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PAPER

An Interactive Mobile Human Resource Management Platform Based on Affective Computing and Dynamic Causal Modeling

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ABSTRACT

Traditional human resource management approaches rely on low-frequency, questionnaire-based methods to capture employee emotional states, whereby elevated risks of privacy leakage are introduced and the relationships between emotion and performance are statistically modeled. Such limitations hinder adaptation to the evolving demands of mobile-enabled management environments. Leveraging the portability of mobile devices and the heterogeneity of embedded sensors, an interactive mobile human resource management platform based on affective computing was proposed. To address the requirements of mobile scenarios, an integrated technical framework combining edge–cloud collaboration and dynamic causal inference was constructed. Three critical challenges were addressed, including the lightweight deployment of affective computing models on edge devices, privacy-preserving mechanisms for sensitive data, and the dynamic modeling of causal relationships among employee emotional responses, work engagement, and performance outcomes. A robust technical paradigm is thus provided for the intelligent upgrading of mobile human resource management systems, while new research directions are established for the interdisciplinary integration of affective computing and mobile office systems.

KEYWORDS

mobile human resource management platform, affective computing, edge-side lightweight models, federated learning, dynamic causal inference

1 INTRODUCTION

With the rapid advancement of mobile internet technologies [1, 2] and the widespread adoption of smartphones [3, 4], human resource management paradigms have been progressively shifted toward mobile environments [5]. Mobile human resource management platforms have thus been established as critical tools for improving organizational efficiency and enhancing employee experience [6].

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Existing mainstream mobile human resource platforms have primarily focused on fundamental functions such as process approval and data recording [7, 8]. However, the perceptual capabilities enabled by embedded mobile sensors have not been fully exploited. As a result, real-time acquisition and intelligent response to employee emotional states remain insufficiently supported, leading to a misalignment between human resource management practices and the core capabilities of mobile technologies. Consequently, the increasing demand for refined and human-centered management has not been adequately satisfied.

Despite growing research interest, several limitations remain evident, particularly in terms of adaptation to mobile scenarios. Traditional emotional data collection has largely relied on self-reported questionnaires [9], by which normal work routines are disrupted and data timeliness is compromised. Furthermore, the potential of mobile devices for unobtrusive data acquisition has not been effectively utilized. Affective computing models have predominantly been deployed on cloud infrastructures [10], whereby significant risks of privacy leakage associated with raw emotional and behavioral data have been introduced [11, 12], while compatibility with resource-constrained mobile environments—characterized by low power consumption and limited storage—has been inadequately addressed. In addition, the relationships among employee emotional responses, work engagement, and performance have typically been modeled using static analytical approaches [13, 14], whereby the dynamic and time-varying nature of employee states in mobile contexts has been overlooked. Consequently, causal relationships among these variables cannot be accurately captured. Moreover, a lack of closed-loop intervention mechanisms tailored to mobile environments has been identified. As a result, the integration of emotion perception, relational analysis, and proactive intervention into a unified management framework remains underdeveloped, thereby constraining the intelligent evolution of mobile human resource management platforms.

To address the aforementioned limitations, the objective is to develop an interactive mobile human resource management platform that is adapted to mobile environments while ensuring privacy preservation and intelligent responsiveness. The dynamic causal relationships among employee emotional responses, work engagement, and performance are to be systematically revealed, and a feasible solution for upgrading human resource management through mobile technologies is to be established. Technical support and theoretical insights are thereby provided for the interdisciplinary integration of affective computing and mobile human resource management.

The principal contributions are summarized below. First, an edge-side lightweight affective computing model based on knowledge distillation is designed, whereby the challenge of achieving high-accuracy emotion recognition under resource-constrained mobile conditions is effectively addressed, and efficient model execution on mobile devices is enabled. Second, a dynamic causal modeling approach integrating a time-varying structural equation model and transfer entropy is proposed, through which the limitations of traditional static correlation analysis are overcome, and the time-varying causal relationships among employee emotional responses, work engagement, and performance in mobile contexts are accurately captured. Third, a federated learning-driven edge–cloud collaborative model evolution architecture is constructed, by which both privacy preservation and personalized model adaptation are achieved. This architecture is further aligned with the multi-terminal and multi-scenario deployment requirements of mobile human resource management platforms, thereby significantly enhancing system practicality and scalability.

