Disruptive Risk Identification Technology in Textile Intelligent Manufacturing Using Heterogeneous Graph Neural Network

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ABSTRACT The increasing deployment of wireless sensing, industrial Internet of Things (IIoT), and electromagnetic information transmission technologies in textile intelligent manufacturing has generated massive multi-source heterogeneous data, making accurate disruptive risk identification essential for ensuring reliable system operation and efficient information propagation. However, conventional approaches struggle to capture latent correlations and cross-domain propagation paths, particularly under small-sample conditions. To address this issue, this paper proposes a disruptive risk identification method based on a heterogeneous graph neural network (HGNN). A heterogeneous knowledge graph is constructed to model entities and relationships among equipment, processes, materials, and quality information, while a dynamic update mechanism enables real-time graph evolution. Meta-path-guided multi-head graph attention is employed to achieve adaptive semantic aggregation and cross-type information propagation, and graph-level representation learning combined with anomaly scoring accurately identifies disruptive sources and transmission paths. Experimental results demonstrate that the proposed method achieves an average recognition accuracy of 86.6% across five representative meta-paths. In small-sample scenarios with only 2.3% abnormal samples, the recall and F1-score reach 81.3% and 83.0%, respectively, significantly outperforming existing heterogeneous graph models. The proposed framework provides an effective solution for intelligent risk warning in textile manufacturing and offers valuable methodological support for reliable information processing and decision-making in electromagnetic-enabled industrial sensing and communication environments.

INDEX TERMS heterogeneous graph neural network, heterogeneous knowledge graph, disruptive risk identification, industrial internet of things, intelligent manufacturing

I. INTRODUCTION

As an essential component of Industry 4.0, textile intelligent manufacturing is gradually transitioning from traditional manufacturing to digitalization and intelligence. However, during this process, the widespread existence of multi-source heterogeneous data—such as equipment failures, process fluctuations, material defects, and environmental changes—exposes the manufacturing system to disruptive risks characterized by suddenness, broad impact, and rapid transmission speed [1,2]. Such risks are often triggered by abnormalities in a single link and quickly spread throughout the entire production process via complex related chains, potentially leading to severe consequences such as full-line shutdowns and batch product scrapping. Traditional anomaly identification methods typically rely on the analysis of a single variable or local relationships, making it difficult to fully capture the potential influencing factors of disruptive risks and their cross-domain propagation paths. As a result, warnings for low-incidence, high-impact disruptive events are often delayed. Therefore, the challenge of uniformly modeling multi-source heterogeneous data and accurately identifying both the source of disruptive risks and their chain impact paths has become a critical issue in textile intelligent manufacturing.

Previous research has explored various methods of anomaly identification in textile intelligent manufacturing. Early approaches predominantly relied on statistical analysis, such as control charts and regression models, to identify anomalies by monitoring fluctuations in single process parameters. For example, Tran [3] proposed a CUSUM-γ^2 control chart for monitoring the coefficient of variation, combined with a rapid initial response strategy and the Nelder–Mead optimization algorithm, to achieve earlier and more accurate anomaly detection. This method is suitable for monitoring single-parameter fluctuations in textile industry quality control. Kins [4] introduced the application of statistical process control in the textile process, including Shewhart control charts, capability index evaluation, and basic regression analysis methods, emphasizing process stability management and fluctuation identification in dynamic production contexts. Although statistical analysis-based methods can monitor fluctuations in single process parameters and identify anomalies, they struggle to accurately track the coupling relationships between variables and the global impact paths in complex processes with multiple links. With the advancement of machine learning, methods such as support vector machines (SVM) and random forests have been used to fuse multiple features. Yaşar [5] demonstrated that fusing multiple features (such as texture, color, and frequency domain) and combining them with an SVM classifier significantly improves fabric defect recognition accuracy compared to single-feature methods. Miao [6] used random forests to analyze the effects of multiple input features on textile quality indicators and to extract key features for defect prediction. These existing methods have made progress in single-parameter monitoring and local relationship modeling, but they struggle to adapt to the multi-source triggering characteristics of disruptive events, especially in small-sample scenarios. They cannot effectively capture the cross-domain propagation path of "weak connection and strong influence," and their accuracy in identifying systemic risks with low incidence and high chain effects is insufficient, making them inadequate for early warning of disruptive events in textile intelligent manufacturing.

In recent years, graph neural networks (GNNs) have been increasingly applied to manufacturing systems. Lallier [7] modeled the two-dimensional nesting problem in textile cutting as a graph structure, combining it with convolutional neural networks (CNN) and GNN to estimate material utilization, which is suitable for intelligent manufacturing scenarios focused on fabric savings and layout optimization. Longhini [8] proposed the concept of Elastic Context, which encodes the stress-strain behavior of textile materials into a graph structure and uses GNN to learn a general elastic behavior model to support robot-fabric interaction and grasping tasks. Due to significant differences in entity types—such as equipment, materials, and processes—in textile data, homogeneous graphs struggle to depict cross-type associations, resulting in limited recognition accuracy in complex scenarios. HGNN provides a new technical pathway to address these challenges. Zhu [9] constructed a heterogeneous graph structure connecting different types of nodes, such as machines, processes, and material flows, and used HGNN combined with a Bayesian neural network to model complex manufacturing systems, integrating heterogeneous feature fusion analysis for different equipment and process nodes in textile production lines. Li [10] proposed a Chi Graph Anomaly Detection framework that supports heterogeneous graph anomaly detection across multiple node and edge types. It captures complex semantics and high-frequency abnormal signals through multi-graph Chi-Square filtering, which can be applied in monitoring abnormal states in heterogeneous networks composed of multiple pieces of equipment and sensors in textile workshops. However, existing HGNN approaches mainly focus on static relationship modeling, making it difficult to adapt to the dynamic evolution of "trigger-propagation-outbreak" processes for disruptive events. Especially in small-sample scenarios, the lack of targeted semantic enhancement mechanisms fails to fully meet the core needs of real-time tracking and early warning of disruptive risks in textile intelligent manufacturing.

