Multidimensional Trend Analysis of Human-Error Events via Network Analytics and GNN

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1. Introduction

Nuclear power plants are high-reliability systems characterized by redundant and diversified equipment and procedure-based operations, so the frequency of incidents is low. In this setting, vulnerabilities primarily arise from human performance, and human errors can lead to outcomes ranging from near misses to reactor trips, making continuous monitoring essential. Nuclear plants worldwide have widely adopted the trend-analysis approach recommended by the Institute of Nuclear Power Operations (INPO), using statistical analyses of reports, observations, and inspections to track changes and identify areas for improvement [1][2].

However, because human error emerges from nonlinear interactions among multiple factors, simple aggregation and conventional statistics are insufficient to capture common, cascading, and latent relationships. Accordingly, we construct a directed network graph that represents direct, root, and contributing causes—together with relevant equipment and systems—as nodes, and encode co-occurrence linkages as edges; on this basis, we design a network-analysis-based trend-analysis scheme. We then employ graph-theoretic metrics (e.g., Degree, Betweenness, PageRank) to identify influential factors and critical junctions, and apply graph neural networks (GNN) to learn higher-order interactions and nonlinear patterns that conventional statistics tend to miss [3]. Finally, by integrating traditional trend analysis with network- and deep learning–based analytics into a single methodology, we propose a multidimensional framework that jointly diagnoses the structural and contextual dimensions of human error.

2. Background

2.1 Trend Analysis Overview and Examples of Applications in Other Industries

Trend analysis is a method that systematically characterizes changes in data over time to forecast the future, understand past patterns, and identify the causes of change. In other industries, real-time monitoring enables the early identification of vulnerable areas, and proactive improvement measures are implemented to continuously enhance system reliability [2].

Table I: Case studies of trends in other industries

Industry	Description
Aviation	Track abnormal events and noncompliance; improve training/checklists.
Medical	Monitor monthly falls/infections/med errors; audit at change points.
Manufacturing/ Semiconductor	Detect yield/defect trends and process drift; optimize maintenance timing.
Finance/ IT Operations	Monitor abnormal logins and ticket trends; auto-respond on threshold breaches.

Examples of trend analysis from other industries are presented in Table I. From the plant perspective, trend analysis is essential for regularly monitoring human performance, identifying vulnerable areas, and establishing corresponding improvement strategies. At the enterprise level, comprehensively understanding trends across all plants enables the early identification of vulnerable domains or underperforming plants and supports the development and implementation of proactive improvement actions [4].

2.2 Overview of Network Analysis and GNN

Network analysis models the connection structure between events, factors, and contexts to identify 'what is connected to what, to what extent, and in what direction.' By defining nodes (e.g., direct/root/contributing causes, devices, systems) and edges (co-occurrence, temporal/causal relationships), we can assign weights and directions to explore structural patterns. The following metrics are used for this purpose.

Table II: Network Graph Metrics Examples

Indicators	Description
Degree (DG)	Number of edges connected to a node (immediate connectivity).
Frequent (FQ)	How often the element appears (basic importance proxy).

Betweenness Centrality (CB)	Share of shortest paths passing through the node (broker/bridge role)
PageRank Centrality (CP)	Influence from links received, weighted by the importance of linking nodes (recursive prestige).

The trend analysis designed in this study uses all four metrics from Table II to determine a comprehensive importance ranking of event factors and to interpret the events.

Graph neural networks (GNN) aggregate information on a network graph to update node representations, thereby learning nonlinear interactions among data and higher-order neighborhood context. Among GNN types, the Graph Attention Network (GAT) learns attention coefficients that weight neighbors' contributions, assigning greater importance to contextually salient connections. The resulting attention scores can be used to quantify influence between nodes.

3. Experiment

3.1 Network graph structure design

Network analysis visualizes and quantifies structural relationships among elements, thereby enhancing the interpretability of trend analysis by revealing connectivity, relational patterns, and centrality that content- or frequency-based approaches often miss [5].

To capture asymmetry and flow, we adopt a directed graph and explicitly encode information flow, dependency, and causal direction via edge orientation (e.g., A→B). Additionally, based on the procedural definitions of root, direct, and contributing causes for human-error events, we design the precedence/dependency structure and apply it to the GAT model.

3.2 GAT model training and attention score calculation

Building on the constructed directed network graph, we train a GAT model to quantitatively evaluate the importance of each node and edge. As nodes exchange information with their neighbors, the GAT applies an attention mechanism—rather than relying on simple connection strength—enabling the model to learn directly from data which paths are truly important [6].