2 PLATFORM ARCHITECTURE AND CORE TECHNOLOGIES

2.1 Overall architecture design

An interactive mobile human resource management platform is constructed based on an edge–cloud collaborative hybrid architecture. Mobile terminals are utilized as the primary front-end carriers, through which multimodal data acquisition, on-device affective inference, and lightweight data preprocessing are performed. Through refined resource scheduling strategies, low-power operation and real-time emotional response are ensured. The cloud is designated as the global service node, where model aggregation and updating and global optimization are conducted. A secure collaborative mechanism is employed to enable iterative model parameter optimization, while raw data are retained locally on mobile devices throughout the entire process. In this manner, privacy preservation, efficient inference, and multi-terminal adaptability are jointly achieved at the architectural level, thereby providing a robust foundation for the deployment and stable operation of the platform's core technologies.

2.2 Edge-side lightweight affective computing model based on knowledge distillation

To resolve the fundamental trade-off between resource constraints on mobile devices and high-accuracy emotion recognition, a dual-stream lightweight neural network tailored to mobile scenarios is designed. The inherent limitation of conventional edge-side models, in which accuracy and computational efficiency are difficult to balance, is thereby overcome. Within the temporal branch, a hybrid architecture combining a one-dimensional convolutional neural network and a gated recurrent unit is adopted. The network depth is optimized to three convolutional layers and one gated recurrent unit layer, whereby redundant parameters are reduced and computational complexity is minimized. This branch is specifically designed for processing one-dimensional time-series signals, such as touch interaction patterns and accelerometer data, enabling the dynamic temporal characteristics of employee emotional responses to be effectively captured. Within the visual branch, a structured channel pruning strategy is applied to MobileNetV3, with a pruning ratio of 40%. Redundant channels are removed while the core feature extraction modules are preserved, thereby ensuring compatibility with low-resolution video frames acquired from front-facing mobile cameras. As a result, resource consumption during inference is significantly reduced. At the feature fusion layer, an attention mechanism is introduced to dynamically allocate weights between the temporal and visual features according to specific application contexts. In video conferencing scenarios, the contribution of visual features is enhanced, whereas in interaction scenarios involving only platform operations, the temporal feature contribution is increased. Through this strategy, emotion recognition accuracy is significantly improved across diverse mobile usage scenarios.

Knowledge distillation is further optimized for mobile deployment, whereby a balance between high recognition accuracy and model lightweighting is achieved. The teacher model is constructed based on a hybrid architecture integrating ResNet-50 and a Transformer and is trained on publicly available affective datasets, including AffectNet and FER-2013. Particular emphasis is placed on enhancing the recognition performance of emotional states commonly observed in mobile contexts, such as anxiety, concentration, fatigue, and pleasure, thereby providing a high-quality knowledge transfer foundation for the student model. During the distillation process, a dual-loss function combining soft labels and hard labels is adopted, which is formulated as:

$$L = \alpha L_{soft} + (1-\alpha)L_{hard} \tag{1}$$

where, $\alpha = 0.7$, L_{soft} denotes the cross-entropy loss between the outputs of the teacher model and the student model, and L_{hard} represents the cross-entropy loss between the student model predictions and the ground-truth labels. In addition, constraints on mobile inference efficiency are incorporated, whereby the student model size is compressed to within 5 MB, and the inference latency for a single prediction is controlled within 50 ms, thus satisfying real-time response requirements in mobile environments. To further enhance model robustness, Monte Carlo dropout is introduced to perform uncertainty estimation. A default confidence threshold of 0.7 is defined. When multimodal feature inconsistencies result in a recognition confidence below this threshold, the corresponding time step is labeled as an ambiguous emotional state. In this manner, erroneous triggering of subsequent intervention mechanisms is effectively avoided, thereby ensuring the reliability and stability of model outputs. The architecture of the proposed dual-stream edge-side lightweight affective computing model based on knowledge distillation is illustrated in Figure 1.