To address the limitations of existing methods in modeling multi-source heterogeneous data and capturing complex causal chains, this paper innovatively proposes a disruptive risk identification technology based on HGNN. Disruptive risk specifically refers to situations in textile manufacturing systems where a single-stage anomaly—such as equipment failure or deviation in key process parameters—propagates across domains through complex networks of connections among equipment, materials, and processes, ultimately leading to severe, global, and highly cascading events, such as large-scale product defects, batch scrapping, or unplanned production line downtime. To accurately identify such risks, this paper constructs a heterogeneous knowledge graph (HKG) with a dynamic update mechanism. This graph formalizes entities such as equipment and processes, as well as risk associations, into multiple types of nodes and edges, and incorporates incremental learning to enable real-time tracking of the entire evolutionary process from trigger to propagation to outbreak. Unlike existing HGNN applications that primarily focus on static relationship modeling or general anomaly detection, the core innovations of this paper are: first, the dynamic update mechanism addresses the limitation of static graphs in adapting to real-time changes in the manufacturing process, enabling dynamic tracking of risk evolution; second, the design of a meta-path-guided multi-head graph attention mechanism allows for path weight quantification and multi-head parallel computation, enabling precise focus on the disruptive propagation chain of weak connection and strong influence in small-sample scenarios and effectively strengthening the semantic modeling of key causal paths. This method integrates graph-level representation learning and anomaly scoring modules to achieve comprehensive identification, from local node anomalies to global risk paths.

II. HGNN DESIGN

CONSTRUCTION OF HETEROGENEOUS KNOWLEDGE GRAPH FOR DISRUPTIVE IDENTIFICATION

Given that disruptive events in textile intelligent manufacturing systems are characterized by multi-source triggering and cross-domain propagation, traditional static graphs are inadequate for capturing the potential risk chains. This paper constructs a HKG for disruptive identification. Through multi-dimensional entity modeling and dynamic risk association characterization, the source and propagation path of disruptive events can be accurately tracked [11,12].

The construction of the HKG begins with extracting key entities and their relationships from production data [13]. These entities include equipment, processes, raw materials, and quality inspection results. Each type of entity is defined as a node type T_i, and the interaction relationships among them are defined as an edge type R_j. For example, there may be an "execution" relationship between equipment and processes and a "generation" relationship between processes and products. Ultimately, the entire manufacturing system is modeled as a heterogeneous graph $G = (V, E)$, where V represents the node set and E represents the edge set. To ensure semantic consistency in heterogeneous graphs, this paper introduces domain expert knowledge to validate the graph and employs natural language processing techniques to automatically extract implicit relationships from production logs. Additionally, to quantify the importance of nodes and edges, the calculation formulas for node weight $w(v_i)$ and edge weight $w(e_{ij})$ are defined:

$$w(v_i) = \frac{\sum_{e_{ij} \in E} w(e_{ij})}{\sum_{v_k \in V} \sum_{e_{kl} \in E} w(e_{kl})} \tag{1}$$

$$w(e_{ij}) = \exp\left(-\left\|f(v_i) - f(v_j)\right\|^2\right) \tag{2}$$

$f(v_i)$ and $f(v_j)$ represent the eigenvectors of nodes v_i and v_j, respectively. This approach fully describes the static structure of the textile manufacturing system and dynamically reflects real-time changes in the manufacturing process. The core concept behind node weights draws on "weighted degree centrality" in complex networks. The denominator essentially represents the ratio of the weighted degree of node v_i to the total edge weights in the entire graph. The larger this ratio, the stronger the node's connections with other nodes in the network and the more frequent its interactions, indicating a higher potential for the node to serve as a "hub" in the risk propagation network and, naturally, a higher level of influence.

To improve the scalability of the HKG, this paper also introduces a dynamic update mechanism. Assume that the heterogeneous graph at the current moment is G_t, and the newly added nodes and edges at the next moment are ΔV and ΔE, respectively. The goal of dynamic graph updating is to efficiently integrate ΔV and ΔE into the existing graph structure without retraining the entire model. To achieve this, an incremental learning method is used to update only the features of the newly added nodes and their neighbors, avoiding global recalculation. Assuming the initial feature of the newly added node v_{new} is h_{new}, its updated feature h'_{new} can be expressed as:

$$h'_{new} = \sigma\left(\sum_{j \in N(new)} \alpha_{new,j} W h_j\right) \tag{3}$$

Through this method, the real-time updates to the HKG is achieved, thus supporting dynamic monitoring and identification throughout the manufacturing process. When calculating edge weights, special attention must be paid to the heterogeneity of multiple parameter types in textile manufacturing systems. Because process parameters such as temperature (unit: °C), tension (unit: N), and production speed (unit: m/min) vary significantly in both dimension and numerical range, directly substituting them into the Euclidean distance formula would cause larger parameters to dominate the calculation results, while the influence of smaller parameters would be severely diminished. This undermines the original intent of "multiple parameters collaboratively reflecting entity associations." Therefore, before calculating the Euclidean distance of node eigenvectors, all parameters must be standardized using the Z-score method, converting each parameter to a normalized value with a mean of 0 and a standard deviation of 1.

