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PAPER

Advancing Enterprise Financial Control and Risk Management through Mobile Interactive Technologies

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ABSTRACT

With the deep integration of the digital economy and enterprise operations, mobile interactive technologies—characterized by real-time connectivity and ubiquitous access—have emerged as a critical solution to overcoming the spatial and temporal limitations inherent in traditional financial monitoring. However, existing research predominantly relies on conventional information technology frameworks, which exhibit substantial limitations in multidimensional financial data correlation mining, lightweight deployment on mobile terminals, and the integration and analysis of heterogeneous data. These limitations hinder the timely identification of risks in dynamic business environments. In this study, a financial monitoring algorithmic framework was proposed for enterprise environments under mobile interactive networks, integrating self-attention mechanisms and graph convolutional networks (GCNs). A formal definition of financial data monitoring was established, and a hierarchical algorithmic architecture was developed. Attribute-wise and relation-wise self-attention mechanisms were employed to capture the multidimensional characteristics of financial entities and the dynamic associations among transaction participants. GCNs were utilized to extract deep semantic representations from heterogeneous graph data. In addition, a domain-specific loss function and anomaly detection mechanism were designed based on financial business rules. The proposed framework addresses the limitations of traditional monitoring methods reliant on structured data and offers a robust, real-time solution for dynamic financial surveillance across regions and systems. The findings contribute both theoretical and practical value by advancing the precision of enterprise financial control and supporting the development of intelligent risk management systems.

KEYWORDS

mobile interactive technologies, financial data monitoring, self-attention mechanism, graph convolutional networks (GCNs), risk management

1 INTRODUCTION

As the digital economy increasingly permeates enterprise operations, mobile interactive technologies—marked by real-time responsiveness, ubiquity, and

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interactivity—have begun to reshape traditional models of financial control [1–4]. With the widespread deployment of 5G networks [5], cloud computing, and intelligent terminals [6, 7], enterprise financial data have exhibited characteristics of multisource heterogeneity and dynamic circulation [8–10]. In distributed business environments, the demand for capital flow monitoring, budget execution tracking, and real-time risk alerting has grown more pressing [11, 12]. For instance, group enterprises and supply chain nodes generate massive volumes of transactional data on a daily basis. Traditional financial monitoring systems based on fixed terminals have proven inadequate due to delayed data acquisition and insufficient cross-system coordination, thus falling short of providing management with timely insights into financial risks. Mobile interactive technologies enable comprehensive connectivity among users, devices, and data [13, 14], offering new solutions for real-time data flow and intelligent analysis. As such, these technologies have become critical enablers of improved financial control accuracy and accelerated risk responsiveness in modern enterprises.

Existing research on financial data monitoring has largely remained confined within the framework of conventional information technologies, such as process control based on enterprise resource planning (ERP) systems [15] or statistical model-driven risk warning methods [16]. However, these approaches exhibit significant limitations in the context of mobile interactive environments. On one hand, traditional methods often fail to extract the multidimensional relational characteristics of financial data, particularly by neglecting the dynamic interactions between transactional entities and their relationships, resulting in suboptimal anomaly detection accuracy. On the other hand, the algorithmic architectures employed in current systems typically lack the scalability required for lightweight deployment on mobile terminals [17], leading to inefficiencies in real-time data processing and imbalances between performance and energy consumption. Moreover, the fusion and analysis of heterogeneous data within mobile interactive networks have not yet been addressed by a systematic technical framework [18], thereby constraining advancements in the intelligence level of financial monitoring systems.

This study centers on the problem of enterprise financial data monitoring within mobile interactive network environments and proposes an intelligent monitoring algorithmic framework that integrates self-attention mechanisms with graph convolutional networks (GCNs). The scope of the research includes a) the formalization of financial data monitoring definitions; b) the design of a hierarchical algorithmic architecture; c) the incorporation of attribute-wise and relation-wise self-attention mechanisms within the encoder module; d) the use of GCNs as a decoder; e) the development of a loss function incorporating financial business rules; and f) the construction of an anomaly detection mechanism based on graph structural features. The contribution of this study lies in overcoming the dependency of traditional monitoring algorithms on structured data by innovatively integrating graph neural network (GNN) technologies with mobile interactive scenarios. A robust and real-time monitoring solution is thus provided for enterprise financial data monitoring. The outcomes offer not only theoretical support for establishing dynamic financial monitoring platforms across regions and systems in group enterprises but also methodological references for intelligent risk control in the financial technology domain. Furthermore, the proposed approach promotes a data-driven and intelligent decision-making paradigm in financial control and risk management.