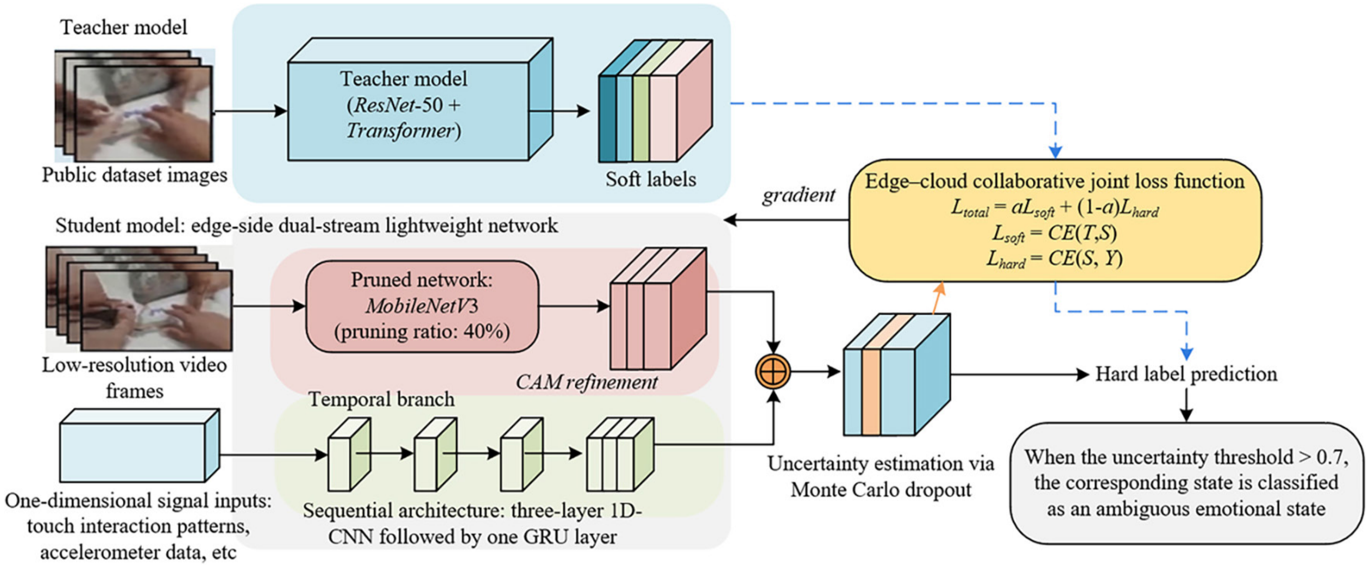

Fig. 1. Architecture of the edge-side dual-stream lightweight affective computing model based on knowledge distillation

2.3 Federated learning–driven privacy-preserving model evolution mechanism

To address the dual requirements of privacy preservation and efficient model collaboration in multi-terminal mobile human resource management scenarios, an edge–cloud collaborative federated learning architecture is designed.

The limitations of conventional federated learning approaches, including poor adaptability to mobile environments and low communication efficiency, are thereby mitigated. Each employee's mobile device is treated as an independent client, where the local model is fine-tuned using continuously collected affective and behavioral data. The fine-tuning strategy is optimized to accommodate mobile resource constraints and is triggered only when the device is idle, charging, and connected to WiFi, thereby avoiding interference with computational resources and battery consumption. On the cloud side, an optimized secure federated averaging algorithm is employed for model parameter aggregation. During aggregation, only model parameter gradients uploaded from individual clients are processed, while no raw data are accessed, thereby eliminating privacy leakage risks at the source. Gradient transmission is implemented using a homomorphic encryption scheme, with encryption and decryption latency controlled within 100 ms, ensuring both transmission security and real-time performance. The global model parameters are updated as follows:

$$w_{global} = \sum_{i=1}^{N} \frac{n_i}{N} w_i \tag{2}$$

where, w_{global} denotes the updated global model parameters, N represents the total number of clients participating in the aggregation, n_i denotes the sample size of the i-th client, and w_i represents the local model parameters of the i-th client. Furthermore, an incremental gradient transmission strategy is incorporated, whereby only the differential gradients between the local model and the global model are uploaded. As a result, mobile network bandwidth consumption is significantly reduced, enabling robust operation under unstable mobile network conditions.

