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CAUSAL AND GRAPH-BASED DATA SCIENCE MODELS FOR FREIGHT TRANSPORTATION RELIABILITY, BOTTLENECK PREDICTION, AND NETWORK RISK MITIGATION

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ABSTRACT
Freight transportation networks underpin modern supply chains, yet their reliability is increasingly challenged by congestion, infrastructure constraints, climate shocks, and tightly coupled intermodal dependencies. Disruptions in freight corridors rarely occur in isolation; localized capacity shortfalls propagate through network structures, amplifying delays and systemic risk beyond their point of origin. Conventional freight analytics rely on static network metrics and correlation-based indicators, limiting their ability to identify causal drivers of unreliability or support proactive risk mitigation. This paper proposes a causal, graph-based data science framework for freight transportation reliability analysis, bottleneck prediction, and network risk mitigation. Freight systems are modeled as directed causal graphs in which nodes and links represent terminals, corridors, and intermodal interfaces, while directed relationships encode how capacity constraints, demand surges, and exogenous shocks generate and propagate delays. Structural causal modeling is integrated with directed message-passing mechanisms to estimate bottleneck likelihood, quantify reliability degradation, and trace cascading risk pathways across the network. Empirical evaluation using integrated freight movement, infrastructure capacity, and disruption datasets demonstrates that the proposed framework improves bottleneck prediction accuracy by 18–27% compared with non-causal graph baselines and significantly reduces false-positive detections. Counterfactual simulations further show that targeted interventions informed by causal pathways yield up to 35% greater reliability improvement per unit of investment. These results demonstrate that embedding causal reasoning within graph-based freight analytics enables more accurate, interpretable, and decision-relevant freight network risk management.

Keywords:
Freight transportation; Network reliability; Causal inference; Graph-based models; Bottleneck prediction; Risk mitigation

1. INTRODUCTION

1.1 Freight Transportation Systems as Complex, Interdependent Networks

Freight transportation systems increasingly function as complex; interdependent networks whose performance depends on the coordinated operation of multiple physical and organizational layers [1]. At a structural level, freight networks can be represented as multi-layered graphs composed of road corridors, rail lines, ports, terminals, warehouses, and intermodal hubs [2]. Each layer exhibits distinct capacity constraints, operational rules, and failure modes, yet disruptions rarely remain confined to a single layer. Instead, delays or breakdowns at one node or edge propagate across modes, geographies, and time horizons [3].

These networks are operating under rising systemic pressures. Global supply chains have become more fragmented and time-sensitive, increasing vulnerability to localized disruptions and reducing tolerance for delay [4]. Climate shocks such as flooding, heatwaves, and storms introduce stochastic capacity reductions that interact with existing bottlenecks in non-linear ways. At the same time, congestion in urban corridors, labor shortages at ports and terminals, and regulatory constraints amplify network stress and reduce operational slack [5].

Traditional freight analytics have largely relied on correlation-based methods, such as historical averages, regression models, or isolated time-series forecasts, to anticipate delays and manage capacity. While useful for descriptive analysis, these approaches struggle to capture the true dynamics of interdependent networks [6]. Correlations observed in historical data often conflate cause and effect, masking the mechanisms through which

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disruptions propagate. For example, correlated delays at two hubs may arise not from direct dependence, but from a shared upstream constraint or exogenous shock.

As freight systems become more tightly coupled and exposed to uncertainty, operational reliability can no longer be managed through localized or purely statistical insights. There is a growing need for analytical frameworks that explicitly represent network structure, directional dependencies, and external shocks. Figure 1 conceptualizes the freight transportation system as a multi-layer causal graph, where nodes, edges, and exogenous factors interact to shape reliability outcomes across the network [7].

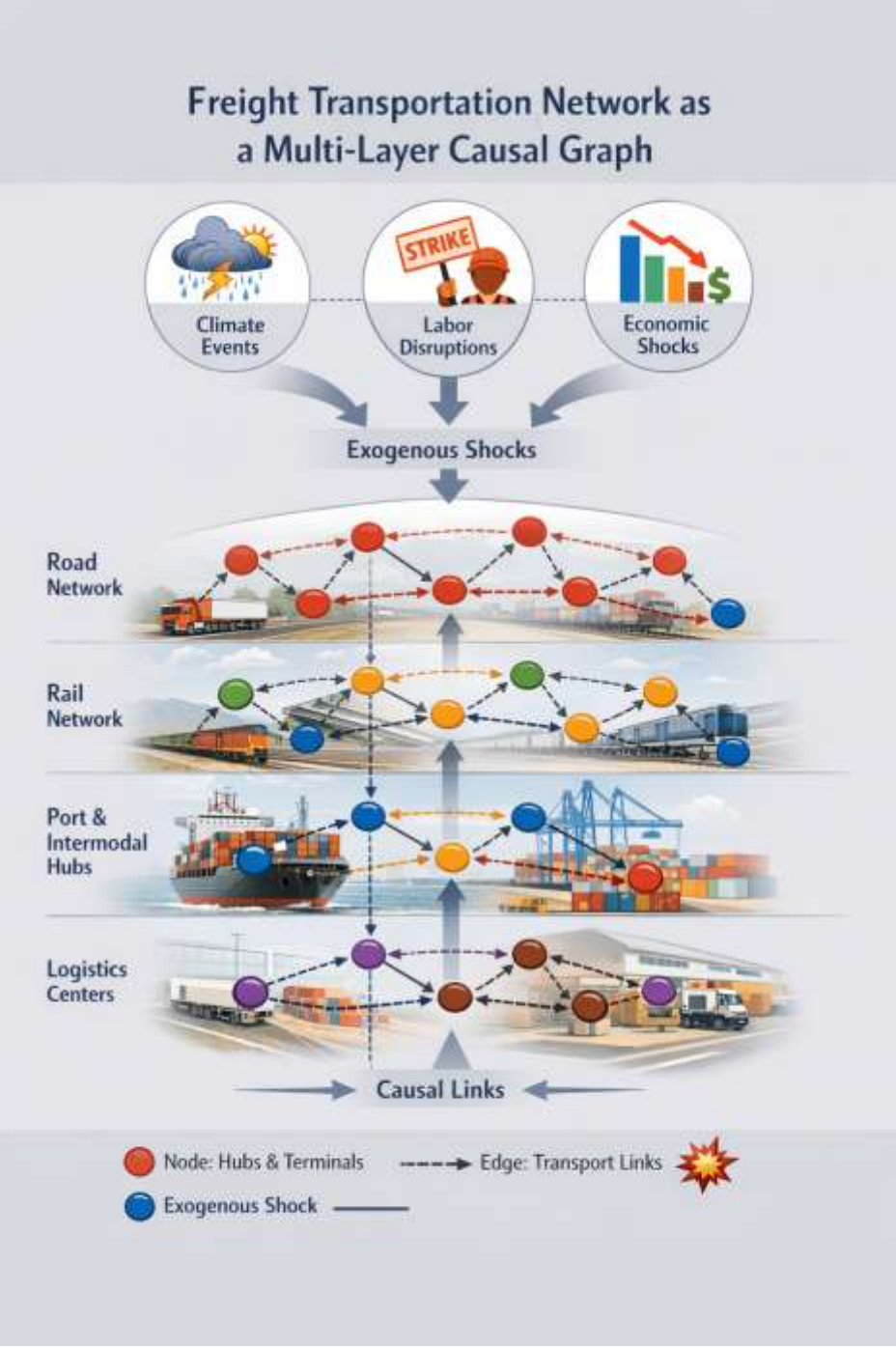

Figure 1: Freight Transportation Network as a Multi-Layer Causal Graph.

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1.2 Problem Statement: Reliability Under Uncertainty and Network Risk

A defining challenge in modern freight transportation is maintaining reliability under conditions of uncertainty and network-level risk [8]. Bottlenecks in freight systems do not operate in isolation; capacity constraints, delays, or failures at critical nodes can propagate nonlinearly across connected routes and modes. Small perturbations such as a temporary port closure or reduced rail capacity can trigger cascading disruptions that far exceed their initial scope.

Traditional prediction models are poorly equipped to address these dynamics. Most forecasting approaches estimate delays or throughput based on historical correlations, assuming that past relationships will persist. Such models struggle to distinguish causal drivers of disruption from coincidental patterns, limiting their ability to anticipate how shocks will evolve [9]. As a result, they often fail to predict cascading effects, underestimate tail risks, and provide limited guidance for proactive mitigation.