2 ENTERPRISE FINANCIAL DATA MONITORING BASED ON MOBILE INTERACTIVE NETWORKS

Mobile interactive networks, characterized by real-time responsiveness, portability, and interactivity, enable the circumvention of the spatial and temporal limitations inherent in traditional fixed-terminal monitoring. Through these networks, financial data can be collected, transmitted, and processed on mobile terminals in real time, ensuring that key financial information—such as capital flows, account balances, and transaction details—can be accessed dynamically by enterprise management at any time and from any location. This capability facilitates the timely detection of abnormal fluctuations and potential risk factors.

2.1 Formal definition

Enterprise financial data monitoring within mobile interactive networks can be formally defined as a heterogeneous graph structure. The node set N comprises two categories: the mobile terminal device node set $SE = (T_1, T_2, \ldots, T_u, \ldots, T_v)$, representing mobile devices deployed in financial scenarios for data collection, transmission, and interaction; and the financial attribute node set $ATTR_u$, which encapsulates core attributes pertinent to financial monitoring. The edge set R includes two types of edges. The first type comprises association edges between device nodes and attribute nodes, representing the relationships through which financial attribute data are collected, processed, or transmitted by mobile terminals. The edge attributes x_{uk} record key parameters of these data interactions. The second type includes interaction edges between device nodes, which describe the coordination and collaboration among mobile terminals. The edge attributes T_{uk} encode the business logic underlying inter-device interactions. By employing a GCN architecture, the monitoring requirements of financial data are embedded within the node features and edge relationships of the graph structure. Real-time financial data captured by mobile devices can thus be subjected to graph convolution operations, enabling multidimensional modeling and dynamic monitoring of capital flows, business flows, and risk flows within the enterprise.

2.2 Algorithmic architecture

The enterprise financial data monitoring algorithm based on mobile interactive networks was structured around a GNN core, through which a multi-level graph learning model tailored to financial scenarios was constructed. A knowledge graph of mobile terminal devices was defined as $H = (N, E, A)$, where N represents the mobile terminal device entities involved in financial operations, E comprises the attribute relationships and business associations among devices, and A denotes the financial feature values collected by these devices. Subsequently, a graph attention network (GAT) was employed to construct two distinct self-attention models: one for attribute-level perception and another for relational-level perception. After applying masking operations to the input financial data, the encoder module—based on the mobile terminal perception knowledge graph—was used to encode the graph and generate a matrix representation H that characterizes both financial devices and their associated business relationships. This facilitates the extraction of structural features from multisource heterogeneous financial data in graph form. Thereafter, GCNs were used to build the decoder of the perception knowledge graph. The output from the encoder was fused with pre-layer features of the decoder, and then propagated through multiple GCN layers to yield a reconstructed representation H'. The model was trained using a scaled cosine error loss function to enhance the representational precision of financial entities, attributes, and relationships embedded within the graph. Through this process, a perception-based GNN warning model was established. Finally, downstream tasks were executed on the pretrained model. Using an anomaly classification algorithm, real-time financial data collected by mobile terminals were analyzed to identify potential risks. This enables intelligent early warnings for anomalies in capital flow, deviations in budget execution, and risks associated with investment and financing activities. Figure 1 shows the attribute-relationship knowledge graph of mobile terminal devices.