To accommodate the heterogeneous requirements arising from multiple users [15] and diverse job roles [16] in mobile human resource management scenarios, a mechanism is developed to achieve a balance between personalized model adaptation and global model generalization. In this manner, both model applicability and generalization performance are enhanced. At the client level, each local model is fine-tuned on top of the global base model by incorporating individual-specific emotional expression patterns. Through this strategy, behavioral differences across employees in distinct job roles are effectively captured, enabling personalized model adaptation at scale. At the global level, a periodic update strategy is adopted, whereby gradient updates from all participating clients are aggregated on a weekly basis. The federated averaging algorithm is employed to integrate feature representations across clients, thereby ensuring that the global model retains generalizable affective characteristics applicable to employees across different roles and industries. As a result, the overall model generalization capability is significantly enhanced. To mitigate the risk of global model degradation caused by malicious clients uploading falsified gradients, a gradient clustering mechanism is introduced. Cosine similarity between client gradient vectors is computed to perform clustering analysis, through which anomalous gradient samples are identified and excluded from aggregation. In this way, the reliability and stability of global model updates are ensured, facilitating robust large-scale deployment in multi-user mobile human resource management environments and supporting long-term model evolution. The complete federated learning-driven edge-cloud collaborative model evolution and secure aggregation mechanism are illustrated in Figure 2.

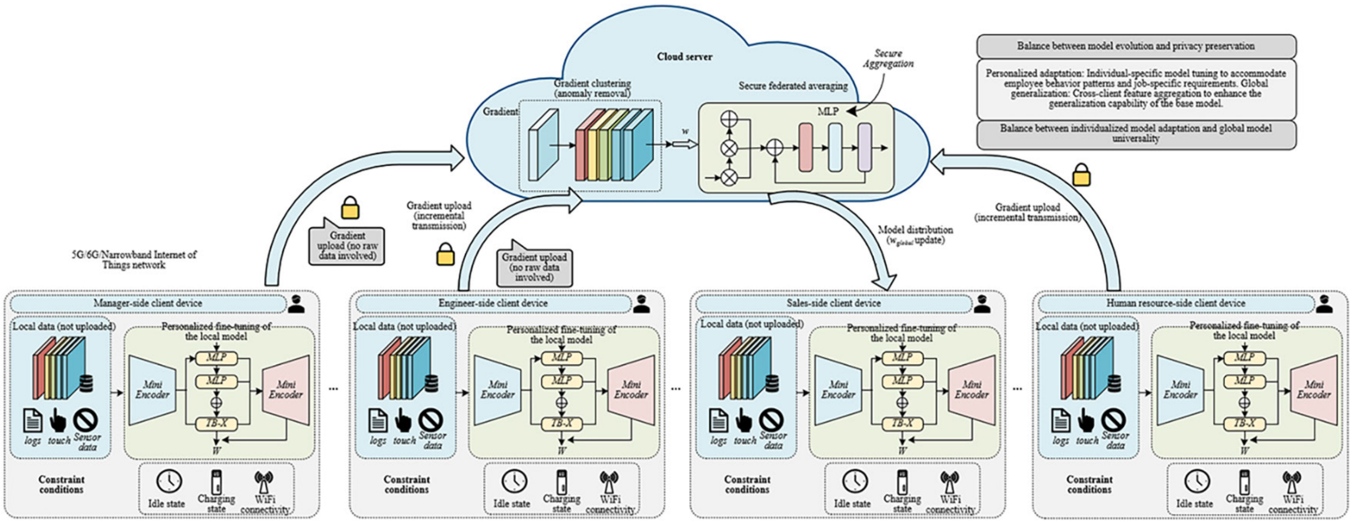

Fig. 2. Federated learning–driven edge–cloud collaborative model evolution and secure aggregation mechanism

2.4 Dynamic causal modeling of emotion–engagement–performance relationships

To accommodate the temporal characteristics and heterogeneity of mobile data, the time-varying structural equation model is specifically optimized, whereby the limitations of conventional static modeling in capturing dynamic relationships among employee emotional responses, work engagement, and performance are overcome. First, multi-granularity data collected from mobile devices are temporally aligned. Minute-level emotional data, hourly work engagement data, and daily performance data are calibrated onto a unified temporal scale. A sliding window with a duration of 1 hour is employed for smoothing, through which noise introduced by mobile sensors is effectively reduced while preserving the inherent temporal fluctuation characteristics of mobile data. For the estimation of time-varying path coefficients, a hybrid approach combining Kalman filtering and maximum likelihood estimation is adopted. The path coefficients corresponding to "emotion → engagement," "engagement → performance," and "prior performance → subsequent emotion" are defined as piecewise functions of time, enabling the construction of a time-varying structural equation model framework tailored to mobile scenarios. The core structural equation is formulated as:

$$\eta(t) = \Lambda(t)\eta(t) + B(t) + \xi(t) + \varepsilon(t) \tag{3}$$

where, $\eta(t)$ denotes the vector of time-varying endogenous variables, including emotional responses, work engagement, and performance indicators; $\Lambda(t)$ represents the matrix of time-varying path coefficients; $B(t)$ denotes the coefficient matrix of exogenous variables; $\xi(t)$ represents the vector of exogenous variables; and $\varepsilon(t)$ denotes the stochastic error term. To address the sparsity inherent in mobile data, the model structure is further simplified through the removal of redundant paths and irrelevant parameters, thereby reducing computational complexity. In this manner, efficient cloud-side execution is ensured while maintaining a high level of estimation accuracy.

To overcome the limitation that conventional correlation analysis cannot establish causal relationships, a causal validation framework integrating transfer entropy analysis and controlled variable experiments is introduced, thereby enhancing methodological rigor. Transfer entropy is employed to quantify the direction and magnitude of information flow from the emotional time series to the performance time series. It is defined as:

$$TE(X \rightarrow Y) = H(Y) - H(Y|X) \tag{4}$$

where, $H(Y)$ denotes the Shannon entropy of the performance time series Y, and $H(Y|X)$ represents the conditional entropy of Y given the emotional time series X. A larger TE value indicates a stronger causal influence of emotional responses on performance outcomes. On this basis, a controlled variable experimental design is implemented to further validate causal effects. By fixing the level of work engagement as an intermediate variable, differences in employee performance under varying emotional states are compared. Through this design, the direct causal impact of emotional responses on performance is isolated, and the confounding effect of work engagement is effectively controlled. This innovative approach enables a methodological transition from correlation-based analysis to causality-driven inference, allowing the dynamic causal relationships among employee emotional responses, work engagement, and performance to be accurately captured in mobile environments. A robust theoretical foundation is thereby provided for the design of adaptive intervention strategies within the mobile human resource management platform.

3 EXPERIMENTAL DESIGN AND RESULTS ANALYSIS

3.1 Experimental design

To evaluate the effectiveness of the proposed interactive mobile human resource management platform and its core innovations, an eight-week field experiment was conducted. A total of 100 employees from an Internet-based company were selected as participants. All participants were required to install a customized mobile human resource management application, which was developed to support both Android and iOS operating systems. The application package size was controlled within 20 MB to ensure smooth installation and efficient operation on mobile devices. A controlled experimental design was adopted, in which participants were randomly assigned to a control group and an experimental group, with 50 employees in each group. Key demographic and occupational variables, including age, job role, and years of work experience, were strictly controlled across the two groups to ensure the objectivity and scientific validity of the experiment. In the control group, only data collection functions were activated, while no intervention mechanisms or core innovative modules were enabled. In contrast, the experimental group was provided with the full functionality of the platform, including the edge-side lightweight affective computing model, the federated learning–driven model evolution mechanism, and the dynamic causal modeling module.

3.2 Experimental results and analysis

Upon completion of the experiment, the collected data were subjected to statistical analysis. The results were systematically organized across four evaluation dimensions, namely model performance, privacy preservation, relational modeling, and intervention effectiveness. The core findings under each dimension are presented below, all of which provide strong empirical evidence supporting the effectiveness of the proposed core technologies and their suitability for mobile deployment.

Model performance results and analysis. Model performance was evaluated in terms of recognition accuracy, computational efficiency, and adaptability to mobile environments for the edge-side lightweight affective computing model. The experimental results are summarized in Figure 3 and Table 1. A comparative analysis with conventional edge-side affective computing models was also conducted to highlight the advantages of the proposed design.

