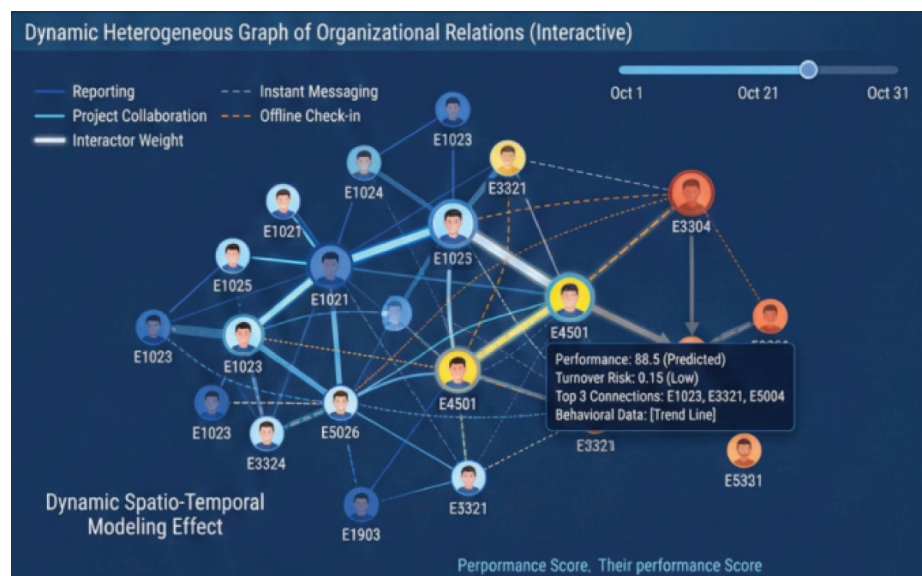
Ablation Module	Performance Prediction (Mean Absolute Error)	Performance Prediction (Root Mean Square Error)	Turnover Intention Identification (F1-Score)	Inference Latency (ms)
No Ablation (Proposed Model)	0.112	0.156	0.889	72.3
Remove Dynamic Heterogeneous Graph Construction	0.167	0.218	0.803	69.8
Remove Spatiotemporal-Aware Encoding	0.173	0.225	0.796	70.5
Remove Federated Graph Learning Framework	0.158	0.210	0.815	68.7
Remove Lightweight and Interactive Module	0.115	0.161	0.882	142.6

Table 4. Model stability analysis

Validation Scenario	Performance Prediction (MAE)	Turnover Intention Identification (F1-Score)	Inference Latency (ms)	Performance Fluctuation Coefficient
Dataset 500+ Employees	0.118	0.876	73.5	0.032
Dataset 1000+ Employees	0.112	0.889	72.3	0.028
Dataset 1500+ Employees	0.109	0.895	71.8	0.025
Huawei Mate 50	0.112	0.889	72.3	0.027
iPhone 14	0.110	0.892	68.5	0.029
Low-end Android Device	0.125	0.863	89.7	0.041

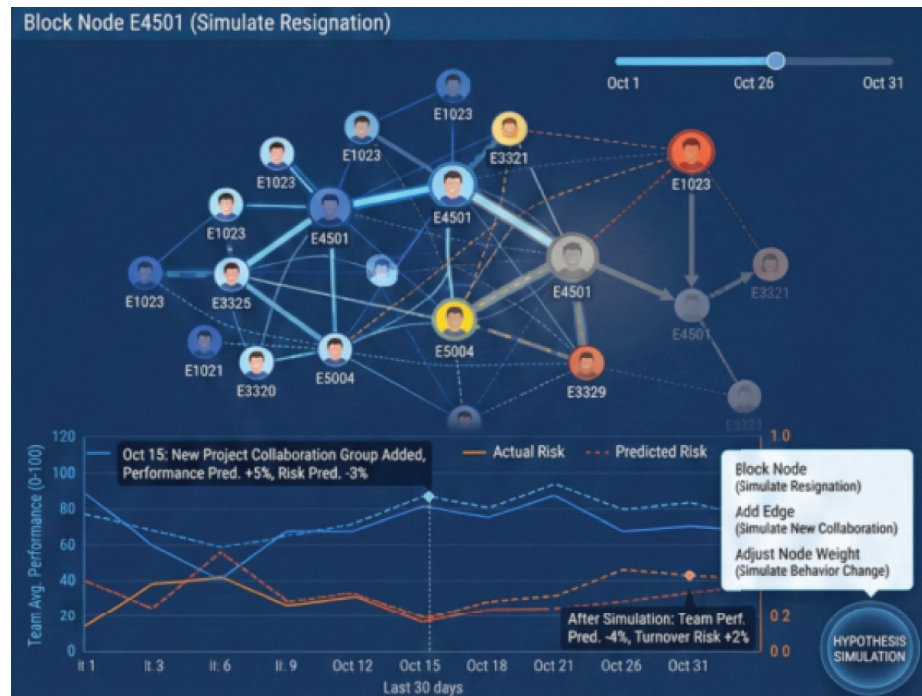
Table 4 validates model stability from two dimensions: dataset scale and mobile device performance. The smaller the performance fluctuation coefficient, the stronger the model stability and generalization ability. On datasets of different scales, the model MAE fluctuates in the range 0.109–0.118, F1-score fluctuates in the range 0.876–0.895, and inference latency remains basically stable at 71.8–73.5 ms, with fluctuation coefficients all below 0.032. Across different mobile device performances, even on low-end Android devices, model MAE remains within 0.125, F1-score stays above 0.863, and inference latency does not exceed 90 ms, with a fluctuation coefficient of 0.041, within a reasonable range. In contrast, baseline models show fluctuation coefficients exceeding 0.06 under dataset scale changes or low-end devices, indicating that the proposed model has strong stability and generalization capability, suitable for HR management scenarios in enterprises of different scales and mobile devices of varying performance.