To better illustrate the construction of heterogeneous knowledge graphs, this paper uses a textile weaving workshop as an example to define the following specific node and edge types. Node types include equipment, processes, raw materials, quality, and parameters. Edge types describe the interactions among them precisely: equipment and processes are connected through an "execution" relationship; processes and raw materials are connected through a "consumption" or "use" relationship; processes and products are connected through a "generation" relationship; and parameter nodes are connected to equipment through a "monitoring" relationship and to processes or quality through an "influence" relationship. This fine-grained definition unifies the modeling of physical entities, operational processes, material flows, and quality results in the production system, laying the foundation for the subsequent precise tracking of the disruptive transmission chain of "equipment anomaly–parameter fluctuation–process deviation–quality defect."

META-PATH DEFINITION AND CROSS-DOMAIN SEMANTIC RELATIONSHIP EXTRACTION

A meta-path is a high-level abstraction tool for describing semantic relationships among cross-type entities in heterogeneous graphs [14]. In the textile intelligent manufacturing scenario, meta-paths effectively capture the causal chains among various entities, such as equipment, process, material, and quality inspection [15,16]. For example, the meta-path "equipment–process–product" can reveal how equipment parameters affect product quality through the process chain.

Let the node type set be $T = \{T_1, T_2, \ldots, T_m\}$ and the edge type set be $R = \{R_1, R_2, \ldots, R_n\}$. A meta-path P can be formalized as a series of alternating node types and edge types:

$$P : T_1 \xrightarrow{R_1} T_2 \xrightarrow{R_2} \cdots \xrightarrow{R_k} T_{k+1} \tag{4}$$

The above equipment–process–product meta-path can be formalized as:

$$P_{\text{Device}-\text{Process}-\text{Product}}: \quad \text{Device} \xrightarrow{\text{Executes}} \text{Process} \xrightarrow{\text{Produces}} \text{Product} \tag{5}$$

In order to quantify the importance of a meta-path, the path influence coefficient $\gamma(P)$ is introduced. This coefficient combines two indicators: one is the abnormal contribution of path-related entities (such as the historical abnormality triggering rate of the equipment node in a given path and the abnormal sensitivity of process parameters), calculated by counting the participation frequency and impact range of the entities in past disruptive events; the other is the propagation efficiency of the path (such as the average number of transmission steps for the abnormal signal from the source entity to the terminal entity along the path). Fewer steps indicate higher propagation efficiency and a larger $\gamma(P)$ value. The optimized meta-path weight formula is:

$$w(P) = \frac{f(P) \cdot \gamma(P)}{\sum_{P' \in S} f(P') \cdot \gamma(P')} \tag{6}$$

S represents the set of all possible meta-paths. This weight reflects the relative importance of a meta-path in the global semantics.

Using data-driven path mining as a foundation, the model retrospectively analyzes historical disruptive events based on the constructed HKG. Utilizing a graph traversal algorithm, the model exhaustively enumerates all possible paths from the anomaly source to the final quality defect. These paths are then subjected to frequency statistics and pattern clustering to identify frequently occurring patterns with clear physical meaning. For example, paths such as "equipment $\rightarrow$ process $\rightarrow$ product" appear repeatedly in historical data, indicating that equipment status ultimately determines product quality by influencing the processes it executes. This is then validated and refined using expert knowledge from the textile industry. A team of experts reviews the candidate meta-paths, eliminating those with unclear physical meaning or logically invalid paths. The path structure is then standardized based on the inherent laws of the process flow. Finally, the model combines data frequency and expert consensus to identify core meta-paths.

DISRUPTIVE SIGNAL PROPAGATION BASED ON MULTI-HEAD ATTENTION

In HGNN, information propagation is a key step for node feature learning. Since nodes and edges in the textile manufacturing system have different types and semantics, traditional graph convolutional networks (GCNs) struggle to capture the complex relationships among cross-type entities. Therefore, this paper designs an information propagation method based on the Multi-head Graph Attention Network (Multi-head GAT). The core idea of Graph Attention Network (GAT) is to dynamically adjust the intensity of information propagation by calculating attention weights between nodes [17,18]. For any two connected nodes v_i and v_j, their attention weight α_{ij} is defined as:

$$\alpha_{ij} = \frac{\exp\left(\text{LeakyReLU}\left(a^T[Wh_i \| Wh_j]\right)\right)}{\sum_{k \in N(i)} \exp\left(\text{LeakyReLU}\left(a^T[Wh_i \| Wh_k]\right)\right)} \tag{7}$$

h_i and h_j represent the feature vectors of nodes v_i and v_j, respectively. W is a learnable weight matrix. a is the parameter vector of the attention mechanism. $N(i)$ represents the neighbor set of node v_i. To enhance the model's adaptability to multiple entity types, a multi-head attention mechanism is employed. Attention weights are calculated in parallel through multiple independent attention heads, and the results are concatenated or averaged [19,20]. Assuming there are K attention heads in total, the updated feature h_i' of node v_i is expressed as:

$$h_i' = \left(\frac{1}{K} \sum_{k=1}^{K} \sum_{j \in N(i)} \alpha_{ij}^{(k)} W^{(k)} h_i \right) \tag{8}$$

Through this Multi-head GAT, the model can adaptively capture information propagation patterns under different meta-paths [21]. For example, in the meta-path equipment–process–product, the model can prioritize the impact of equipment parameters on the process while reducing the influence of other irrelevant factors.