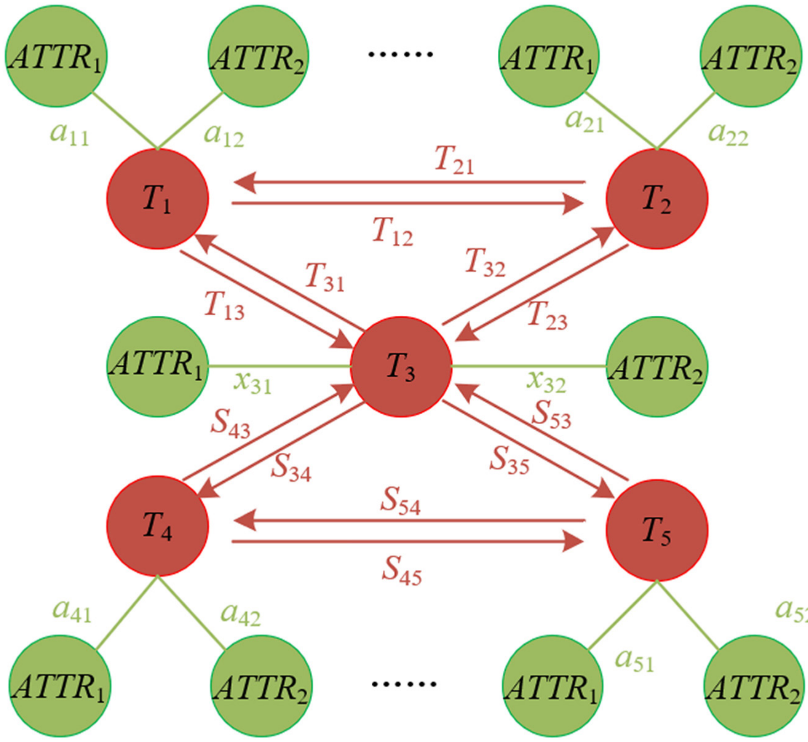

Fig. 1. Attribute-relationship knowledge graph of mobile terminal devices

2.3 Encoder

(1) Input. Figure 2 presents the architectural design of the encoder. The input to the encoder consists of a multidimensional feature set composed of attribute triplets associated with mobile terminal devices. The core objective is to transform fundamental device information, financial attributes, and real-time data into a structured format suitable for GNN processing. Specifically, in the context of enterprise financial scenarios, the input includes three key components for each mobile terminal device: a) A device name vector n_{uL}, trained using word embedding algorithms, which captures the semantic role of the device within financial operations; b) An attribute vector n_{ATTRk}, which contains inherent characteristics of the device and reflects its static properties within the financial monitoring system; c) An attribute value vector n_{VATTRk}, representing real-time financial data collected by the device, which conveys dynamic financial information generated in operational contexts. These three vectors collectively form the attribute triplet for each device. The encoder receives this triplet as input and fuses the business semantics of the device name, the static features of its attributes, and the dynamic financial data of attribute values. This process yields a sensor attribute vector that encapsulates both the device's identity and essential financial monitoring elements. Assuming the total number of devices is denoted by l, the embedding vector n_u of the u-th mobile terminal device can be expressed as:

$$n_u = n_{uL} + \sum_{k=1}^{l} n_{ATTR_k} + \sum_{k=1}^{l} n_{VATTR_k} \tag{1}$$

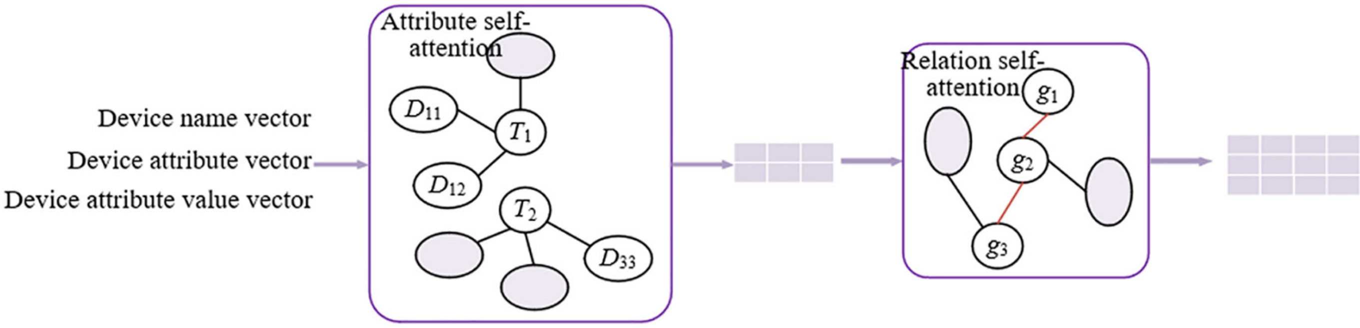

Fig. 2. Overall architecture of the encoder

(2) Attribute self-attention construction. The attribute self-attention mechanism within the encoder is designed to dynamically capture the relevance weights between mobile terminal device attributes and financial monitoring objectives. A masking mechanism was employed to enhance the learning of key financial features. Specifically, for each attribute vector associated with a mobile terminal device, a random sampling and masking process was applied to the input attributes—i.e., a subset of attributes was randomly selected—to compel the model to learn inter-attribute dependencies under conditions of partial information. On this basis, a self-attention mechanism was applied to compute the self-attention representation T_u for the device attributes. This mechanism measures the varying importance of different attributes belonging to the same device in the context of financial monitoring. Let the weight of the k-th attribute of the u-th mobile terminal device T_u be denoted by x_{uk}; the computation is formulated as follows:

$$T_u = ATTR_{AT} = \sum_{k=1}^{l} x_{uk} ATTR_k \tag{2}$$

(3) Relation self-attention construction. The relation self-attention mechanism within the encoder is intended to reconstruct feature representations of mobile terminal devices in the financial relationship graph by capturing business associations and risk propagation logic between devices. Specifically, in the relationship graph composed of mobile terminal devices under enterprise financial scenarios, relation-driven feature reconstruction was performed for each device node T_u, generating a new representation g_u that incorporates information from its neighboring nodes. Through the relation self-attention mechanism, interaction weights between devices were computed, and the financial attributes of neighboring devices were aggregated according to these weights into the target device's representation. This mechanism facilitates the construction of relational features that reflect business collaboration and risk transmission among devices. For instance, when monitoring a high-value transaction, relation self-attention is designed to emphasize the weights between the initiating device, the recipient account's device, and any risk control-related devices, enabling the model to focus on critical node interaction along the capital flow path. In a budget overrun alert scenario, the relationships between the budgeting device, departmental cost-accounting devices, and financial approval devices were highlighted. By simulating the coupled logic of "business flow – capital flow – information flow" inherent in enterprise financial processes, the reconstructed representation g_u for each device node is enriched not only with its own attributes but also with collaborative features and risk-related information from upstream and downstream devices. This significantly enhances the model's ability to detect cross-device financial anomalies and provides a relationally interpretable foundation for downstream GNN modeling of risk propagation paths and optimization of monitoring strategies. Let the number of mobile terminal devices adjacent to the u-th device T_u be denoted as o, and let the weight between the target device and its k-th neighbor be denoted as q_k. Then the following expression applies:

$$g_u = \sum_{k=1}^{o} t_{uk} q_k t_k \tag{3}$$

(4) Output. The output of the encoder is a structured graph representation H_R, which integrates device features and business relationships. This graph was constructed via a GAT to model device interaction graphs for financial monitoring purposes. Specifically, the encoder first encodes the attribute features of each mobile terminal device and aggregates the contextual information from neighboring devices through the self-attention mechanism, generating node representations g_u that encapsulate both intrinsic device attributes and collaborative relationships. In parallel, the inter-device attention weights t_{uk} were computed using GAT, dynamically reflecting the interaction intensity between devices in financial operations. A directed graph H_R was thus formed, in which the nodes are represented by g_u and the edges are represented by t_{uk}. This output not only retains the essential financial attributes of each device but also explicitly models critical relationships such as capital flow paths, approval processes, and risk propagation chains through the attention mechanism. As a result, the graph structure provides an input that is both semantically rich and dynamically correlated. This enables downstream GNNs to integrate cross-device collaborative features and detect financial anomalies across terminals. Furthermore, it supports multidimensional modeling and real-time monitoring of enterprise capital flows, business flows, and risk flows. Let the connection between mobile terminal device node T_u and node T_k be denoted by r_{uk}, and the connection between node T_u and node T_j be denoted by r_{uj}. The calculation can then be expressed as:

$$r_{uk} = x\left(\left[Qg_u \,\|\, Qg_k\right]\right) \tag{4}$$

$$e_{ATT} = t_{uk} = \frac{\exp(\text{LeakyReLU}(e_{uk}))}{\sum_{j=1}^{v} \exp(\text{LeakyReLU}(e_{uj}))} \tag{5}$$

2.4 Decoder

(1) Input. Figure 3 illustrates the overall architecture of the decoder. In the enterprise financial data monitoring algorithm based on mobile interactive networks, the decoder receives as input a composite tensor that integrates device attribute features with business relationship structures. The core objective is to transform the graph-structured output from the encoder into multidimensional feature representations that support financial anomaly detection. Specifically, the decoder accepts three components as input: a) An attribute matrix A, composed of attribute vectors a_u corresponding to each mobile terminal device, where each a_u includes real-time financial features and basic attributes of the device; b) A relationship matrix X, in which each element X_{uk} denotes the intensity of business association between devices, reflecting the data interaction pathways within enterprise financial processes; c) A degree matrix F and an identity matrix U, which are used to normalize the relationship matrix to ensure that device nodes with varying degrees of connectivity receive balanced weights during feature propagation. This input configuration enables the decoder to integrate real-time financial data from individual devices with their inter-device business collaboration relationships. Through this integration, the decoder is able to reconstruct the normal behavioral patterns of financial data based on graph-structured features and to identify deviations indicative of anomalous behavior.

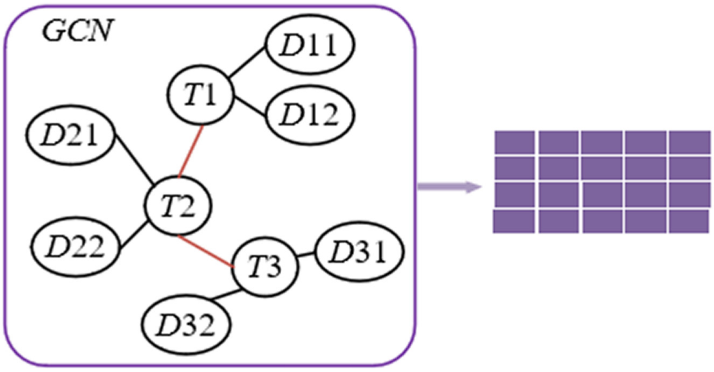

Fig. 3. Overall architecture of the decoder

(2) GCN-based graph convolution. In the decoder, graph convolution based on the GCN begins by integrating a device's own attributes with information from its neighborhood through a feature fusion mechanism. For each mobile terminal device node T_u, the feature vector at the m-th layer, denoted as G_u^m, contains multidimensional financial attributes. A linear transformation was first applied using the weight matrix Q, after which self-loop connections were introduced using the identity matrix U to ensure that a node's own features are preserved during neighborhood aggregation:

$$\tilde{X} = X + U \tag{6}$$

To address the imbalance in feature scales caused by varying node degrees in the enterprise financial network, the inverse of the degree matrix F was introduced to normalize neighborhood information. In financial contexts, core financial systems often connect to a large number of devices, whereas peripheral data acquisition terminals typically have lower connectivity. Direct neighborhood aggregation would cause the feature vectors of central nodes to dominate, while features of peripheral nodes would be diluted. Following feature fusion and normalization, the GCN performs layer-wise propagation to construct the relational network among financial devices. For all node feature matrices G^m at layer m, the subsequent layer's representation was generated through the following matrix operation. An activation function δ introduces nonlinear transformations to enhance the model's ability to capture complex financial relationships:

$$G^{m+1} = \delta\left(\tilde{F}^{-\frac{1}{2}}\tilde{X}\tilde{F}^{-\frac{1}{2}}G^m Q^m\right) \tag{7}$$

Within the context of enterprise financial monitoring, this process enables the dynamic capture of capital flow paths, approval dependencies, and risk transmission relationships among devices. For example, when a point-of-sale terminal triggers a high-value receipt, the GCN strengthens its association with accounts receivable management systems and tax accounting devices through neighborhood aggregation. This mechanism enables the model to focus on the completeness and compliance of revenue recognition. After multiple layers of convolution, the final decoded graph H_F not only retains the local financial characteristics of each device but also explicitly encodes cross-device collaborative anomalies through the graph structure. This provides a structured knowledge representation that supports downstream financial risk alerting.

2.5 Loss function

The design principle of the loss function centers on capturing anomalous patterns in financial data by comparing the structural similarity between the encoded and decoded graphs. Specifically, an attribute matrix X and a latent attribute matrix C, along with a shared relationship matrix E, were extracted from both the encoder output graph H_R and the decoder output graph H_R. Cosine similarity was employed to evaluate the directional consistency between the column vectors of X and C, while also taking into account the structural preservation of the relationship matrix E. For example, if a strong association between a reimbursement terminal and the budgeting system is observed in the encoded graph but significantly weakened in the decoded graph, this may indicate a budget execution anomaly. This design allows the model to focus on reconstructing patterns in financial data. Under normal conditions, the encoder and decoder are expected to operate in tandem, resulting in high similarity between X and C. However, when abnormal transactions or system faults occur, the latent attribute matrix C deviates from the original attribute matrix X, leading to a decrease in cosine similarity and subsequently triggering an alert. In this way, the loss function transforms the problem of anomaly detection in enterprise financial monitoring into reconstruction error optimization within a graph structure, thereby enabling the identification of complex risk scenarios that are often not addressed by conventional rule-based systems. Formally, each row of X represents the attribute vector a_u of a mobile terminal device T_u, and each row of C represents its corresponding latent attribute vector c_u. Let the set of all attribute vectors of mobile terminal devices be denoted by $\tilde{N}$. The loss function between H_R and H_F is expressed as follows:

$$M(H_R, H_F) = \frac{1}{|\tilde{N}|}\sum_{n_u \in \tilde{N}}\left(1 - \frac{a_u^S c_u}{\|a_u\| \cdot \|c_u\|}\right) \tag{8}$$

2.6 Anomaly detection

The anomaly detection mechanism of the enterprise financial data monitoring algorithm based on mobile interactive networks is designed to quantify deviations between predicted and observed behavior by learning the normal interaction patterns among devices using GNNs. Specifically, a relational graph of mobile terminal devices was first constructed by the encoder based on historical financial data, capturing attribute dependencies and interaction patterns across devices. The decoder then generates predicted values G_u^m, which represent the expected state features of each device under normal business conditions. When real-time financial data are introduced, the decoder produces the corresponding observed values $\hat{G}_u^m$. By comparing the predicted and observed values, behaviors that deviate from the learned patterns can be identified. These discrepancies were quantified using multiple metrics and evaluated in conjunction with each device's topological position in the graph and the strength of its relational links, allowing for a comprehensive risk assessment. For instance, if a device exhibits an unusually high frequency of outgoing financial transactions that significantly exceeds historical norms—and its associated budget control devices have not registered corresponding updates—the system is likely to flag this as a potential budget overrun risk. In this way, the algorithm transforms enterprise financial monitoring into a pattern-matching task on a graph structure, allowing not only for the detection of individual anomalies but also the identification of coordinated anomalies across devices. A real-time, interpretable risk alert mechanism is thereby enabled.

$$ERR(s) = \left| G_u^m - \hat{G}_u^m \right| \tag{9}$$

If the error exceeds a fixed threshold, then financial data at time s are labeled as anomalous.