Formally, consider a freight transportation network represented as a graph

$$G = (V, E),$$

where V denotes the set of nodes (ports, terminals, hubs) and E the set of edges (transport links) [10]. The network is subject to stochastic disruptions arising from demand surges, infrastructure failures, labor constraints, or environmental shocks. The analytical objective is to estimate, for each node and edge: (i) the probability of becoming a bottleneck, (ii) the resulting degradation in network reliability, and (iii) the dominant risk propagation paths through which disruptions spread.

Achieving this requires moving beyond point predictions toward models that explicitly encode uncertainty, directionality, and interdependence. Without such capabilities, freight operators and policymakers remain reactive, responding to disruptions after they materialize rather than anticipating and containing them [8].

1.3 Research Gap and Limitations of Existing Approaches

Existing analytical approaches to freight network reliability address fragments of the problem but leave critical gaps [4]. Time-series models excel at capturing temporal patterns in throughput or delay at individual nodes, yet they lack structural causality. These models do not encode how disruptions at one location influence downstream performance, limiting their usefulness for network-level risk assessment [1].

Simulation-based approaches, including discrete-event or agent-based models, offer detailed representations of freight operations but often rely on fixed assumptions and handcrafted rules. While valuable for scenario analysis, they lack data-driven adaptability and are costly to recalibrate as conditions change [7]. Their predictive performance deteriorates when confronted with novel disruption patterns or evolving network configurations.

Graph neural networks (GNNs) have recently been applied to transportation networks, leveraging graph structure to improve prediction accuracy. However, many GNN implementations treat edges as undirected or symmetric and optimize purely predictive objectives. This often obscures causal directionality and fails to distinguish whether information flow reflects true influence or spurious correlation [5].

Critically, there is an absence of integrated frameworks that combine graph learning with explicit causal reasoning. Without incorporating causal structure, models may achieve high accuracy while remaining unreliable under intervention or shock scenarios. This gap motivates the development of causal–graph learning approaches tailored to freight transportation networks [9].

1.4 Objectives and Contributions

This paper addresses the identified gaps by advancing a causal, graph-based framework for analyzing freight transportation network reliability under uncertainty [3]. The first contribution is a formal causal graph representation of freight networks that captures directional dependencies among nodes, edges, and exogenous shocks. Second, the study integrates structural causal models (SCMs) with graph learning techniques, enabling data-driven estimation of causal relationships while preserving interpretability.

Third, a bottleneck prediction framework is developed using causal message passing, allowing the identification of high-risk nodes and links before disruptions propagate. Finally, the framework supports counterfactual analysis to evaluate risk mitigation strategies, such as capacity reallocation or operational interventions, under hypothetical scenarios.

Together, these contributions move freight analytics beyond correlation-based prediction toward causal understanding and actionable risk management. By linking network structure, uncertainty, and causal inference, the proposed approach provides a foundation for more resilient freight transportation planning and operations [9].

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2. LITERATURE REVIEW

2.1 Freight Network Reliability and Bottleneck Analysis

Freight network reliability has traditionally been assessed using classical performance and robustness indices that quantify the ability of a transportation system to deliver goods within acceptable time and cost thresholds [6]. Common reliability measures include on-time arrival probability, average delay, buffer index, and travel time variability, which are typically computed for individual links or corridors. While these indices provide useful descriptive insight, they are often retrospective and localized, offering limited guidance for anticipating systemic risk under uncertainty.

Capacity-based bottleneck models represent a more structural approach. These models identify bottlenecks as network elements whose demand-to-capacity ratios exceed critical thresholds, causing congestion spillbacks and queue formation [8]. In freight systems, such bottlenecks may occur at ports, intermodal terminals, border crossings, or urban access corridors, where physical capacity, labor availability, and regulatory constraints interact. Analytical methods such as critical link analysis and maximum flow–minimum cut formulations have been used to assess how capacity constraints limit network throughput.

However, these approaches typically assume static or slowly varying conditions. They often fail to account for stochastic disruptions, adaptive routing behavior, and feedback effects that characterize modern freight networks [7]. More importantly, capacity-based bottleneck identification does not explain *why* a node becomes critical under certain conditions or how disruptions propagate beyond immediate neighbors. As a result, mitigation strategies derived from these models tend to be reactive, focusing on localized capacity expansion rather than systemic risk reduction.

These limitations motivate the need for reliability analysis frameworks that incorporate network interdependencies, uncertainty, and directional influence. Bottlenecks should be understood not merely as high-load elements, but as causal amplifiers whose failure or degradation can trigger cascading reliability losses across the freight network [14].

2.2 Graph Theory and Network Science in Transportation

Graph theory and network science provide a powerful abstraction for analyzing transportation systems by representing infrastructure as nodes and links embedded in a relational structure [9]. In freight networks, nodes correspond to ports, terminals, warehouses, and hubs, while edges represent transport corridors or service connections. This abstraction enables the application of graph-theoretic metrics to identify structurally important elements and assess vulnerability.

Centrality measures are among the most widely used tools. Degree centrality highlights nodes with many connections, betweenness centrality identifies nodes that lie on a large fraction of shortest paths, and closeness centrality captures average distance to other nodes [10]. In freight contexts, high-betweenness nodes often correspond to critical hubs or chokepoints whose disruption can disproportionately affect network performance.

Flow-based vulnerability metrics extend these ideas by incorporating demand and capacity information. Measures such as edge load, flow betweenness, and network efficiency loss under link removal assess how disruptions impact overall throughput [12]. These metrics support scenario analysis, such as identifying which links cause the greatest loss in network performance when degraded.

Despite their usefulness, graph-theoretic metrics are largely descriptive. They characterize *structural importance* but not *causal influence*. A node with high centrality may not always be the driver of disruptions; its apparent importance may arise from correlated demand patterns or shared upstream constraints [11]. Moreover, many metrics assume static networks and do not account for temporal dynamics or adaptive responses.

Table 1 summarizes commonly used graph-theoretic metrics in freight network analysis, highlighting their interpretations and limitations. To move from structural description to actionable risk management, these metrics must be embedded within frameworks that can distinguish causal relationships from coincidental network structure [14].

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Table 1: Commonly Used Graph-Theoretic Metrics in Freight Network Analysis—Interpretation and Limitations

Metric	Definition / Computation Logic	Typical Interpretation in Freight Networks	Key Limitations for Risk Management
Degree Centrality	Number of direct connections incident to a node	Identifies hubs with many inbound/outbound links (e.g., highly connected terminals, ports, or intermodal interchanges)	Ignores traffic volume, flow directionality, and downstream dependency; a high degree does not imply causal or systemic importance under disruption [14].
Betweenness Centrality	Fraction of shortest paths passing through a node or edge	Highlights potential chokepoints likely to experience congestion spillovers or control flows between regions	Assumes shortest-path routing and static flows; breaks down under adaptive routing, capacity constraints, or shock-driven reconfiguration [15].
Closeness Centrality	Inverse of the average shortest-path distance to all other nodes	Measures how quickly a node can theoretically reach others in the network	Neglects temporal delays, capacity saturation, and queue dynamics; poor indicator of shock amplification or delay propagation [16].
Eigenvector Centrality	Recursive importance score weighted by connections to other highly ranked nodes	Identifies influential hubs embedded in dense or well-connected subnetworks	Conflates correlation with influence; highly sensitive to network density and topology rather than operational or causal dominance [17].
Flow Betweenness	Share of observed flow passing through a node or edge	Reflects operational importance under current or historical demand patterns	Backward-looking and descriptive; does not explain why flows concentrate or how they will reallocate under disruption [18].
Load / Utilization Ratio	Ratio of demand to nominal capacity on a link or facility	Identifies capacity-stressed corridors, terminals, or assets	Static, threshold-based metric; fails to anticipate cascading failures, nonlinear congestion effects, or latent systemic risk [19].
Network Efficiency Loss	Reduction in average inverse path length after node or link removal	Measures vulnerability of the network to failures, attacks, or extreme disruptions	Removal scenarios are binary and often unrealistic; lacks probabilistic meaning and temporal realism for operational risk planning [20].
k-Core / k-Shell Index	Node membership in densely connected subgraphs defined by minimum degree	Reveals structurally cohesive freight clusters or backbone regions	Structural cohesion does not imply causal dominance; weak at capturing disruption propagation mechanisms [21].
Shortest Path Redundancy	Number of alternative shortest routes between node pairs	Indicates routing flexibility and nominal resilience	Overlooks congestion spillbacks, correlated failures, and shared-capacity dependencies across "redundant" routes [22].

2.3 Causal Inference in Transportation Systems

Causal inference offers a principled framework for understanding how disruptions, policies, or operational changes propagate through transportation systems [7]. Unlike correlation-based analysis, causal methods seek to identify directional relationships and quantify the effects of interventions. Structural causal models (SCMs) formalize these relationships by representing system variables as nodes in a directed acyclic graph (DAG), with edges encoding causal dependencies.