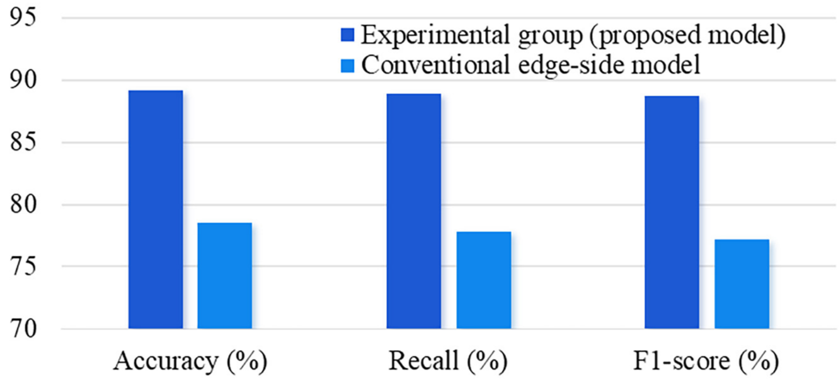

Fig. 3. Model performance experimental results

Table 1. Model performance results

Evaluation Metric	Experimental Group (Proposed Model)	Conventional Edge-Side Model	Improvement
Average inference latency (ms)	42	126	66.7%
Daily average power consumption (%)	4.3	11.8	63.6%
Model size (MB)	4.8	28.3	82.3%

As shown in Figure 3 and Table 1, superior performance is demonstrated by the proposed edge-side lightweight affective computing model. The accuracy, recall, and F1-score are all reported to exceed 88%, with improvements of more than 13% observed relative to conventional edge-side models, thereby ensuring high precision in emotion recognition. In terms of mobile adaptability, the average inference latency is reduced to 42 ms, satisfying real-time response requirements. The daily average power consumption is controlled at 4.3%, and the model size is compressed to 4.8 MB. Compared with conventional models, inference speed is improved by 66.7%, power consumption is reduced by 63.6%, and model size is reduced by 82.3%. These results provide strong empirical evidence that the integration of knowledge distillation and the dual-stream lightweight architecture is effective, enabling efficient deployment under resource-constrained mobile conditions while achieving a balance between high accuracy and low computational overhead.

Privacy preservation results and analysis. The privacy preservation dimension was evaluated with a focus on the security and mobile network adaptability of the federated learning–driven edge–cloud collaborative architecture. The experimental results are summarized in Figure 4, where comparisons are made with a conventional cloud-based centralized model to highlight differences in privacy protection performance.

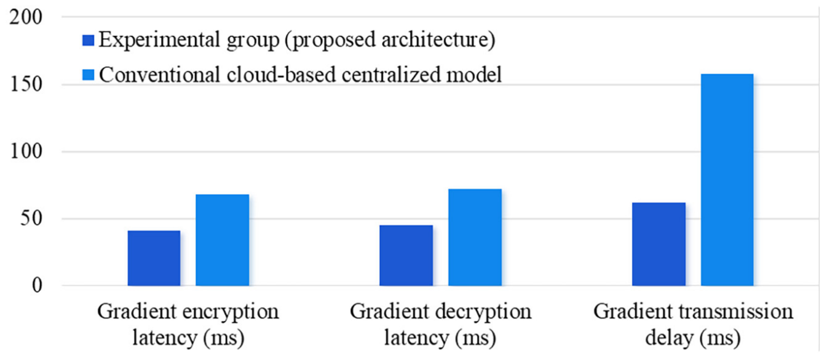

Fig. 4. Privacy preservation experimental results

As illustrated in Figure 4, the proposed federated learning architecture demonstrates superior performance in both privacy preservation and transmission efficiency. The latency for gradient encryption and decryption is measured at 41 ms and 45 ms, respectively, both of which are maintained within 50 ms. The gradient transmission delay is reduced to 62 ms. In comparison with the conventional cloud-based model, improvements exceeding 37% are achieved in both encryption and decryption efficiency, while transmission latency is reduced by 60.8%, indicating strong adaptability to mobile environments characterized by unstable network conditions and limited bandwidth. Throughout the experiment, no instances of raw data leakage are observed under the proposed architecture, whereas three data leakage incidents are recorded in the conventional cloud-based centralized model. These findings provide compelling evidence that the federated learning framework, through its design principle of retaining raw data on-device and transmitting only encrypted gradients, ensures robust privacy protection for employee data. Furthermore, the incorporation of optimization strategies, such as incremental gradient transmission, significantly enhances communication efficiency in mobile network environments.

Relational modeling results and analysis. The relational modeling dimension was evaluated to assess the effectiveness of the dynamic causal modeling approach, with particular emphasis placed on the goodness-of-fit of the time-varying structural equation model and the causal relationships between employee emotional responses and performance. The experimental results are summarized in Figure 5 and Table 2, and are compared with those obtained using a conventional static structural equation model.