GLOBAL GRAPH REPRESENTATION AND IDENTIFICATION OF DISRUPTIVE TRANSMISSION CHAINS

After completing node-level feature learning, the next step is to achieve global modeling of the entire textile manufacturing system through graph-level representation learning. This paper designs a representation learning method based on graph pooling to aggregate local node features into global graph features [22,23]. Assume the graph G contains N nodes, and the feature vector of each node is $h_i \in \mathbb{R}^d$. First, the initial representation g of the graph is calculated by weighted summation:

$$g = \sum_{i=1}^{N} \beta_i h_i \tag{9}$$

β_i is the importance weight of node v_i, calculated via the attention mechanism.

To further enhance the expressive power of the global representation, a multilayer perceptron (MLP) is introduced to perform a nonlinear transformation on g [24]:

$$z = \text{MLP}(g) \tag{10}$$

The final vector, $z \in \mathbb{R}^D$, is the global representation of the graph.

Based on the global representation z, an anomaly scoring module is designed to identify disruptive events with global influence. The anomaly scoring function S(G) is defined as:

$$S(G) = \|z - z_{\text{normal}}\|^2 \tag{11}$$

z_{normal} is a global representation under normal conditions. The higher the score, the more severe the anomaly in graph G. The K-means clustering algorithm is used to represent the global representation of the 12,000 normal samples. The core cluster with the highest number of samples in the cluster center is selected, and the weighted average of all sample representations in the cluster is calculated. The final weighted average vector is z_{normal}. Through this module, the model can accurately identify the source of disruptive events in the textile manufacturing process and simulate their propagation paths.

The key implementation details of the model are as follows: the network structure adopts a three-layer HGNN, comprising one input layer, one multi-head attention hidden layer (with K = 8 attention heads and an output dimension of 64 for each head), and one graph pooling output layer. Training parameters are set to a batch size of 32, 100 training epochs, and the Adam optimizer (initial learning rate 0.001, decaying to 0.8 of the previous round every 20 epochs). The early stopping strategy terminates training if the F1-score of the validation set does not improve for 10 consecutive rounds. Hyperparameter search uses five-fold cross-validation combined with grid search, with search ranges including the number of attention heads (4/6/8), learning rate (0.01/0.001/0.0001), and batch size (16/32/64).

III. EXPERIMENTAL DESIGN

DATASET AND DISRUPTIVE EVENT ANNOTATION RULES

This paper selects the Textile Weaving Dataset for Production & Rejection as experimental data. This dataset, collected and publicly released by a weaving factory in Bangladesh, covers the complete production chain— ranging from equipment operating status, process parameters, and raw material information to final product quality inspection. A portion of the dataset is shown in Table 1:

This dataset comprehensively covers key entities and their associated information in the textile manufacturing process, including equipment, process parameters, raw material characteristics, and quality inspection results. It supports the construction of various node and relationship types, making it well-suited for heterogeneous graph modeling. Furthermore, the dataset contains numerous real-world anomaly and rejection records, providing a reliable foundation for validating the HGNN-based disruptive anomaly identification method and supporting the data-driven identification of key anomaly nodes and their chain reactions.

The experimental data partitioning and validation strategy is as follows: Considering the temporal continuity of textile manufacturing data, a time series partitioning strategy is adopted, dividing the dataset into a training set (70%, data from months 1 to 8) and a test set (30%, data from months 9 to 12) in chronological order to avoid overestimating model performance due to future data leakage. To ensure result reliability, five-fold cross-validation is used, and all experimental indicators are calculated through ten repeated experiments to ensure objectivity and stability in model performance evaluation. This approach meets the requirements for data temporality and experimental reproducibility in textile intelligent manufacturing scenarios.

COMPARISON MODELS AND EVALUATION INDICATORS

To validate the effectiveness of our approach, we selected GCN, GAT, R-GCN, and HAN as comparison models. As a baseline, GCN is only applicable to homogeneous graphs and employs equal aggregation, making it unable to handle heterogeneity and differences in node importance. GAT introduces an attention mechanism that can distinguish neighbor weights, but it is still limited to homogeneous graphs and struggles to model cross-type causal chains, such as equipment $\rightarrow$ process $\rightarrow$ quality. R-GCN handles heterogeneous graphs through relationship-specific weights, but its aggregation mechanism lacks dynamic awareness of path importance, limiting its learning capabilities with small sample sizes. While HAN can capture heterogeneous semantics through meta-paths, its standard implementation is based on static graphs and fixed meta-path processing, making it difficult to adapt to the dynamic evolution of production systems and unable to specifically strengthen "weakly connected, strongly influential" paths.