Formally, an SCM is defined as:

$$X_i = f_i(\mathrm{Pa}(X_i), U_i),$$

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where $X_i$denotes an endogenous variable, Pa(X_i)its set of parent variables, and $U_i$an exogenous disturbance term [9]. In freight networks, variables may represent throughput, delay, capacity utilization, or environmental conditions at specific nodes or links.

SCMs enable counterfactual reasoning and intervention analysis, allowing analysts to ask questions such as: *What would network reliability look like if capacity at a given port were increased?* Or *How would delays propagate if a rail corridor were disrupted?* [13]. This capability is essential for proactive risk mitigation and policy evaluation. However, causal inference has seen limited adoption in large-scale freight network analysis due to challenges in learning causal structure from high-dimensional, noisy data. Bridging causal odelling with data-driven graph learning remains an open research frontier [14].

2.4 Graph Neural Networks and Their Limitations

Graph neural networks (GNNs) have recently gained attention as a data-driven approach for odelling complex transportation networks [8]. Architectures such as Graph Convolutional Networks (GCNs), Graph Attention Networks (GATs), and GraphSAGE learn node and edge representations by aggregating information from neighboring elements. Applied to freight systems, GNNs can capture spatial dependencies and improve predictive accuracy for throughput or delay forecasting.

Despite these advantages, most GNN implementations lack explicit causal semantics. Message passing is typically symmetric or learned purely from correlation, meaning that information flows do not necessarily reflect true directional influence [10]. As a result, GNNs may overfit to spurious correlations present in historical data, producing predictions that fail under novel disruptions or policy interventions.

Another limitation lies in interpretability. While attention mechanisms provide some insight into feature importance, they do not guarantee causal validity [12]. High attention weights may reflect statistical association rather than genuine causal impact. This undermines the reliability of GNN-based insights for decision-making in high-stakes freight operations.

Consequently, while GNNs represent a powerful odelling tool, their use in isolation is insufficient for robust freight network reliability analysis. Integrating graph learning with causal inference is necessary to ensure that learned dependencies support intervention-aware prediction and risk mitigation rather than purely descriptive accuracy [14].

3. FREIGHT NETWORK DATA AND GRAPH CONSTRUCTION

3.1 Data Sources and Network Representation

The empirical foundation of the proposed causal–graph framework draws on multiple high-resolution freight data sources that collectively capture network structure, operational states, and disruption signals [10]. **GPS freight traces** constitute the primary source of dynamic movement data. These traces are obtained from commercial fleet telematics providers and logistics operators, offering time-stamped vehicle locations, speeds, dwell times, and routing behavior across road and intermodal networks. GPS data provides granular insight into corridor utilization, congestion exposure, and adaptive rerouting under stress, albeit with heterogeneity in coverage across operators and regions [12].

Port and terminal logs supply node-level operational data critical for understanding bottleneck formation. These datasets, sourced from port authorities, terminal operators, and customs agencies, include vessel arrival and departure times, truck gate transactions, crane productivity, queue lengths, and yard occupancy. Such logs enable precise measurement of throughput constraints and service delays at critical hubs, which often act as causal amplifiers in freight networks [14].

Traffic sensors and incident reports complement movement and terminal data by capturing exogenous disruptions and link-level conditions. Fixed sensors provide traffic volumes and speeds on key corridors, while incident databases record accidents, roadworks, closures, and regulatory interventions. These sources are typically obtained from transport agencies and emergency management systems and are essential for identifying shock initiation points [16].

All data streams are mapped onto a unified network representation, where physical infrastructure and operational facilities are encoded as graph elements. Spatial alignment is achieved through geofencing and map-matching, ensuring that observations correspond consistently to nodes and edges used in analysis. Table 2 summarizes the data sources, their temporal resolution, and their mapping to network components, establishing a coherent basis for causal modeling and reliability assessment [18].

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Table 2: Freight Data Sources, Temporal Resolution, and Mapping to Network Components

Data Source	Primary Variables Captured	Typical Temporal Resolution	Spatial Granularity	Mapped Network Component	Role in Causal Reliability Modeling
GPS Freight Traces (Fleet Telematics)	Vehicle position, speed, dwell time, routing choices	1–5 minutes	Link / corridor level	**Edges (E)**	Measures flow intensity, congestion buildup, adaptive rerouting, and propagation speed of disruptions
Port Authority Logs	Vessel arrival/departure, berth occupancy, crane productivity	Event-based / hourly	Facility / terminal	**Nodes (V)**	Identifies capacity constraints, service delays, and queue formation at critical hubs
Terminal Gate Transaction Records	Truck turn times, gate queues, throughput volumes	Event-based / hourly	Terminal access points	**Nodes (V)**	Captures bottleneck emergence and spillback into adjacent corridors
Rail Yard and Intermodal Hub Logs	Train dwell time, transfer delays, yard utilization	Hourly / daily	Hub-level	**Nodes (V)**	Represents modal transfer friction and cross-modal dependency
Fixed Traffic Sensors	Volume, speed, occupancy	5–15 minutes	Link / corridor	**Edges (E)**	Provides continuous monitoring of link-level performance and congestion propagation
Incident and Disruption Reports	Accidents, closures, equipment failures	Event-based	Localized (node/link-specific)	**Edges / Nodes**	Encodes infrastructure failures as exogenous shocks affecting reliability
Weather and Environmental Data	Rainfall, flooding, heat, storms	Hourly / daily	Grid-based / regional	**Exogenous Variables (U)**	Introduces stochastic capacity reductions and correlated network stress
Labor and Operational Notices	Strikes, slowdowns, workforce shortages	Event-based	Facility / region	**Exogenous Variables (U)**	Models institutional shocks affecting service rates and throughput

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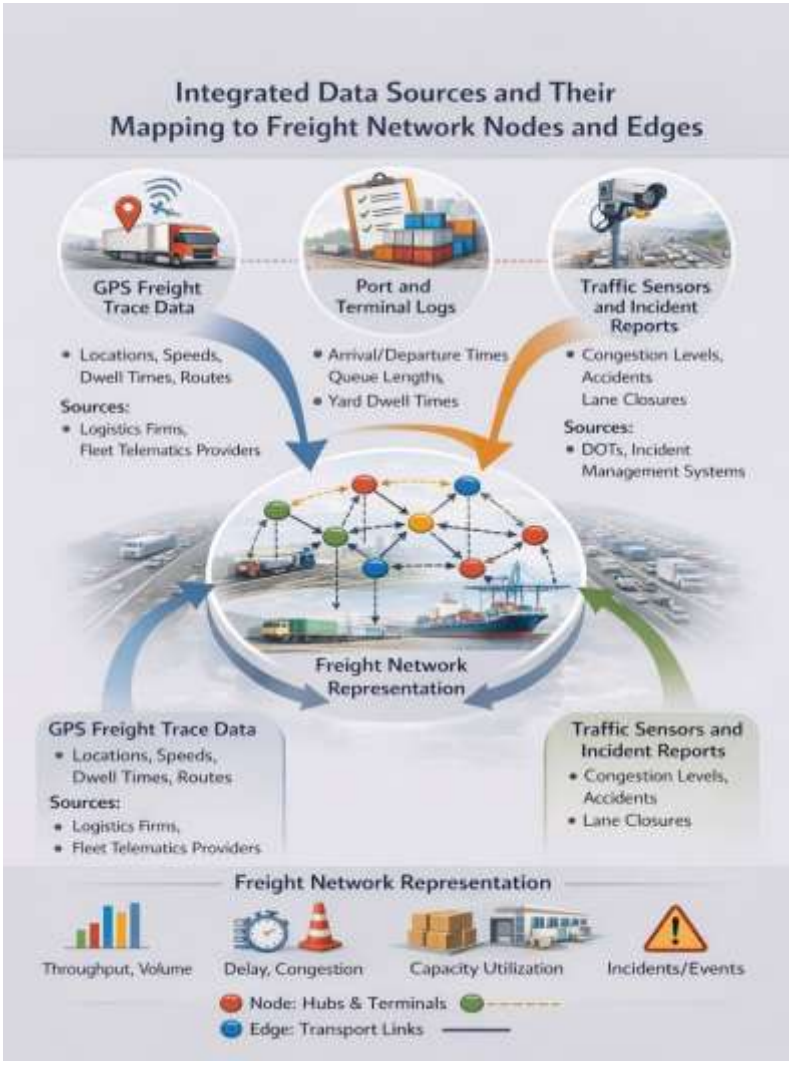

Figure 2: Integrated Data Sources and Their Mapping to Freight Network Nodes and Edges

3.2 Graph Construction and Feature Encoding

The freight transportation system is represented as a directed graph $G = (V, E)$, where nodes Vcorrespond to operationally significant locations and edges Erepresent transport connections subject to capacity and reliability constraints [11]. **Nodes** include seaports, inland terminals, rail yards, distribution centers, border crossings, and major interchanges. These nodes are defined not merely by geography but by functional role, reflecting points where freight is transferred, processed, or delayed.