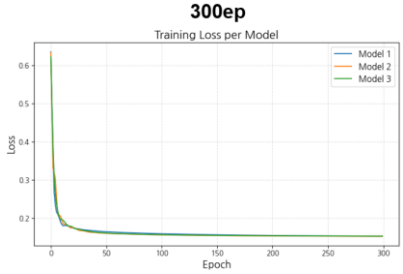

Fig. 1. Visualization of loss convergence during the GAT model training process

To improve training efficiency and generalization, we applied early stopping and model ensembling during training.

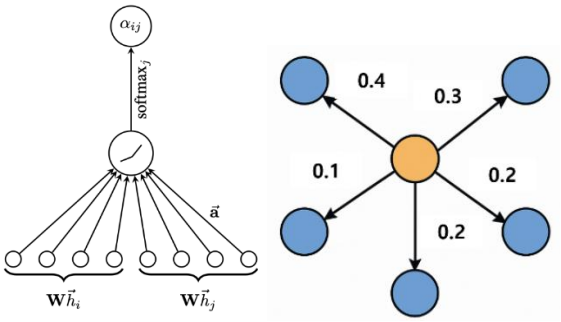

Fig. 2. Example of calculating attention scores using a neural network in the GAT model

The GAT model produces attention scores α_{ij} as shown in Fig. 2, and for a given node the sum over outgoing edges is not normalized, so it can be less than or greater than 1. In this study, we apply this mechanism to human-error event data to identify key factors that exert substantial influence on each event. In addition, using the AIS(Attention-based Influence Score) we developed, we normalize and aggregate the network's attention scores to quantify the strength of information propagation on a directed graph on a 0–1 scale. Furthermore, by integrating AIS with multidimensional trend analysis, we reveal critical factors that statistical indicators alone tend to miss and enhance the reliability and explainability of diagnosing human-error trends and vulnerabilities.

3.3 Multidimensional trend analysis in progress and radar chart visualization

Fig. 3. Multidimensional Trend Analysis Radar Chart

We visualized the metrics introduced in Table II and the AIS-based metrics (AIS, CB, CP, FQ, DG) using a radar chart in Fig. 3. for an at-a-glance comparison. The radar chart simultaneously displays node-level patterns, making it useful for intuitively identifying key influencing factors, hub nodes, and frequently occurring vulnerabilities. However, because the plotted area can vary with axis placement, the final ranking for precise numerical comparison was computed as the sum of the individual metric values. Using this visualization

together with quantitative analysis, we systematically diagnosed the key vulnerabilities in the human-error network.

3.4 Influencer Analysis Using Attention Score

The influence-factor analysis conducted in this study aims to determine which causal elements exert the greatest impact on specific equipment or systems within the network graph and conversely, identify which equipment/systems are most affected by a given causal element. The analysis leverages attention scores produced by the GAT model to quantitatively compare the network's effective flow of influence. Specifically, we trace all directed paths from each causal element (e.g., root, direct, contributing causes) to target nodes (e.g., pumps, compressors, fans). For each path, we compute its influence by multiplying the attention scores of all edges along the path, and then aggregate these path influences to evaluate the cumulative impact that each causal element exerts on the corresponding equipment or system.

Table III: Example of Influence Factor Analysis Results

Target Node	Source Node	Influence Score
pumps, compressors, fans	Aging of the device (root cause)	0.1143
	Blockage, obstruction, obstacle, (direct cause)	0.0745
	Inadequate preventive maintenance (root cause)	0.0653

Table III presents the top three influencing factors (source nodes) for each target node—pump, compressor, and fan. In the analysis, for each source node we computed the Influence Score as the sum, over all directed paths reaching the given target node, of the products of the attention scores along those paths. Applying this influence-factor analysis provides practical and reliable evidence for prioritizing causal elements that affect vulnerable equipment or systems, enabling preventive actions and tailored improvement strategies [7].

4. Conclusions

This study presented a multidimensional trend-analysis framework that integrates traditional trend analysis with network analysis and deep learning based (GNN) analytics to jointly diagnose the structural and contextual dimensions of key factors in human-error events. By combining network analytics and GNN within the trend analysis pipeline, the framework demonstrates the potential to reveal patterns that are difficult to capture with statistical indicators alone. The proposed framework can be directly applied to prioritizing vulnerable equipment and systems, establishing preventive actions, and targeting training and procedural improvements, thereby complementing conventional statistics-centered approaches. For future work, we plan to enhance the explanatory design of the network graph and optimize the GNN models to further improve analytical performance; doing so is expected to increase the reliability and explainability of human-error event analysis.

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