IV. RESULTS ANALYSIS

COMPARATIVE ANALYSIS OF DISRUPTIVE EVENT IDENTIFICATION ACCURACY

Path identification accuracy is the core indicator for evaluating the model's ability to capture multi-entity causal chains. The experiment selected five typical meta-paths in textile manufacturing (equipment–process, raw materials–process, equipment–process–product, raw materials–process–quality, device–process–procedure–quality) to compare the recognition effects of the HGNN proposed in this paper with those of the GCN, GAT, R-GCN, and HAN models. The results are shown in Figure 1.

As shown in Figure 1, HGNN performs significantly better than the comparison models on all paths. In long causal chain paths such as "device–process–procedure–quality," HGNN's accuracy reaches 82%, which is 12 percentage points higher than that of HAN. In the "equipment–process–product" path, HGNN's accuracy is 89%, 13 percentage points higher than the next-best model, HAN. These results demonstrate that HGNN can more accurately capture key causal relationships between entities of different types through the meta-path-guided attention mechanism, especially in complex paths with multiple serial links.

Notably, HGNN demonstrates a significant performance advantage on long causal chain paths, such as "equipment–process–step–quality." This advantage arises because long paths are more sensitive to information attenuation and noise. In traditional graph neural networks, as multi-hop

TABLE 1. Sample of the dataset

ID	Month	Construction	Rec_Beam_length (yds)	Shrink_allow	act_shrink (%)	Previous_pdn
12207-8	January	40+40/2/40/110x80	5752.336	12.5	12.26173158	5047
12207-8	January	40+40/2/40/110x80	5883.568	12.5	64.12041129	1952
12207-8	January	40+40/2/40/110x80	3094.888	12.5	24.13295732	2207
12207-8	January	40+40/2/40/110x80	5894.504	12.5	14.734132	5026
12207-8	January	40+40/2/40/110x80	5850.76	12.5	21.46319453	4391
12207-8	January	40+40/2/40/110x80	5905.44	12.5	22.69839335	4340
12207-8	January	40+40/2/40/110x80	5905.44	12.5	33.04478582	3754
12207-8	January	40+40/2/40/110x80	38286.936	12.5	27.79260268	TOTAL

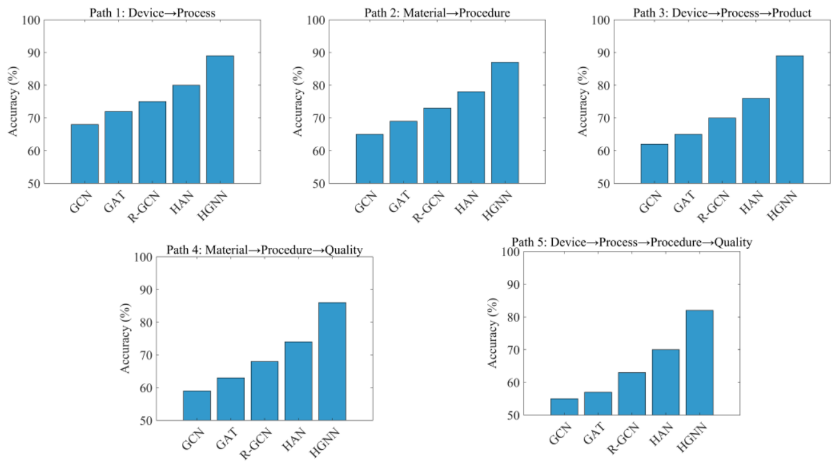

FIGURE 1. Recognition effect under different paths

information propagation increases, the effective signal at the source gradually weakens due to layer-by-layer aggregation. Simultaneously, interference from irrelevant nodes is continuously introduced, diluting the key causal signal in the final node representation. The HGNN proposed in this paper effectively alleviates this problem through two core designs. First, its meta-path-guided attention mechanism provides clear "semantic navigation" for information propagation. When calculating attention, the model not only focuses on direct neighbors but also constrains and guides the direction of information flow through predefined long meta-paths.

To further compare the different methods, the path recognition performance of each model was statistically analyzed, as shown in Table 2:

TABLE 2. Path recognition performance of different models

Model	Average accuracy (%)	Highest accuracy (%)	Minimum accuracy (%)	Standard deviation (%)
GCN	61.8	68	55	4.5
GAT	65.2	72	57	4.1
R-GCN	69.8	75	63	3.6
HAN	75.6	80	70	3.2
HGNN	86.6	89	82	1.8

The data in Table 2 show that the average accuracy of HGNN is 86.6%, which is 11 percentage points higher than that of HAN. Its lowest accuracy (82%) is still higher than HAN's highest accuracy (80%), and the standard deviation is only 1.8%, indicating that HGNN is more stable across different paths. This is attributed to HGNN's accurate modeling of the HKG and dynamic adjustment of meta-path weights, which effectively strengthen information dissemination along key causal chains.

RECALL RATE AND F1-SCORE IN SMALL-SAMPLE SCENARIOS

The false alarm rate directly affects the practical application value of the model. The experiment verified HGNN's noise suppression capability by analyzing the proportion of false alarms in the normal production cycle (without abnormal events) and evaluating changes in the false alarm rate under different noise intensities. The results are shown in Figure 2. The horizontal axis is the abnormality score, the vertical axis is the frequency of the sample size, and the dotted line represents the false alarm threshold.