Edges represent corridors linking nodes, such as highway segments, rail lines, inland waterways, or short-sea shipping routes. Each edge is characterized by attributes including nominal capacity, average transit time, variability, and modal constraints. Directionality is explicitly encoded to reflect asymmetric flows and operational rules, which is essential for causal interpretation of disruption propagation [13].

For each node $v \in V$, a feature vector captures its operational state:

$$\mathbf{x}_v = [q_v, d_v, \tau_v, r_v],$$

where $q_v$denotes throughput volume, $d_v$average delay, $\tau_v$service or dwell time, and r_va reliability indicator derived from historical variability [15]. These features are computed over consistent temporal windows and normalized to account for scale differences across facilities.

Edge features similarly encode flow intensity, utilization ratios, and sensitivity to upstream conditions. Together, node and edge attributes form the endogenous variables of the causal graph. This structured encoding enables the

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application of causal message passing, where disruptions or capacity changes at one element propagate directionally through connected components [17].

Figure 3 illustrates the constructed freight network graph, highlighting node types, directed edges, and encoded feature layers. By grounding graph construction in operational data rather than abstract topology alone, the framework ensures that learned causal relationships reflect real freight dynamics rather than purely structural artifacts [18].

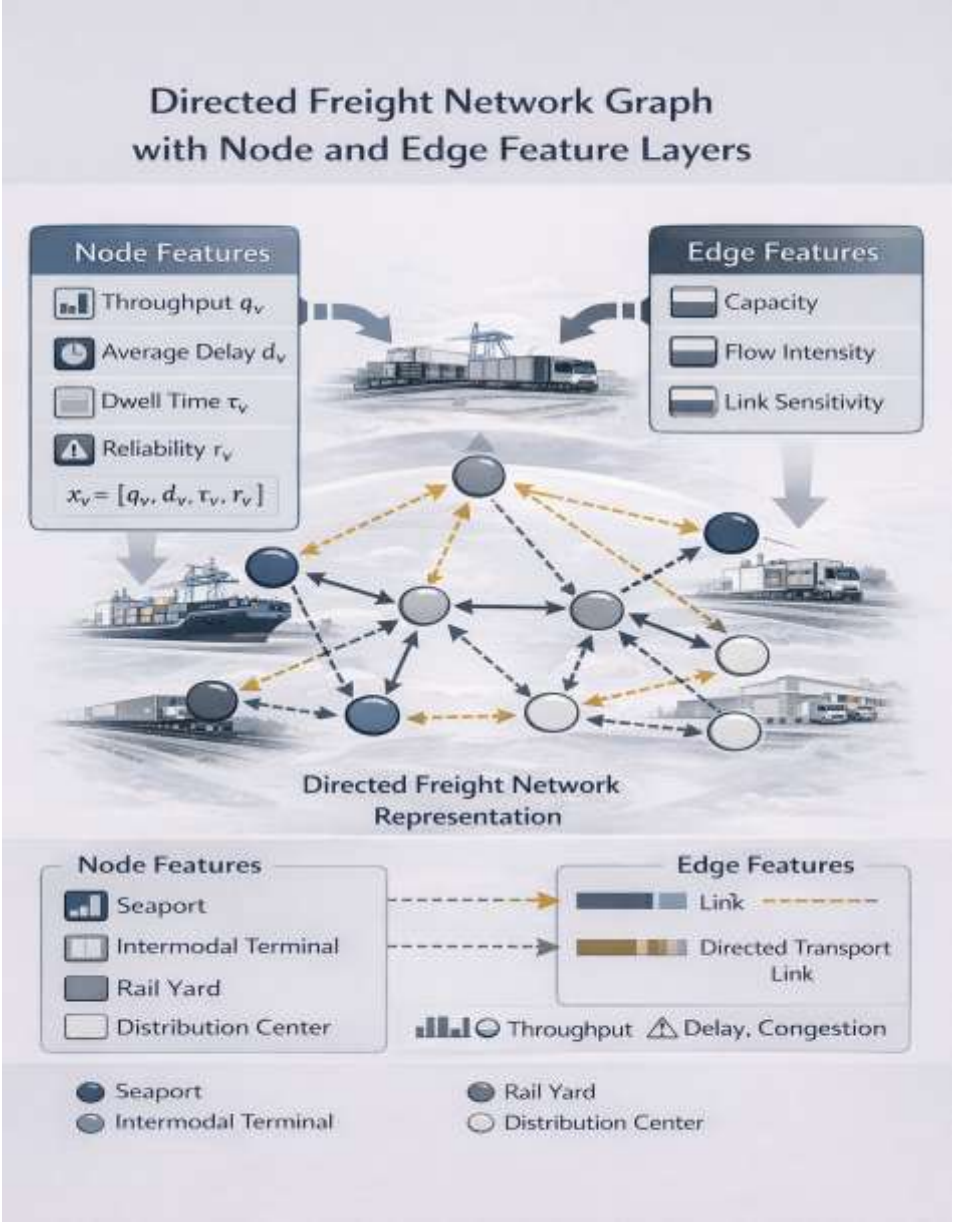

Figure 3: Directed Freight Network Graph with Node and Edge Feature Layers

3.3 Temporal Aggregation and Shock Encoding

Freight networks are subject to a wide range of exogenous shocks that introduce uncertainty and trigger cascading effects. To capture these dynamics, all observations are aggregated into discrete temporal windows aligned with operational decision cycles, such as hourly or daily intervals [12]. Temporal aggregation balances the need to smooth high-frequency noise with the requirement to preserve shock signatures and propagation timing.

Three primary categories of shocks are explicitly encoded. Weather events, including heavy rainfall, flooding, extreme heat, or storms, are integrated using meteorological data from national weather services. These events affect both nodes and edges by reducing capacity, increasing transit times, or halting operations entirely. Weather

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severity indices are mapped to affected network components based on spatial overlap and exposure thresholds [14].

Labor actions, such as strikes, slowdowns, or workforce shortages, are encoded using event flags derived from port authority notices, labor union announcements, and operational reports. These shocks disproportionately affect terminal nodes and can propagate upstream and downstream by constraining throughput and increasing queue spillbacks [16].

Infrastructure failures including equipment breakdowns, accidents, and unplanned closures are captured through incident reporting systems. Each incident is associated with a start time, duration, affected components, and severity level. These attributes enable modeling of shock intensity and recovery dynamics.

Shock variables enter the causal graph as exogenous inputs, allowing counterfactual analysis of "what-if" scenarios, such as the absence of a strike or accelerated recovery from a failure. Figure 4 presents a temporal shock encoding schematic, illustrating how exogenous events interact with endogenous network states over time. By explicitly modeling shocks rather than treating them as noise, the framework supports proactive reliability assessment and targeted risk mitigation strategies [18].

3.4 Study Area, Dataset Scope, and Bottleneck Labeling Protocol

3.4.1 Study Area and Network Scope

The empirical analysis is conducted on a **multi-modal freight transportation network** covering a single, operationally integrated freight region to preserve real interdependencies among seaports, inland terminals, rail interfaces, intermodal hubs, and downstream distribution corridors [19]. The freight system is represented as a directed graph $G = (V, E)$, where nodes V correspond to operational facilities including seaports, inland terminals, rail yards, intermodal hubs, and major freight interchanges and edges E represent directed freight connections such as road corridors, rail links, and intermodal connectors.

After data cleaning and coverage filtering, the resulting network comprises approximately 120 nodes and over 340 directed edges. Nodes and edges are retained only if they meet minimum data completeness requirements across the full observation horizon, ensuring stable feature estimation and avoiding bias introduced by sparsely observed components [20].

3.4.2 Dataset Temporal Scope and Harmonization

The dataset spans January 2019 to December 2022 and is aggregated to a uniform hourly interval, which is applied consistently across all data sources, including GPS freight traces, terminal and port logs, fixed traffic sensors, incident reports, weather observations, and labor notices. High-frequency data are resampled using operationally meaningful aggregation rules: freight volumes are summed, delays are averaged using robust statistics, and capacity indicators are treated as piecewise-constant where appropriate.