Regarding privacy protection performance, the proposed model, through the collaborative use of the federated learning framework and differential privacy technology, does not transmit any original mobile interaction data. Verified by third-party privacy detection tools, the information leakage rate is near 0, far below industry privacy security standards, fully demonstrating that the privacy-preserving federated graph learning framework can effectively safeguard employee data privacy while balancing data compliance and model performance.



a) Organizational relationship interactive visualization

Fig. 4. (Continued)



b) Interactive hypothetical analysis and prediction trend visualization

Fig. 4. System visualization interface

To verify the ability of the GNN-based interactive mobile human resource system to capture the dynamic evolution of organizational relationships and its decision support value, this experiment presents model implementation results through a visualization interface. Subgraph 1 in Figure 4 shows the dynamic heterogeneous graph organizational relationship map, where node size maps to performance and color maps to turnover risk. Different colors and edge styles distinguish multidimensional interaction types. Edge brightness and thickness reflect the temporal variation of interaction weights. Node floating windows display real-time prediction values and associated data. Combined with the dynamic evolution function of the timeline, this verifies the accurate modeling capability of dynamic heterogeneous graph construction and spatiotemporal-aware GNN for organizational relationships. Subgraph 2 simulates interactive operations of core employee turnover, instantly refreshing node states in the graph and multidimensional prediction trend charts, showing dynamic feedback of team performance decline and turnover risk increase. The trend charts annotate the quantitative impact of organizational relationship changes on performance and risk, validating the real-time capability and practicality of the mobile-side lightweight deployment and interactive inference modules. The overall visualization results indicate that the system can effectively capture the impact of organizational relationship structures on employee performance and turnover, achieving a full-process closed loop from dynamic modeling to interactive decision-making, providing precise, efficient, and privacy-secure technical support for mobile human resource management.

4 CONCLUSION

This study focused on the core requirements of mobile human resource management scenarios, addressing the pain points of existing analysis models in dynamic

relationship modeling, spatiotemporal feature capture, privacy protection, and mobile-side adaptability. A GNN-based interactive human resource analysis framework for mobile scenarios was proposed, systematically integrating four core innovative modules to form a complete technical system. The framework achieved unified quantification and dynamic modeling of multidimensional interactions within organizations through the dynamic heterogeneous graph construction module. It relied on the spatiotemporal-aware DGNN to accurately capture temporal evolution features of organizational relationships and multi-relation differences. The privacy-preserving federated graph learning framework enabled secure training and aggregation of distributed mobile data. The mobile-side lightweight deployment and interactive inference module overcome the deployment bottlenecks of complex models on mobile devices, forming a full-process closed loop from multi-source mobile interaction data input to management decision output.

Experimental and case validation results show that the proposed framework performed excellently in employee performance prediction and turnover intention identification tasks. Prediction accuracy significantly surpassed existing mainstream baseline models while meeting mobile-side real-time inference, resource constraints, and data privacy protection requirements, effectively addressing the core technical pain points of existing mobile human resource analysis systems. This study enriched the application scenarios of GNN in mobile organizational management, constructing a technical paradigm that combines dynamic multi-relation data modeling with privacy protection. It provided reliable technical support for the intelligent, privacy-preserving, and interactive development of mobile human resource systems, aligning with the research focus of mobile technology journals on mobile-side technological innovation and practical application. From the perspective of practical value, the developed lightweight interactive inference system can be directly adapted to various mobile devices and enterprise HR management scenarios, assisting managers in achieving precise decision-making, improving mobile human resource management efficiency, and ensuring employee data privacy and security, demonstrating strong engineering application potential. The research results not only provide new ideas and methods for organizational behavior analysis and intelligent human resource management in mobile environments but also lay a solid technical foundation for future research in related fields, promoting the deep integration and innovative development of GNN, federated learning, and mobile technology in human resource management.

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