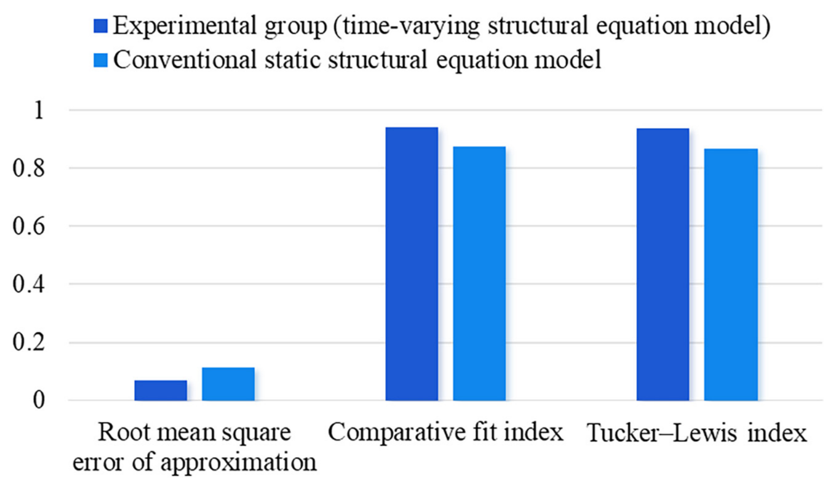

Fig. 5. Relational modeling experimental results

Table 2. Relational modeling results

Evaluation Metric	Experimental Group (Time-Varying Structural Equation Model)	Conventional Static Structural Equation Model	Improvement
Transfer entropy (emotion → performance)	1.87	0.92	103.3%
P-value (transfer entropy test)	0.007	0.156	–
Model fitting time (s)	18.3	32.7	44.0%

As shown in Figure 5 and Table 2, a superior model fit is achieved by the proposed time-varying structural equation model. The root mean square error of approximation is reported as 0.068, which is below the commonly accepted threshold of 0.08, while both the comparative fit index and Tucker–Lewis index exceed 0.93. These results indicate that the model is capable of accurately fitting multi-granularity time-series data in mobile environments. Compared with the conventional static structural equation model, the root mean square error of approximation is reduced by 39.3%, demonstrating a substantial improvement in model fit, while the model fitting time is reduced by 44.0%, thereby meeting the requirements for efficient cloud-based computation. The transfer entropy analysis further reveals that the transfer entropy value from emotional responses to performance reaches 1.87, with a P-value of 0.007, which is below the 0.01 significance level. This finding indicates a statistically significant causal information flow from emotional responses to performance outcomes. In contrast, the conventional static structural equation model yields a transfer entropy value of only 0.92, with a P-value greater than 0.1, thereby failing to establish a significant causal relationship. These results provide strong evidence that the proposed dynamic causal modeling approach effectively overcomes the limitations of static analytical methods and enables accurate identification of time-varying causal relationships among employee emotional responses, work engagement, and performance in mobile contexts.

Intervention effectiveness results and analysis. The intervention effectiveness dimension was evaluated to assess the practicality and effectiveness of the overall intervention mechanism embedded within the platform. A comparative analysis was conducted between the experimental group and the control group across key performance indicators. The results are summarized in Table 3.

Table 3. Intervention effectiveness results

Evaluation Metric	Experimental Group	Control Group	Difference
Improvement in work engagement (%)	12.3	2.1	10.2%
Improvement in work performance (%)	16.7	2.5	14.2%
Intervention acceptance (1–10 scale)	8.2	–	–
Emotional stability (coefficient of variation)	0.23	0.41	43.9%
Improvement in on-time task completion rate (%)	14.5	3.2	11.3%

As shown in Table 3, work engagement and performance are increased by 12.3% and 16.7%, respectively, in the experimental group, whereas the corresponding improvements in the control group are limited to 2.1% and 2.5%. The differences exceed 10% in both cases, indicating that the intervention mechanism effectively enhances employee work states. In terms of emotional stability, the coefficient of variation is reduced to 0.23 in the experimental group, compared with 0.41 in the control group, representing a reduction of 43.9%. This result suggests that emotional fluctuations are effectively mitigated, leading to improved emotional stability. Furthermore, the on-time task completion rate is increased by 14.5%, providing additional evidence of enhanced work efficiency resulting from the intervention mechanism. The intervention acceptance score reaches 8.2, indicating a high level of employee acceptance toward the intervention strategies delivered by the platform, with no evident resistance. These findings demonstrate that the intervention mechanism is well aligned with mobile usage scenarios, exhibiting strong practicality and user acceptability. Consequently, a transition is achieved from passive data recording to proactive, human-centered management within mobile human resource management systems.