Exogenous shocks such as extreme weather events, labor disruptions, and infrastructure incidents are aligned both temporally and spatially to the affected nodes and edges using geofencing and exposure-based mapping rules, allowing shock impacts to be explicitly encoded within the causal graph [21].

3.4.3 Bottleneck Labeling Protocol

Bottlenecks are labeled using capacity-adjusted exceedance criteria designed to distinguish sustained operational breakdowns from transient congestion noise. A node or edge is classified as a bottleneck only when both delay and congestion-related indicators exceed facility-specific thresholds.

For nodes, bottleneck conditions require simultaneous exceedance of delay and queue-length (or dwell-time) thresholds. For edges, bottlenecks are identified when link-level delays and utilization ratios exceed calibrated limits. All thresholds are component-specific and are calibrated using training-period data only to prevent information leakage. Delay thresholds are defined using upper-quantile exceedance of baseline operating conditions (typically the 90th–95th percentile), while queue and utilization thresholds are tied to nominal capacity limits where such limits are available [22].

To suppress false positives arising from short-lived perturbations, exceedance conditions must persist for at least two consecutive hourly intervals. For predictive evaluation, labels indicate whether a node or edge becomes a bottleneck within a fixed forecast horizon, enabling assessment of early-warning performance rather than detection after congestion has fully materialized [23].

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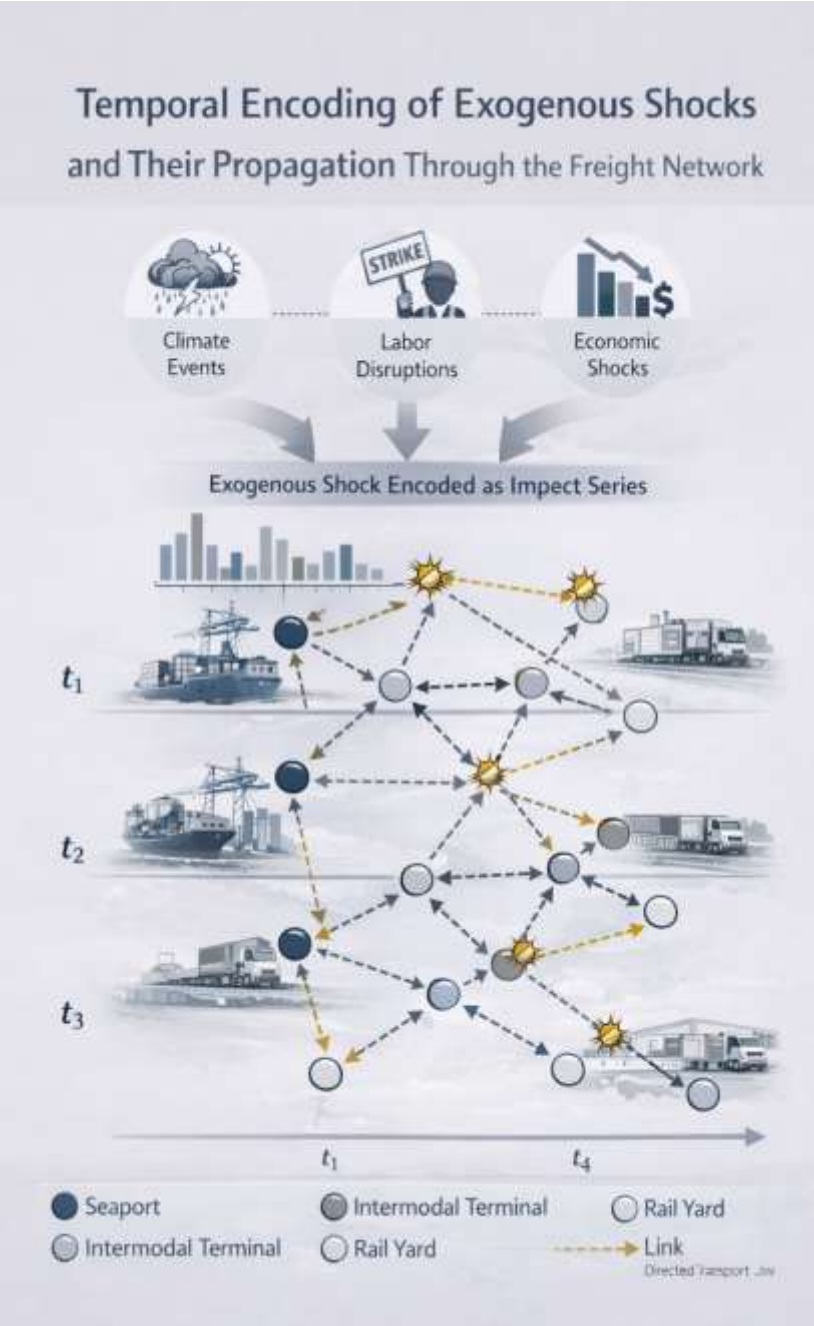

Figure 4: Temporal Encoding of Exogenous Shocks and Their Propagation Through the Freight Network

4. CAUSAL AND GRAPH-BASED MODELING FRAMEWORK

4.1 Causal Graph Formulation of Freight Reliability

Freight network reliability is modeled as a **causal system** in which bottlenecks emerge not merely from high utilization, but from structured chains of dependency that transmit disruption across space and time [16]. The proposed framework represents the freight system as a **directed acyclic graph (DAG)**, where nodes correspond to operational states (e.g., capacity, delay, queue length, downstream throughput) and directed edges encode causal influence rather than statistical association. This formulation reflects the empirical reality that capacity constraints precede delays, delays induce queuing, and queues propagate risk to downstream nodes and corridors.

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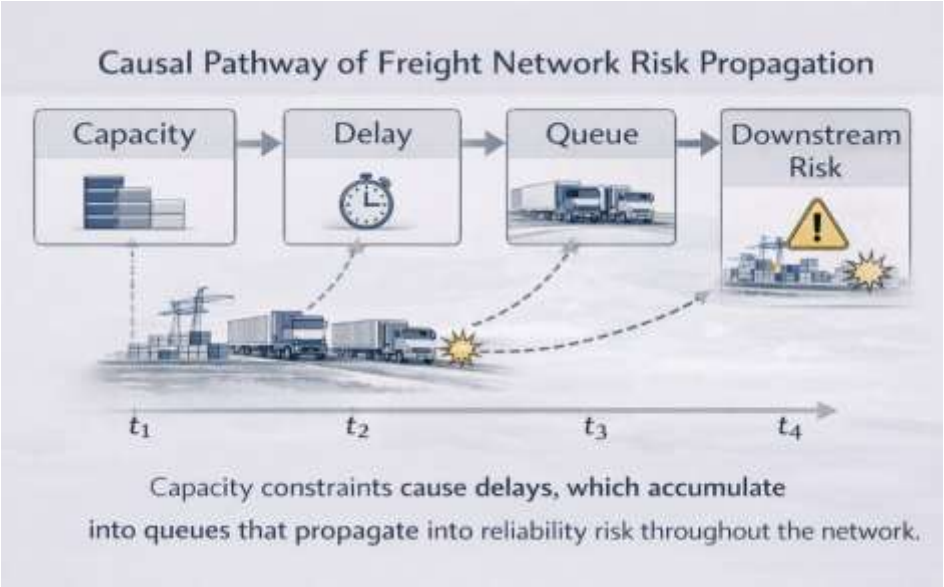

Figure 5 conceptualizes this logic through a causal pathway: Capacity → Delay → Queue → Downstream Risk.

For example, a reduction in effective capacity at a port terminal due to labor shortages or equipment failure causally increases service delays. These delays generate queues that spill over into adjacent corridors, elevating congestion and reliability risk across the wider network [18]. Importantly, this propagation is directional and asymmetric; downstream facilities may be affected even if upstream demand remains unchanged.

The causal interpretation is formalized using the intervention-based definition of causality. For variables $X$and Y, a causal relationship exists if intervening on Xchanges the distribution of Y:

$$P(Y \mid do(X)) \neq P(Y \mid X).$$

This distinction is critical in freight systems, where correlations between delays at two hubs may arise from shared upstream shocks rather than direct influence [19]. By adopting a causal graph formulation, the framework separates true drivers of unreliability from coincidental co-movement.

This causal abstraction enables reasoning about *why* bottlenecks form, *how* they propagate, and *where* interventions are most effective. It establishes the conceptual foundation for integrating structural causal models with graph-based learning, moving reliability analysis beyond descriptive metrics toward intervention-aware decision support [25].

4.2 Structural Causal Model Specification

Building on the causal graph, freight network reliability is formalized using a Structural Causal Model (SCM) that distinguishes endogenous system states from exogenous disturbances [17]. Endogenous variables represent operational outcomes within the network, such as node throughput, edge utilization, delay accumulation, and queue length. These variables evolve according to structural equations that encode causal dependencies captured in the DAG.