The monitoring results obtained through mobile interactive networks facilitate systematic enhancements in financial control and risk management through multidimensional data integration and dynamic strategy response. Upon detection of an anomaly, risk levels and impact scopes can be pushed in real time to mobile terminals, enabling rapid decision-making actions by enterprise management. These may include freezing suspicious transaction accounts, suspending data interactions on high-risk devices, or automatically triggering multi-tier approval workflows—thus enabling immediate intervention in financial risk events. Furthermore, based on the device relational graph learned by the GNN, a dynamic risk assessment model can be developed to support retrospective analysis of historical monitoring data, aiming to identify potential risk accumulation zones and optimize financial control rules, thereby forming a closed-loop management system of monitoring–analysis–optimization. Additionally, latent relational features embedded in the monitoring results can inform financial decision-making. For example, personalized risk alerts may be delivered to business units via mobile terminals to support strategic adjustments in investment planning, cost control measures, or supply chain settlement policies—ultimately reducing the likelihood of risk occurrences at the source. By leveraging the real-time and interactive advantages of mobile interactive networks, this monitoring approach extends beyond post hoc anomaly detection. Through its deep integration with operational systems, it contributes to the construction of a full-cycle financial governance system encompassing prevention, control, and optimization.

3 EXPERIMENTAL RESULTS AND ANALYSIS

Table 1. Evaluation results of anomaly detection in enterprise financial data monitoring using different algorithms

Method	Detection Accuracy	Recall	F1-Score
GRU-VAE	95.36%	58.95%	0.73
StarGAN	97.51%	62.31%	0.76
GraphSAGE	94.36%	67.89%	0.82
Proposed model	98.59%	72.31%	0.87

Table 2. Comparison of F-scores for different self-supervised algorithms on enterprise financial monitoring datasets

Self-Supervised Method	Reimbursement Records	Transaction Flows	Budget Execution
MaskGNN	0.82	0.71	0.73
Graph-BERT	0.84	0.73	0.78
InfoGraph	0.85	0.72	0.82
Proposed model	0.87	0.74	0.79

Table 1 presents the evaluation results of various algorithms in anomaly detection tasks within the context of enterprise financial data monitoring. Specifically, the gated recurrent unit-variational autoencoder (GRU-VAE) model achieved a detection accuracy of 95.36%, recall of 58.95%, and an F1-score of 0.73. The Star generative adversarial network (StarGAN) model yielded a detection accuracy of 97.51%, recall of 62.31%, and an F1-score of 0.76. The Graph Sample and Aggregate (GraphSAGE) model attained a detection accuracy of 94.36%, a recall of 67.89%, and an F1-score of 0.82. In comparison, the proposed model achieved a detection accuracy of 98.59%, recall of 72.31%, and an F1-score of 0.87, outperforming all other methods across all three metrics. Notably, substantial improvements were observed in detection accuracy and F1-score. According to these experimental results, the model's superior performance in terms of accuracy (98.59%), recall (72.31%), and F1-score (0.87) strongly validates the effectiveness of the proposed algorithmic framework in monitoring enterprise financial data under mobile interactive network environments.

Table 2 presents a comparison of F1-scores achieved by different self-supervised algorithms across three enterprise financial monitoring datasets. Specifically, masked graph neural network (MaskGNN) yielded F1-scores of 0.82, 0.71, and 0.73 across the three datasets of reimbursement records, transaction flows, and budget execution, respectively. Graph bidirectional encoder representations from transformers (Graph-BERT) achieved scores of 0.84, 0.73, and 0.78. Information graph representation learning (InfoGraph) obtained 0.85, 0.72, and 0.82. The proposed model recorded F1-scores of 0.87 for reimbursement records, 0.74 for transaction flows, and 0.79 for budget execution. It can be observed that the proposed model achieved the highest F1-score on the reimbursement records dataset and outperformed some of the compared algorithms on the transaction flow dataset. According to these findings, the proposed model achieved an F1-score of 0.87 on the reimbursement records dataset, outperforming all compared algorithms. On the transaction flows dataset, it attained an F1-score of 0.74, also surpassing several baseline methods. These results strongly validate the effectiveness of the proposed algorithmic framework in handling various types of financial monitoring data.