3.3 Ablation study

To further evaluate the necessity and contribution of each core innovation, an ablation study was conducted. The full platform, incorporating all proposed components, was defined as the baseline model. Three ablation variants were constructed by selectively removing (i) the edge-side lightweight affective computing model, (ii) the federated learning–driven model evolution mechanism, and (iii) the dynamic causal modeling module. The performance of each ablation variant was compared with that of the baseline model. The results are summarized in Table 4.

Table 4. Summary of ablation study results

Experimental Group	Baseline Model	Ablation Group 1	Ablation Group 2	Ablation Group 3
Edge-side lightweight model	Retained	Removed	Retained	Retained
Federated learning mechanism	Retained	Retained	Removed	Retained
Dynamic causal modeling	Retained	Retained	Retained	Removed
Model accuracy (%)	89.2	76.5	88.9	89.0
Daily average power consumption (%)	4.3	12.1	4.5	4.4
Data leakage incidents	None	None	2 incidents	None
Transfer entropy	1.87	1.85	1.86	0.91
Performance improvement (%)	16.7	10.2	9.8	7.3

The ablation study results indicate that all three core innovations contribute significantly to overall platform performance. When the edge-side lightweight affective computing model is removed (Ablation Group 1), model accuracy is reduced to 76.5%, daily average power consumption increases to 12.1%, and performance improvement declines to 10.2%. These findings demonstrate that this component is essential for ensuring both high recognition accuracy and low-power operation in mobile environments. In its absence, effective adaptation to resource-constrained mobile scenarios is compromised, resulting in a substantial reduction in platform practicality. When the federated learning–driven model evolution mechanism is removed (Ablation Group 2), no substantial decline in model accuracy is observed; however, two instances of raw data leakage are recorded, and performance improvement decreases to 9.8%. These results confirm that the federated learning framework is critical for privacy preservation. In addition, its capacity for continuous model evolution enhances adaptability to individual employees, thereby indirectly influencing intervention effectiveness. When the dynamic causal modeling module is removed (Ablation Group 3), the transfer entropy value decreases to 0.91, and performance improvement is reduced to 7.3%. This outcome indicates that the module plays a crucial role in accurately capturing the causal relationships between employee emotional responses and performance outcomes. Without this component, the scientific basis for intervention strategy design is weakened, leading to reduced targeting precision and a substantial decline in intervention effectiveness.

4 CONCLUSION

To address the critical limitations of traditional human resource management in mobile environments—namely insufficient emotion recognition accuracy, high risks of privacy leakage, and the static nature of modeling relationships between emotional responses and performance—an interactive mobile human resource management platform based on affective computing was developed. Three core technical innovations were realized. First, an edge-side lightweight affective computing model based on knowledge distillation was proposed, through which the inherent conflict between resource constraints on mobile devices and high-accuracy emotion recognition was effectively resolved, enabling efficient and low-power model operation. Second, a federated learning–driven privacy-preserving model evolution mechanism was established, whereby the security of raw employee data was ensured at the architectural level, while a balance between personalized model adaptation and global model generalization was achieved. Third, a dynamic causal modeling approach integrating a time-varying structural equation model and transfer entropy was introduced, overcoming the limitations of traditional static analysis and enabling accurate identification of time-varying causal relationships among employee emotional responses, work engagement, and performance in mobile contexts. The findings contribute to addressing key technical bottlenecks in mobile human resource management and introduce a novel technological paradigm and research framework at the intersection of mobile computing, affective computing, and human resource management. The proposed framework further enriches research on intelligent mobile applications and offers both theoretical support and practical guidance for the intelligent transformation of human resource management driven by mobile technologies. Consequently, substantial academic value and strong potential for real-world application are demonstrated.

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