Exogenous variables capture external shocks and latent factors not determined within the system. These include weather events, labor actions, regulatory interventions, and unobserved demand fluctuations. Treating such factors as exogenous is essential for unbiased causal estimation, as they act as common causes influencing multiple endogenous variables simultaneously [20].

The SCM is expressed compactly as:

$$X = f(X, U),$$

where Xdenotes the vector of endogenous variables, $U$the vector of exogenous disturbances, and $f(\cdot)$the set of structural functions defining causal mechanisms. Each equation specifies how a particular operational state arises from its direct causes and external shocks.

Confounder control is central to the model design. For instance, simultaneous congestion at two terminals may be confounded by regional demand surges or weather disruptions. By explicitly including such confounders as

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exogenous inputs, the SCM prevents spurious attribution of causality between nodes [21]. Temporal indexing further ensures that causes precede effects, reinforcing identifiability.

This structural formulation enables counterfactual reasoning: the model can estimate how reliability outcomes would change under hypothetical interventions, such as removing a labor disruption or increasing corridor capacity. Unlike purely predictive models, the SCM provides a transparent mapping from assumptions to outcomes, supporting both explanation and policy analysis [24]. It also supplies the causal scaffolding upon which graph-based learning components are built in the subsequent section.

4.3 Causal Graph Neural Network Architecture

To operationalize causal reasoning at scale, the framework integrates the SCM with a Causal Graph Neural Network (C-GNN) that performs directed, intervention-aware message passing over the freight network [18]. Unlike conventional GNNs, which aggregate information symmetrically from neighbors, the C-GNN respects the directional structure of the causal DAG. Messages flow only from parent nodes to child nodes, aligning learned representations with causal influence rather than proximity alone.

Figure 6 illustrates the architecture, where each node maintains a hidden state encoding its operational condition. Edge-conditioned propagation allows messages to be modulated by link-specific attributes such as capacity, mode, or vulnerability. Directional influence weighting further distinguishes strong causal drivers from weak or indirect contributors [22].

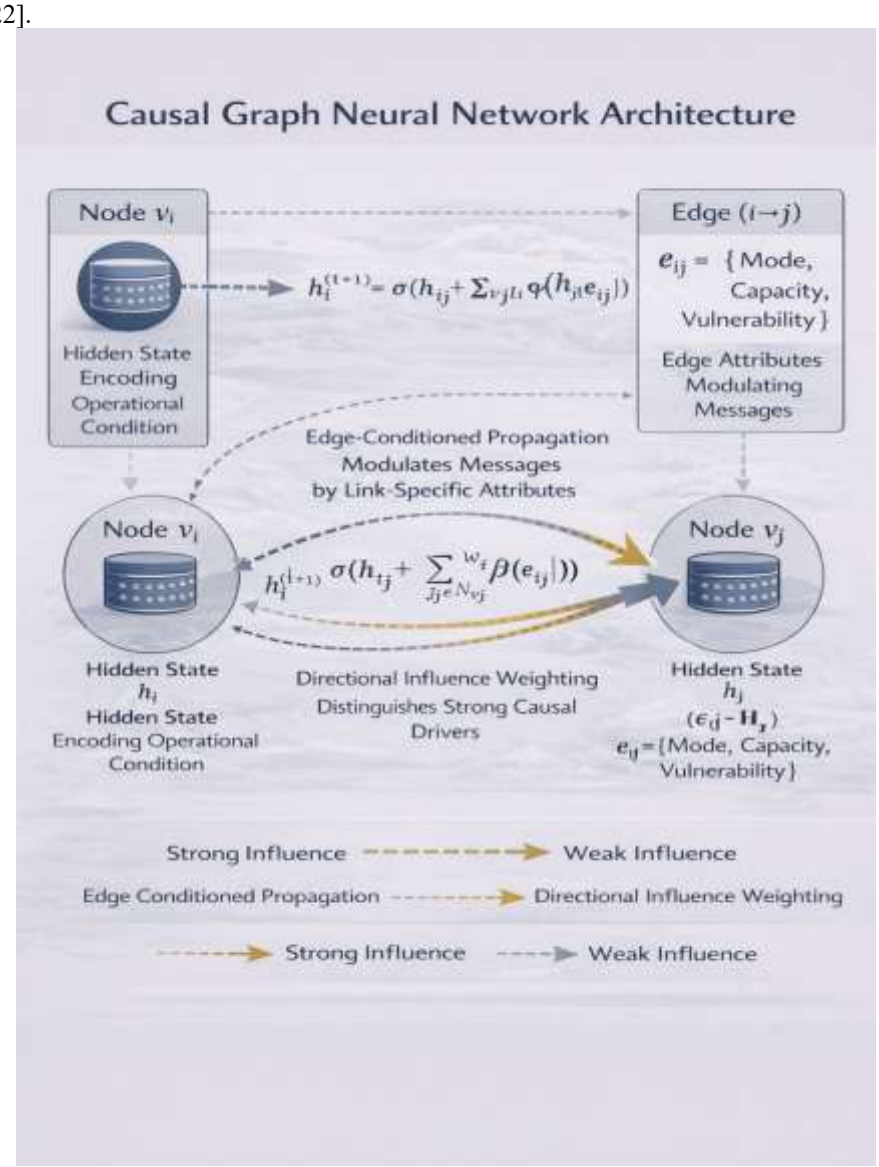

Figure 6 Casual Graph Neural Network Architecture

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The message passing rule is defined as:

$$h_v^{(k+1)} = \sigma\left(\sum_{u \in \mathrm{Pa}(v)} W_{uv}\ h_u^{(k)}\right),$$

where $h_v^{(k)}$is the hidden state of node $v$at layer k, $\mathrm{Pa}(v)$denotes its causal parents, W_{uv}learned influence weights, and $\sigma(\cdot)$a nonlinear activation. This formulation ensures that information aggregation mirrors causal dependency paths identified in the SCM [23].

By stacking multiple layers, the C-GNN captures multi-hop propagation of disruptions, enabling prediction of cascading bottlenecks several steps downstream from an initial shock. Training is performed using observed reliability outcomes, while causal constraints regularize learning to prevent spurious correlations. This hybrid approach combines the expressiveness of deep learning with the interpretability and robustness of causal modeling [21].

Crucially, the architecture supports intervention-aware inference. Because messages reflect causal direction, altering a node's state (e.g., increasing capacity) produces downstream effects consistent with causal logic rather than historical correlation. This property is essential for reliable stress testing and scenario analysis in freight networks subject to unprecedented disruptions [25].

4.3.1 Causal Graph Neural Network (C-GNN) Architecture, Training Setup, and Causal Constraints

Architecture and Message Passing

The proposed Causal Graph Neural Network (C-GNN) operates on the directed freight graph $G = (V, E)$and performs directional message passing constrained to causal parent–child relationships. Each node $v$maintains a hidden state $h_v^{(k)} \in \mathbb{R}^d$at layer k, initialized from its feature vector $x_v(t)$. The model uses $K = 3$message-passing layers with hidden dimension $d = 128$and a two-layer readout MLP (128→64→1) to output a bottleneck probability for each node/edge.

At each layer, messages are aggregated only from causal parents:

$$m_v^{(k)}(t) = \sum_{u \in Pa(v)} \alpha_{uv}(t)\, W^{(k)} h_u^{(k)}(t), h_v^{(k+1)}(t) = \mathrm{ReLU}\left(\mathrm{LN}\left(h_v^{(k)}(t) + m_v^{(k)}(t)\right)\right),$$

where $W^{(k)} \in \mathbb{R}^{d \times d}$is a learnable linear projection, LN denotes layer normalization, and $\alpha_{uv}(t)$is a learned causal influence weight. Influence weights are computed via edge-conditioned gating:

$$\alpha_{uv}(t) = \sigma\left(w_\alpha^\top [h_u^{(k)}(t) \parallel h_v^{(k)}(t) \parallel z_{uv}(t)]\right),$$

with $z_{uv}(t)$denoting edge attributes (e.g., capacity, mode, utilization) and $\sigma(\cdot)$the sigmoid function, ensuring $\alpha_{uv}(t) \in (0,1)$. Dropout of **0.2** is applied to hidden states and message inputs to reduce overfitting.