As shown in Figure 2, the score distribution of HGNN is most concentrated in the low-score region (0–0.2), and the proportion of false positive samples exceeding the threshold is the smallest, while GCN and GAT have more high-scoring samples. This is because HGNN filters redundant noise in multi-source data through the semantic constraints of the HKG, and its dynamic edge weights weaken the interference relationships among irrelevant entities.

Small-sample scenarios are characteristic of disruptive events in textile intelligent manufacturing. Due to their suddenness and low incidence, disruptive events typically comprise only 1%–3% of the total data volume. Traditional models are prone to missed or false detections due to data sparsity. The experiment selected typical disruptive events with a sample size of 2.3% from the dataset, compared the comprehensive performance of different models in small-

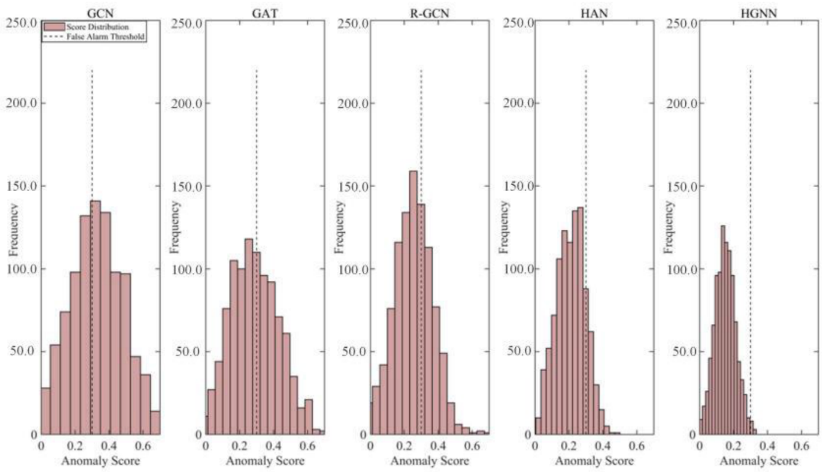

FIGURE 2. False positives of different algorithms

sample scenarios, and introduced five indicators: recall rate, precision rate, F1-score, miss rate, and detection delay. Detection delay is a key metric for measuring the timeliness of model warnings, calculated as follows: the actual trigger timestamp of the disruptive event is obtained from the experimental dataset; the moment when the device sensor first captures the abnormal parameter is recorded as the event's "actual occurrence time." The moment when the model outputs an "anomaly score" via the anomaly scoring module and triggers a warning signal is recorded as the "model judgment time t_1." The anomaly recognition delay is then calculated as the time difference "$t_1 - t_0$" in seconds.

It is defined as the time difference between the actual occurrence of a disruptive event and the first time the model outputs an effective warning signal. The results are shown in Table 3:

TABLE 3. Comprehensive performance in small-sample scenarios

Model	Recall rate (%)	Precision (%)	F1-score (%)	Miss Rate (%)	Detection Delay (s)
GCN	56.8	62.3	59.4	43.2	48.6
GAT	61.5	65.7	63.5	38.5	42.3
R-GCN	67.2	70.1	68.6	32.8	35.9
HAN	72.4	75.6	74	27.6	28.5
HGNN	81.3	84.7	83	18.7	12.8

In the small-sample scenario, analysis of the recognition performance indicators for each model shows that

HGNN performs best across all five metrics: recall rate, precision rate, F1-score, miss rate, and abnormal recognition delay. Its recall rate is 81.3%, 8.9 percentage points higher than that of HAN, and it more effectively captures low-incidence disruptive events. The F1-score is 83%, 9.0 percentage points higher than that of HAN, reflecting a better balance between precision and recall. The miss rate is only 18.7%, 8.9 percentage points lower than that of HAN, and the anomaly recognition delay is reduced to 12.8 seconds, 55.1% shorter than HAN, enabling rapid warning before the spread of small-sample events.

EVALUATION OF CROSS-LINK PROPAGATION PATH RESTORATION

The core value of GAT lies in its adaptive focusing on key entities and causal paths. The experiment visualizes the distribution of attention weights in a fabric defect event and analyzes HGNN's ability to capture core paths such as "equipment–process–quality." The results are shown in Figure 3:

Figure 3 displays the columnar distribution of attention weights for seven types of entities (loom #08, loom #15, yarn C, yarn D, tension parameters, temperature parameters, quality inspection). The weight for "loom #08" is 0.31, and for "tension parameters" is 0.29—both significantly higher than the other entities—indicating that the model accurately identifies the abnormal source equipment and key process parameters. The red high-value area in the inter-entity attention weight heat map clearly shows the path weight of "loom #08– tension parameter–quality inspection," while the weight of irrelevant paths such as "loom #15–temperature parameter" is less than 0.1, verifying the model's ability to focus on key causal chains.

To further assess GAT's ability to capture the core causal chain in textile manufacturing, the differences in attention weight allocation between HGNN and GCN, GAT, R-GCN, and HAN were analyzed for two key meta-paths—"equipment–process" and "process–quality"—that directly affect product quality. The results are shown in Figure 4.

As shown in Figure 4, in the weight distribution on the "equipment–process" path, the average weight of HGNN is 0.32, significantly higher than that of HAN (0.21); in the process–quality path, the average weight for HGNN is 0.35, while HAN's is 0.24. This difference arises because HGNN considers both meta-path frequency and semantic importance. In textile manufacturing, equipment–process–quality is the core causal chain affecting product defects, and the model dynamically increases its priority through the path weight formula, thereby enhancing the pertinence of anomaly identification.