According to the data in Table 3, the total number of authorized payments reached 356,215 transactions, amounting to 4,521,568,000 CNY. Of these, 31,256 transactions—totaling 912,355,400 CNY—were subject to early-warning monitoring, accounting for 9.23% of the total by transaction count and 18.56% by amount. Within this subset, ex-ante monitoring accounted for 32,548 transactions and 875,952,100 CNY, with approved cases totaling 31,256 transactions and 823,655,400 CNY. Cases identified as violations reached 826 transactions, with a total amount of 42,563,200 CNY, representing 2.56% and 4.56% of the monitored totals, respectively. Ex-post monitoring involved 1,458 transactions amounting to 24,583,200 CNY. Among these, 1,126 transactions were approved (16,582,300 CNY), while 469 cases were subjected to corrective actions (7,586,200 CNY), accounting for 1.36% and 0.84% by transaction count and amount, respectively. These results demonstrate the significant practical effectiveness of integrating mobile interactive technologies with the proposed intelligent monitoring algorithm for enterprise financial control and risk management. The high proportion of ex-ante monitoring—94.21% by transaction count and 96.54% by amount—along with approval rates of 91.25% and 91.23%, respectively, indicates that real-time and efficient preemptive monitoring can be achieved through the proposed framework. Violations can be identified and addressed promptly, thereby effectively mitigating financial risks. Although ex-post monitoring retains a degree of effectiveness, the high proportion of ex-ante monitoring highlights the advantage of the proposed algorithm in enabling front-end risk prevention through mobile interactive technologies.

Table 3. Execution statistics of enterprise financial dynamic monitoring

Project and Content	Early-Warning Monitored Authorized Payments		Proportion of Authorized Payments (Early-Warning)	
	No. of Transactions	Amount (10,000 CNY)	Proportion by Transaction Count	Proportion by Amount
I. Total authorized payments	356,215	4,521,568,000		
II. Early-warning monitored payments	31,256	912,355,400	9.23%	18.56%
(1) Ex-ante monitoring	32,548	875,952,100	94.21%	96.54%
— Approved	31,256	823,655,400	91.25%	91.23%
— Violations handled	826	42,563,200	2.56%	4.56%
(2) Ex-post monitoring	1,458	24,583,200	4.56%	2.98%
— Approved	1,126	16,582,300	3.24%	1.89%
— Corrective action	469	7,586,200	1.36%	0.84%

Table 4 provides a statistical overview of the enterprise financial pre-warning rules triggered during ex-ante monitoring. When the current ratio fell below 1.0, 125 alerts were triggered involving 6.7852 million CNY, resulting in 2 confirmed violations totaling 81,200 CNY. Under the debt-to-asset ratio exceeding 70%, 123 alerts (involving 7.1523 million CNY) were generated, though no violations were identified. For net profit declines exceeding 30% over two consecutive periods, 1,586 alerts (involving 16.5926 million CNY) were triggered, with 8 violations recorded, totaling

51,600 CNY. When the year-on-year revenue growth rate dropped below –10%, 335 alerts (involving 7.2532 million CNY) were triggered, with 4 violations totaling 28,900 CNY. The inventory turnover rate falling below 80% of the industry average triggered 415 alerts (involving 45.6232 million CNY), with 13 confirmed violations amounting to 2.8726 million CNY. When the management-to-sales expense growth surpassed twice the revenue growth, 42 alerts were triggered involving 5.2668 million CNY, with no violations identified. When single-day cash outflow exceeded 50% of monthly average net flow, 51 alerts were triggered involving 7.5421 million CNY, also with no violations identified. In total, 2,658 alerts were generated with a cumulative amount of 96.5823 million CNY, out of which 27 were confirmed violations involving 3.2423 million CNY. The experimental findings demonstrate the practical effectiveness of integrating mobile interactive technologies with the proposed intelligent monitoring algorithm. Each pre-warning rule was successfully monitored in real time. For instance, the rule regarding inventory turnover falling below 80% of the industry average triggered 415 alerts, among which 13 violations were detected. This highlights the algorithm's ability to proactively identify inventory-related risks through mobile-enabled ex-ante detection. Similarly, effective monitoring of declining net profit and negative revenue growth illustrates the model's capability to track key business performance indicators and issue early warnings for potential risks. In contrast, rules with no confirmed violations demonstrate the model's precision in compliance monitoring. Overall, by embedding financial business rules into the monitoring logic, the proposed model—enhanced by mobile interactive technologies—enabled effective risk identification. The approach strengthens financial control, reduces violations, and offers robust, real-time technical support for enterprise risk management.