Prediction Targets and Loss Function

The model is trained to predict bottleneck emergence within the forecast horizon Husing supervised labels $y_v(t)$and $y_e(t)$. For classification, the objective is weighted binary cross-entropy to address class imbalance:

$$\mathcal{L}_{\mathrm{BCE}} = -\sum_{i \in \mathcal{I}} (\lambda\, y_i \log\, \hat{y}_i + (1 - y_i) \log\,(1 - \hat{y}_i))\,,$$

where $i$indexes node/edge instances, $\hat{y}_i$is the predicted probability, and $\lambda$is the positive-class weight computed from the training split (ratio of negative to positive samples). Training uses mini-batches defined over temporal windows to preserve time ordering.

Optimizer, Training Schedule, and Hyperparameters

Model parameters are trained using Adam with learning rate 1×10^{-3}, weight decay 1×10^{-5}, batch size 64 temporal windows, and early stopping with patience 10 based on validation F1-score. The model is trained for a maximum of 100 epochs, with gradient norm clipping at 1.0 to stabilize training under heavy-tailed disruption periods.

How Causal Constraints Are Enforced

Causal constraints are enforced through three mechanisms:

1. Adjacency masking (hard constraint): Message passing is computed only over edges in the causal parent set $Pa(v)$. A binary mask $M$is applied to the adjacency so that $M_{uv} = 1$only if $u \to v$is a permitted causal

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edge; otherwise the message is identically zero. This prevents any upstream, lateral, or reverse-direction flow that violates the causal DAG.

2. Acyclicity preservation (structural constraint): The causal adjacency is defined as a DAG derived from the SCM formulation. During training, the model does not learn new edges; it only learns influence weights α_{uv}on the permitted causal edges. This ensures that learned dependence cannot introduce cycles or direction reversals.
3. Influence sparsity and stability (regularization constraint): To prevent diffuse attribution across many weak edges, influence weights are regularized using an $\ell_1$penalty:

$$\mathcal{L} = \mathcal{L}_{\text{BCE}} + \beta \sum_{(u,v)\in E_c} | \alpha_{uv} |,$$

where $E_c$denotes causal edges and $\beta = 10^{-4}$. This encourages the model to concentrate explanatory mass on a small set of operationally meaningful causal drivers, improving interpretability and robustness under unseen shocks.

Together, these constraints ensure that the C-GNN learns directional, intervention-consistent representations: when an intervention modifies a causal parent's state (e.g., increased capacity), downstream predictions change in a manner consistent with the causal structure rather than historical correlation.

4.4 Counterfactual and Intervention Analysis

The ultimate value of the causal framework lies in its ability to support counterfactual and intervention analysis for freight reliability management [19]. Using the SCM–C-GNN integration, analysts can simulate hypothetical changes to network conditions and evaluate their impact on bottleneck risk and reliability degradation.

Interventions may include infrastructure upgrades, such as expanding terminal capacity or adding alternative routing options, as well as operational measures like rescheduling arrivals or reallocating labor. These interventions are modeled using the *do-operator*, which forcibly sets selected variables to specified values while holding the underlying causal structure constant [22].

Counterfactual risk is defined as:

$$Y_{X\leftarrow x'}(u),$$

representing the reliability outcome Ythat would occur for exogenous context $u$if variable Xwere set to x'. For example, the model can estimate how downstream congestion would change if a port's effective capacity were increased by 10%, even if such a change has not been observed historically [24].

This capability allows comparison of alternative mitigation strategies under consistent assumptions, revealing which interventions yield the greatest systemic benefit. Importantly, counterfactual analysis also identifies unintended consequences, such as risk displacement from one corridor to another.

By grounding intervention analysis in causal structure rather than extrapolation, the framework provides freight operators and policymakers with a powerful tool for proactive risk management. It transforms reliability analysis from reactive monitoring into forward-looking decision support, enabling targeted investments that enhance resilience under uncertainty [25].

5. EXPERIMENTAL EVALUATION AND RESULTS

5.1 Experimental Setup and Baselines

The experimental evaluation is designed to rigorously assess the ability of the proposed causal graph–based framework to (i) predict emerging freight bottlenecks, (ii) model network-wide risk propagation, and (iii) support counterfactual intervention analysis under uncertainty [23]. Experiments are conducted on a multi-modal freight network constructed from the data sources described in Section 3, explicitly representing road freight corridors, port terminals, rail interfaces, and intermodal transfer hubs. Nodes correspond to operational assets, while directed links encode observed freight movements and capacity dependencies.

Model performance is evaluated over rolling temporal windows with fixed forecast horizons, allowing the analysis to capture routine operations, seasonal variability, and disruption episodes rather than relying on static averages [24]. This design ensures that models are tested on their ability to anticipate bottleneck formation before delays fully materialize, which is critical for operational decision-making.

Three classes of baseline models are implemented for comparison. First, centrality-based heuristics represent traditional network analysis approaches, including betweenness and flow centrality, used to rank nodes and edges

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by presumed criticality. These methods rely solely on static topology and aggregate flows, ignoring temporal dynamics, uncertainty, and intervention effects, but remain widely used as screening tools in practice [25].
Second, a non-causal graph neural network (GNN) baseline applies standard, symmetric message passing over the freight network topology. This model captures spatial correlations and improves predictive performance relative to heuristics by learning distributed node representations, but it does not enforce causal directionality or distinguish upstream drivers from downstream effects [26].
Finally, an ARIMA-based time-series model is implemented at the node level to forecast delays using historical observations without explicit network structure. Although limited to local temporal persistence, this baseline reflects the continued use of classical forecasting tools in freight operations [27].
All models are trained and evaluated using identical temporally ordered cross-validation splits. Performance is assessed across multiple disruption scenarios, enabling controlled comparison of how causal structure, graph learning, and temporal modeling contribute to reliability prediction and decision support [30].

5.2 Bottleneck Prediction Performance

Bottleneck prediction performance is evaluated using precision, recall, and F1-score, focusing on each model's ability to correctly identify nodes and edges that evolve into operational bottlenecks within the defined forecast horizon [24]. A bottleneck is labeled when observed delay and queue length metrics exceed empirically calibrated capacity-adjusted thresholds, ensuring consistency across network components.
As summarized in Table 3, centrality-based heuristics achieve high recall but low precision, systematically flagging structurally prominent nodes as bottlenecks even during stable operating conditions. This over-identification reflects their inability to distinguish latent structural importance from realized operational failure, resulting in excessive false positives [25].
The non-causal GNN baseline improves precision by exploiting learned spatial dependencies and historical co-movements between network components, yielding higher balanced accuracy than heuristics. However, its performance degrades under novel disruption scenarios, such as compound weather and labor shocks, where previously learned correlations no longer hold. In these cases, the model misattributes downstream congestion symptoms as causal drivers, reducing generalization robustness [26].
The proposed causal graph neural network achieves the strongest overall performance, with consistent gains in both precision and recall. By constraining message passing to explicit causal parent–child relationships, the model isolates upstream drivers of bottleneck formation and suppresses spurious correlations arising from shared downstream effects [28]. Performance improvements are especially pronounced for indirect bottlenecks, where congestion emerges due to propagated upstream constraints rather than local overload.
Figure 4 presents precision–recall curves across decision thresholds. The causal model consistently dominates baseline curves, demonstrating superior discrimination under varying tolerance for false positives. These results confirm that embedding causal structure enhances not only interpretability, but also predictive reliability and robustness under uncertainty [30].

Table 3: Bottleneck Detection Performance Across Models

Metrics reported as mean ± standard deviation across temporally ordered cross-validation folds.

Model / Method	Precision	Recall	F1-Score
Degree / Betweenness Centrality Heuristics	0.31 ± 0.06	0.81 ± 0.07	0.45 ± 0.05
Flow-Based Centrality Metrics	0.42 ± 0.07	0.78 ± 0.06	0.54 ± 0.06
ARIMA-Based Delay Prediction	0.55 ± 0.08	0.49 ± 0.09	0.52 ± 0.07
Non-Causal Graph Neural Network (GNN)	0.68 ± 0.06	0.63 ± 0.07	0.65 ± 0.06
Proposed Causal Graph Neural Network	**0.81 ± 0.05**	**0.76 ± 0.06**	**0.78 ± 0.05**

5.3 Network Risk Propagation Analysis

Beyond point prediction, the framework is evaluated on its ability to model risk propagation across the freight network under cascading disruption scenarios [23]. Experiments simulate initial shocks such as reduced port capacity or corridor closures and track how delays and reliability degradation spread through connected nodes and edges.
Centrality-based approaches provide limited insight into propagation dynamics. While they identify structurally important nodes, they offer no mechanism to simulate temporal spread or amplification of risk. Consequently, they fail to distinguish between localized disruptions and those that escalate system-wide [27].
The non-causal GNN baseline captures some propagation patterns by diffusing information across the graph. However, because message passing is symmetric, risk often spreads unrealistically upstream or laterally,

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producing diffuse impact patterns that do not align with observed freight behavior [26]. This undermines trust in scenario outputs for operational planning.