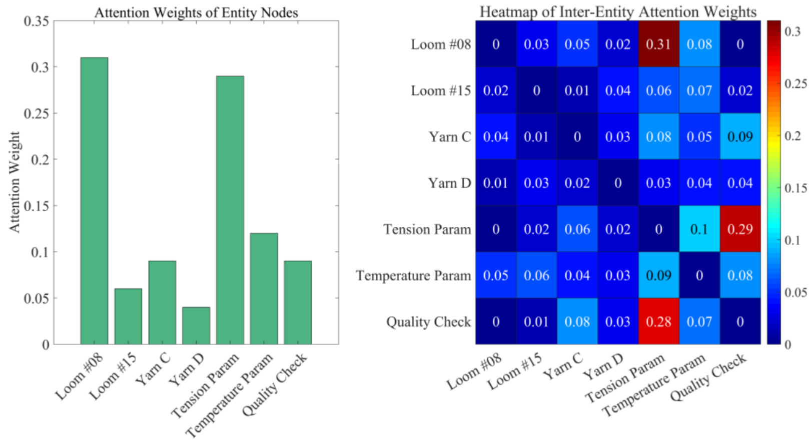

FIGURE 3. Distribution of attention weights among different entities

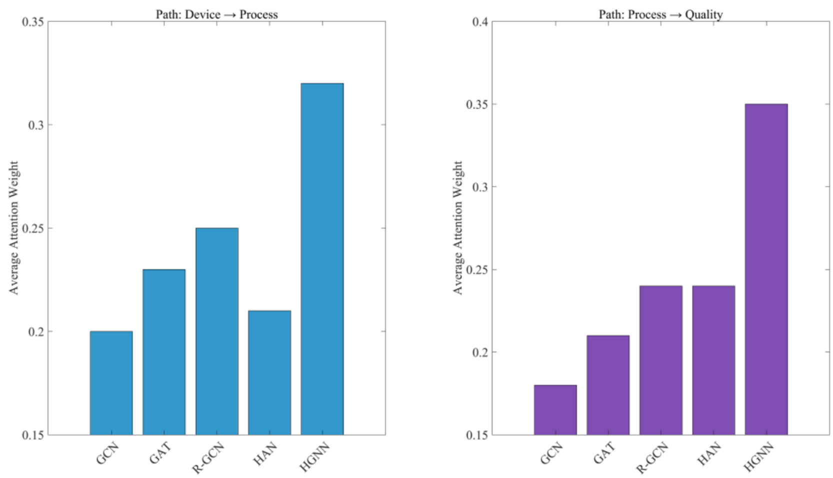

FIGURE 4. Differences in attention weight distribution among different algorithms

VERIFICATION OF THE ADAPTABILITY OF DYNAMIC UPDATES TO EVENT EVOLUTION

Dynamic update stability is a key indicator of the model's ability to adapt to real-time changes in the textile manufacturing system. The experiment verified the effectiveness of the HGNN's incremental learning mechanism by monitoring the fluctuation of model recognition accuracy over 200 consecutive hours. The results are shown in Figure 5:

As seen in Figure 5, the curve for HGNN is the most stable, always remaining within the 85%–88% range, with a fluctuation of less than 3%. The curves for GCN and GAT fluctuate more, with the lowest accuracy dropping to around 56% and 59%, respectively. This difference is due to HGNN's dynamic update strategy. When a new equipment node is added, the model updates only its neighbor features through incremental learning, avoiding performance fluctuations caused by global recalculation. Traditional models require retraining the entire graph structure, leading to accuracy fluctuations.

To fully verify the superiority of the incremental learning dynamic graph update mechanism, the response differences of different models were compared from two dimensions: "number of new nodes–update time" and "edge relationship complexity–accuracy recovery time." "Update time" refers to the time it takes the model to update the features of newly added nodes or edges. That is, the time difference between when the system generates new entity data and when the model completes the feature update for the new node and its neighbors through incremental learning and outputs the updated graph structure. This is measured in seconds and evaluates the model's response speed to dynamic system changes. "Accuracy recovery time" refers to the time difference, in minutes, it takes for recognition accuracy to recover from the "initial update fluctuation value" to the "stable threshold" after the new entity is incorporated. This metric evaluates the model's performance stability after dynamic updates, ensuring that the model can quickly return to a reliable recognition state after the addition of new entities.

The results are shown in Figure 6.

Figure 6 comprehensively illustrates the dynamic update response performance of each model under different update scales. Regarding the relationship between the number