Table 4. Statistical summary of pre-warning rules triggered in enterprise financial ex-ante monitoring

Rule Description	No. of Alerts	Alert Amount (10,000 CNY)	No. of Violations	Violation Amount (10,000 CNY)	Violation Rate (By Count)	Violation Rate (By Amount)
Current ratio < 1.0	125	6.7852	2	81,200	1.69%	1.1%
Debt-to-asset ratio > 70%	123	7.1523	0	0,00	0	0
Net profit decline > 30% for two consecutive periods	1,586	16.5926	8	51,600	0.46%	0.28%
Year-on-year revenue growth rate < –10%	335	7.2532	4	28,900	1.23%	0.42%
Inventory turnover < 80% of industry average	415	45.6232	13	2.8726	3.68%	6.3%
Management/sales expense growth > 2× revenue growth	42	5.2668	0	0	0	0
Single-day cash outflow > 50% of monthly average net flow	51	7.5421	0	0	0	0
Total	2,658	96.5823	27	3.2423	–	–

Table 5 illustrates the distribution of financial violations detected through early-warning mechanisms in enterprise monitoring. The most frequently observed issue was data falsification or concealment, with 315 violations recorded, amounting to 2.2634 million CNY. This was followed by data monopoly and manipulation, which accounted for 25 violations totaling 3.1225 million CNY. Additional violations included logical flaws in early-warning mechanism design (5 cases, 37,800 CNY), violation of accounting standards (9 cases, 462,100 CNY), inaction following early-warning triggers (13 cases, 72,600 CNY), improper intervention in early-warning processes (8 cases, 46,900 CNY), and omission of key indicators in early-warning rule design (2 cases, 9,800 CNY). The fewest violations were associated with information disclosure violations, with only one case identified, involving 2,300 CNY. These findings demonstrate the critical role of mobile interactive technologies and the proposed intelligent monitoring algorithm in enterprise financial control and risk management. Although data falsification or concealment accounted for a relatively high number of violations (315 cases), the proposed anomaly detection framework—built on the integration of financial business rules and graph-based structural features—enabled effective identification of such severe violations. This highlights the model's strong capacity for detecting high-risk patterns. Other issues, such as data monopoly and manipulation, were also effectively addressed through the hierarchical algorithmic architecture, which integrates self-attention mechanisms and GCNs for comprehensive monitoring. The deployment of mobile interactive technologies ensured real-time surveillance, allowing such violations to be detected promptly. This capability significantly enhances the effectiveness of enterprise financial control.

Table 5. Distribution of financial early-warning violations in enterprise monitoring

Violation Type	No. of Violations	Violation Amount (10,000 CNY)
Data monopoly and manipulation	25	3.1225
Data falsification or concealment	315	2.2634
Inaction after early-warning trigger	13	72,600
Improper intervention in early-warning processes	8	46,900
Violation of accounting standards	9	462,100
Violation of information disclosure requirements	1	2,300
Omission of key indicators in early-warning design	2	9,800
Logical flaws in early-warning design	5	37,800

4 CONCLUSION

This study addressed the challenge of enterprise financial data monitoring within mobile interactive network environments by proposing an intelligent monitoring algorithmic framework that integrates self-attention mechanisms with GCNs. The research encompassed the formal definition of financial data monitoring, the design of a hierarchical algorithmic architecture, the introduction of attribute and relational self-attention mechanisms in the encoder, the adoption of GCNs as the decoder, the formulation of a loss function based on financial business rules, and the construction of an anomaly detection mechanism leveraging graph-structured features. The effectiveness of the proposed framework in identifying financial risks and enhancing enterprise financial control and risk management was validated through empirical analyses, including early-warning monitoring execution outcomes, violation distributions, and dynamic capital structure changes. The framework demonstrated strong capabilities in capturing capital structure shifts and monitoring compliance violations in a timely manner, thereby highlighting the advantage of integrating mobile interactive technologies with intelligent algorithms for front-end financial risk prevention.

The primary contribution lies in overcoming the dependency of traditional monitoring algorithms on structured data by innovatively combining GNN techniques with mobile interactive application scenarios. A real-time and robust technical solution was thus provided for enterprise financial data monitoring. However, several limitations were identified. First, the comprehensiveness of the monitoring across certain financial indicators remains to be improved, and the model's adaptability to highly complex financial environments requires further enhancement. Second, the experimental scenarios and enterprise types covered by the current dataset may not be sufficiently diverse, potentially limiting the generalizability of the algorithm. Future research should focus on further optimization of the algorithmic model to improve its precision across diverse financial scenarios. Additionally, efforts should be directed toward the integration of more heterogeneous data sources to broaden the model's applicability. These directions are expected to provide stronger support for enterprise financial management and risk mitigation, thereby advancing the development of intelligent and comprehensive financial monitoring systems.

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