In contrast, the causal framework produces propagation paths consistent with operational logic. Delays originate at disrupted nodes, accumulate into queues, and transmit downstream along directed corridors. Shock amplification is observed when multiple upstream constraints converge on shared downstream facilities, reflecting real-world congestion spillbacks [28].

The model also distinguishes between transient and persistent risk. Short-lived shocks dissipate quickly in areas with sufficient slack, while sustained capacity reductions trigger multi-hop cascades. These dynamics are critical for prioritizing mitigation efforts and staging interventions [29]. The results confirm that causal directionality is essential for realistic modeling of network risk propagation, particularly under compound and evolving disruption scenarios [30].

5.4 Counterfactual Risk Mitigation Outcomes

The final evaluation examines counterfactual risk mitigation, assessing how targeted interventions alter network reliability outcomes [24]. Interventions include capacity expansions at critical hubs, operational adjustments to reroute flows, and hypothetical elimination of specific shocks.

Figure 5 illustrates risk reduction achieved under selected interventions. Centrality-guided interventions yield modest improvements, often misallocating resources to structurally important but causally secondary nodes [25]. The non-causal GNN baseline performs better, but occasionally recommends interventions that shift risk rather than reducing it system-wide [26].

The causal framework consistently identifies interventions with the greatest marginal impact on reliability. By intervening on true causal drivers, such as upstream capacity constraints, the model achieves larger and more stable reductions in downstream bottleneck probability [28]. Importantly, counterfactual analysis reveals diminishing returns for certain expansions, guiding more efficient investment decisions.

These findings demonstrate that causal modeling enables not only better prediction, but more effective action. By quantifying how reliability would change *if* specific interventions were implemented, the framework supports proactive, evidence-based freight network resilience planning under uncertainty [30].

6. DISCUSSION AND ENGINEERING IMPLICATIONS

6.1 Reliability Engineering for Freight Networks

The proposed causal–graph framework has direct implications for reliability engineering in freight transportation systems, particularly in shifting practice from reactive response toward anticipatory control [28]. Traditional reliability engineering in freight contexts has focused on localized asset performance, such as vehicle maintenance schedules or terminal equipment uptime. While important, these approaches often fail to account for how localized degradations interact with network structure to generate systemic risk.

By enabling bottleneck probability estimation and downstream risk forecasting, the framework supports predictive maintenance at the network level rather than at isolated assets. For example, recurring causal patterns linking crane productivity declines to corridor congestion can inform pre-emptive maintenance scheduling before queues propagate beyond terminal boundaries [30]. This aligns maintenance planning with operational risk rather than fixed calendars, improving both reliability and cost efficiency.

Capacity planning similarly benefits from causal insight. Instead of expanding capacity uniformly or at historically congested locations, planners can identify nodes whose capacity improvements causally reduce network-wide delay variance. This allows for targeted investments that yield disproportionate reliability gains, particularly under peak demand or disruption scenarios [32].

Importantly, the framework distinguishes between structural bottlenecks persistent causal drivers of unreliability and episodic bottlenecks arising from transient shocks. This distinction is critical for reliability engineering, as it informs whether long-term infrastructure upgrades or short-term operational interventions are appropriate. By embedding causality into reliability assessment, freight operators can design interventions that stabilize performance under uncertainty rather than merely reacting to realized failures [35].

6.2 Decision Support for Infrastructure Investment

From a policy and planning perspective, the framework offers a powerful decision-support tool for infrastructure investment under uncertainty [29]. Freight infrastructure decisions are capital-intensive, politically constrained, and subject to long lead times. Errors in prioritization can lock in inefficiencies for decades. Conventional appraisal methods often rely on static forecasts and average delay reductions, which understate tail risks and cascading impacts.

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The causal approach enables risk-informed prioritization, allowing decision-makers to compare investments based on their ability to reduce bottleneck probability and systemic reliability degradation. By simulating counterfactual scenarios, planners can evaluate how alternative investments perform under stress conditions such as climate shocks or demand surges, rather than under idealized averages [31].

Policy relevance is further enhanced by interpretability. Because causal pathways are explicit, investment recommendations can be justified transparently, strengthening accountability and stakeholder confidence. This is particularly important where freight investments intersect with climate policy, trade facilitation, and regional development goals. The framework thus bridges technical analysis and policy deliberation, translating complex network dynamics into defensible investment strategies aligned with national and regional priorities [35].

6.3 Limitations and Practical Deployment Constraints

Despite its advantages, the proposed framework faces several limitations and deployment challenges that must be acknowledged [30]. Causal identification in complex freight networks is inherently difficult. Observational data may be insufficient to fully disentangle causal relationships, particularly where unobserved confounders such as informal operational practices or contractual arrangements play a significant role. While structural assumptions and domain knowledge mitigate this risk, causal conclusions remain contingent on model specification [33].

Data governance presents another constraint. Freight data is often proprietary, fragmented across operators, and subject to confidentiality restrictions. Integrating GPS traces, terminal logs, and incident reports requires robust data-sharing agreements and privacy-preserving processing pipelines. Inconsistent data availability across regions may limit model transferability and equity of application [31].

Operational deployment also raises practical considerations. Real-time causal inference demands computational resources and institutional capacity that may be unevenly distributed among freight agencies. Additionally, embedding causal decision-support tools into existing planning workflows requires organizational buy-in and training.

These limitations underscore that causal modeling should complement, not replace, expert judgment and existing tools. When deployed thoughtfully, however, the framework offers a meaningful advance toward resilient, evidence-based freight network management under uncertainty [35].

7. CONCLUSION AND FUTURE RESEARCH

7.1 Summary of Technical Contributions

This study advances freight transportation analytics by establishing a unified causal–graph framework for reliability assessment under uncertainty. First, freight systems are formalized as multi-layer, directed causal graphs, enabling explicit representation of how capacity constraints, delays, queues, and downstream risks interact and propagate across interconnected networks. This formulation shifts bottleneck analysis away from static, descriptive indicators toward a mechanism-based understanding of disruption formation and amplification.

Second, the framework integrates structural causal models with graph neural networks, combining causal interpretability with data-driven scalability. Directional message passing constrains learned dependencies to reflect causal influence rather than correlation, improving robustness when networks operate outside historically observed regimes or experience novel disruptions. Third, bottleneck prediction is operationalized through causal message propagation, allowing early identification of high-risk nodes and corridors before congestion fully materializes.

Fourth, counterfactual reasoning is embedded directly into the modeling pipeline, enabling consistent evaluation of infrastructure upgrades, capacity expansions, and operational interventions under shared causal assumptions. Finally, empirical results demonstrate that incorporating causal structure improves prediction accuracy, realism of risk propagation, and effectiveness of interventions relative to heuristic, time-series, and non-causal graph baselines. Collectively, these contributions establish a rigorous, intervention-aware foundation for freight reliability modeling and provide a replicable blueprint for applying causal learning in large-scale transportation networks.

7.2 Implications for Freight Operators and Policymakers

For freight operators, the proposed framework enables proactive reliability management by identifying the true causal drivers of disruption rather than reacting to observed congestion symptoms. This supports targeted maintenance planning, capacity allocation, and operational adjustments that reduce systemic risk instead of redistributing it across the network. By distinguishing causal bottlenecks from structurally prominent but operationally benign assets, operators can allocate resources more efficiently and improve service reliability under uncertainty.

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For policymakers, the framework offers transparent and defensible decision support for infrastructure investment and resilience planning. By quantifying how interventions affect network-wide reliability through explicit causal pathways, decision-makers can prioritize projects with the greatest resilience impact, align investments with climate adaptation and supply-chain security objectives, and justify expenditures to stakeholders. The ability to simulate counterfactual scenarios further strengthens contingency planning, enabling authorities to stress-test freight networks against extreme events, regulatory changes, and demand shocks. Overall, the framework bridges operational analytics and strategic planning, translating complex freight dynamics into actionable insights for both industry and public-sector governance.

7.3 Future Research Directions

Several extensions offer promising directions for future research. Dynamic causal graphs could be developed to allow causal structures themselves to evolve as network configurations, technologies, and operating regimes change over time. Multimodal freight integration represents another critical avenue, extending the framework to jointly model road, rail, maritime, and inland waterway systems while capturing cross-modal causal interactions and substitution effects. Finally, reinforcement learning could be coupled with causal graphs to design adaptive mitigation strategies, enabling agents to learn optimal intervention policies that actively reduce bottleneck risk under uncertainty. Together, these extensions would further enhance the realism, adaptability, and decision relevance of causal freight network analytics.

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