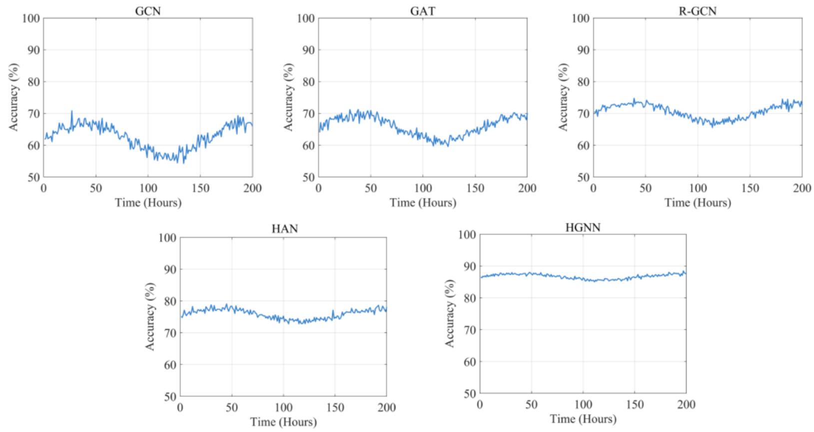

FIGURE 5. Accuracy fluctuations of each model during 200 hours of operation

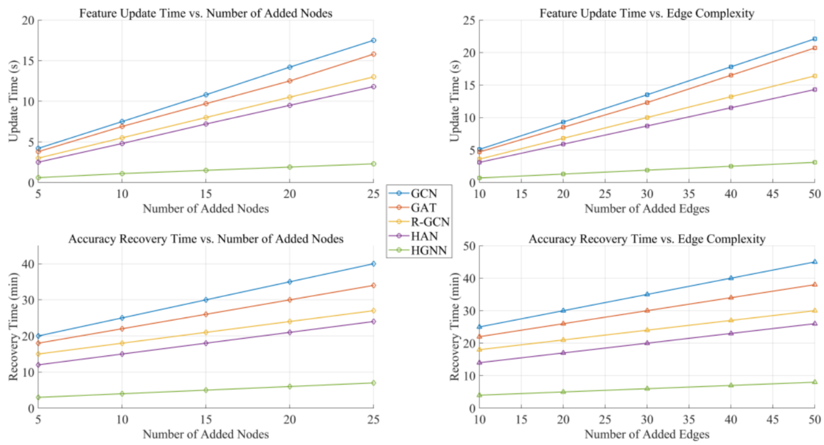

FIGURE 6. Comparison of dynamic update response performance

of newly added nodes, edge relationship complexity, and update time, the time consumption for HGNN increases linearly and slowly with scale. When 25 nodes are added, HGNN takes only 2.3 seconds, just 13% of GCN's 17.5 seconds. When 50 new edges are added, HGNN takes 3.1 seconds, much less than HAN and GCN. In terms of accuracy recovery time under different update scales, HGNN also performs well. When 50 new edges are added, the recovery time is only eight minutes, which is 30.8% of HAN's 26 minutes and 17.8% of GCN's 45 minutes.

To further quantify the economic benefits of the MOMILP model constructed in this paper within a real-world textile enterprise, we tested it using field operational data from a medium-sized textile enterprise in the Yangtze River Delta region (primarily engaged in chemical fiber fabric production, with an annual production capacity of 120 million meters and a supply chain including five raw material suppliers, three production bases, and eight regional distribution centers). The model was analyzed from the perspectives of cost savings and improved economic indicators. The results are shown in Table 4.

As shown in Table 4, in terms of cost breakdown, raw material procurement, production and processing, logistics and transportation, and carbon costs decreased by 17%, 20.5%, 26.0%, and 45.0%, respectively. The reduction in carbon costs was the most significant, confirming the effectiveness of the model's dynamic carbon price response mechanism in mitigating carbon market risks.

V. CONCLUSIONS

This paper addresses the challenges of modeling multi-source heterogeneous data and identifying disruptive risks in small-sample scenarios in textile intelligent manufacturing by proposing a technique based on Heterogeneous HGNN. A heterogeneous knowledge graph is constructed, encompassing entities such as equipment, processes, raw materials, and quality inspections, with a dynamic update mechanism enabling real-time tracking of the "trigger–propagation–outbreak" process, overcoming the limitations of static graphs. Meta-paths are defined, and a meta-path-guided multi-head graph attention mechanism is designed to focus on cross-domain causal chains with "weak connections but strong influences," enhancing identification in small-sample scenarios. Experiments demonstrate that the

TABLE 4. Quantification of economic benefits

Analysis	Dimensions	Specific Indicators	Baseline value	After the optimization of this method	Quantify the improvement effect
Cost	Savings Breakdown	Raw Material Procurement Cost (CNY 10,000/year)	18,600	15,432	Decreased by 17%
		Production and Processing Cost (CNY 10,000/year)	12,800	10,176	Decreased by 20.5%
		Logistics and Transportation Cost (CNY 10,000/year)	5,200	3,848	Decreased by 26.0%
		Carbon Cost (CNY 10,000/year)	1,560	858	Decreased by 45.0%
Core Economic	Indicators	Unit Output Value (CNY/meter)	3.13	2.45	Decreased by 21.7%
		Annual Total Profit (CNY 10,000)	9,200	13,800	Increased by 50.0%
		Return on Investment	1.2 years	0.8 years	Shortened by 33.3%

approach achieves an average recognition accuracy of 86.6% across five typical meta-paths. In a small sample comprising only 2.3% of the data, the F1-score reaches 83.0%, with anomaly identification latency reduced to 12.8 seconds, outperforming existing methods. Future work includes integrating this dynamic heterogeneous graph model with digital twin technology to enable real-time simulation and proactive risk prediction, developing automatic meta-path discovery and optimization via reinforcement learning, and extending the framework to broader discrete manufacturing scenarios to verify its universality and promote standardized intelligent risk prevention and control.

AUTHOR CONTRIBUTIONS

All work in this study was independently completed by Xiaomian Xu.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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