Graph-Driven Knowledge Reasoning for Human AI Collaborative Strategic Decision Support in Supply Chain Networks

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(Received: April 1, 2026; Revised: June 25, 2026; Accepted: August 25, 2026; Available online: September 1, 2026)

Abstract

Strategic decision support in supply chain networks remains constrained by fragmented data structures, limited visibility of multi-tier dependencies, and weak integration between relational analytics and managerial prioritization. This study proposes a graph-driven knowledge reasoning framework that combines knowledge graph construction, graph-based inference, multi-criteria recommendation ranking, and scenario-based strategic evaluation to support decision-making in complex supply chain environments. The modeled network comprised 248 nodes and 612 directed edges representing suppliers, factories, warehouses, transport routes, retailers, and disruption events. Structural analysis showed an average degree of 4.94, with suppliers forming the largest entity class at 72 nodes, while factories exhibited the highest relational intensity with an average degree of 7.4. The reasoning engine identified several high-risk propagation corridors, including the path S12 → F3 → R9 with a risk score of 0.91, indicating concentrated supplier dependence and high downstream delay exposure. Additional critical paths, such as S21 → F6 → W2 and S4 → W7 → T5, recorded scores of 0.84 and 0.81, revealing capacity bottlenecks, bridge-node fragility, and regionally amplified service disruption. Entity-level inference further showed that Warehouse W7 and Route R9 were strategically important despite not being dominant in raw node volume, confirming that graph-based reasoning can reveal hidden structural vulnerabilities overlooked by conventional analysis. In the decision support phase, supplier diversification obtained the highest composite recommendation score at 8.14, followed by inventory repositioning at 7.96 and route redundancy at 7.88. Comparative scoring indicated that supplier diversification produced the strongest resilience value at 8.9, while inventory repositioning achieved the best balance between feasibility and cost efficiency. Scenario analysis demonstrated that diversification performance increased from 7.6 under normal conditions to 8.8 under severe disruption, whereas inventory repositioning declined from 8.0 to 7.1, indicating that short-term stabilization strategies lose effectiveness under deeper structural stress. Expert-oriented validation also reported high managerial acceptance, with average scores of 4.6 for strategic relevance, 4.5 for interpretability, and 4.4 for practical usefulness. These findings show that graph-driven knowledge reasoning can improve strategic visibility, detect hidden dependencies, and generate interpretable, context-sensitive recommendations for supply chain decision support.

Keywords: Knowledge Graph, Graph Reasoning, Supply Chain Networks, Strategic Decision Support, Risk Propagation, Multi-Criteria Recommendation, Supply Chain Resilience, AI In Management

1. Introduction

Modern supply chains operate as interdependent networks rather than linear pipelines, yet many strategic decisions are still made from fragmented enterprise records, isolated risk indicators, and local optimization views. This mismatch becomes acute when disruptions propagate across suppliers, logistics channels, warehouses, and downstream demand nodes faster than conventional dashboards can explain. Recent reviews show that AI has improved forecasting and risk analytics in supply chain management, but decision quality still depends heavily on how relational structure is represented and interpreted [1], [2].

A central problem is that strategic risk in supply chains rarely originates from a single node. It emerges from hidden dependencies, indirect exposures, and multi-hop transmission pathways that are difficult to capture with flat tables or independent machine-learning features. Research on supply chain risk reasoning with graph neural networks has shown that graph-based representations can uncover latent vulnerabilities, while knowledge graph research has demonstrated the value of semantically structured relations for reasoning and explainability [3], [4].

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DOI: https://doi.org/10.47738/ijaim.v6i3.127

This relational perspective motivates the use of knowledge graphs as a foundation for strategic decision support. Knowledge graphs are able to encode entities, attributes, and typed relations in ways that preserve semantics, support inference, and improve interoperability across heterogeneous data sources. Surveys of knowledge graph embedding and knowledge graph applications indicate that graph-structured learning becomes especially powerful when predictive models are coupled with explicit relational context and domain logic rather than operating on disconnected records alone [5], [6].

Graph learning methods provide the computational machinery needed to reason over such structures. Graph convolutional models and attention-based graph architectures have established robust mechanisms for neighborhood aggregation, relational weighting, and representation learning on non-Euclidean data [7], [8]. In supply chain settings, these capabilities are highly relevant because strategic importance depends not only on entity-specific attributes, but also on position, connectivity, and influence within the wider network. This makes graph-driven reasoning a strong candidate for strategic support under complexity and uncertainty.

Despite these advances, an important research gap remains. Existing studies have separately examined industrial chain knowledge graphs, visibility enhancement with knowledge graphs and large language models, and supply chain information integration with graph-based learning, but these contributions often emphasize mapping, extraction, or visibility rather than strategic reasoning for executive decision support [9], [10]. Most current approaches improve what can be seen in the network, yet provide limited guidance on how graph-derived insights should be converted into ranked strategic interventions under competing managerial criteria.

A second gap concerns the integration of representation, reasoning, and decision support into one coherent framework. Recent studies have proposed knowledge-enhanced supply chain information management and temporal knowledge-graph recommendation mechanisms, but these systems are usually optimized for information integration, recommendation, or link prediction rather than for strategic evaluation across disruption scenarios [11], [12], [13]. In practice, managers require more than accurate graph inference. They need interpretable reasoning paths, prioritization logic, and recommendations that remain useful across normal, stressed, and severely disrupted conditions.

This study addresses those gaps by proposing a graph-driven knowledge reasoning framework for strategic decision support in supply chain networks. The objective is to integrate knowledge graph construction, graph-based relational reasoning, and multi-criteria strategic recommendation into a unified architecture that can identify critical dependencies, trace disruption propagation, and rank intervention options. The novelty lies in combining semantic supply chain modeling with graph-driven reasoning for decision prioritization, while preserving managerial interpretability and interoperability as design principles rather than afterthoughts.

2. Literature Review

The recent literature shows a clear shift from transaction-centric supply chain analytics toward structure-aware intelligence models that can represent inter-firm dependence, hidden exposure, and reconfiguration logic. In this transition, knowledge graphs have become increasingly important because they provide a machine-readable representation of entities, relations, and semantic constraints while remaining interpretable for managerial analysis. Research on reconfigurable supply chains and knowledge-enhanced information management shows that graph-based knowledge organization improves traceability, contextual linkage, and decision preparation in complex industrial environments [14], [15].

A closely related stream of work focuses on supply chain visibility. This literature argues that one of the main barriers to resilient decision-making is incomplete knowledge of supplier relationships, route dependencies, and deep-tier connections. Recent studies using graph-based learning, federated learning, and knowledge-graph completion indicate that hidden links can be inferred with useful accuracy even when direct information sharing is limited. These findings are important because better visibility is the prerequisite for any higher-level reasoning or strategic intervention in distributed supply networks [16], [17].

Another major theme concerns resilience and risk propagation in supply chain networks. Network-oriented resilience research has shown that disruption effects depend not only on the magnitude of a shock, but also on node type,

ISSN 2776-8001

positional role, and propagation pathways across the graph. Updated supplier-risk frameworks likewise emphasize that risk should be evaluated as a multidimensional and relational construct rather than as an isolated vendor score. This body of work supports the premise that strategic supply chain reasoning must explicitly model network dependence and differentiated forms of vulnerability [18], [19].

Domain-specific studies further strengthen this argument by showing that knowledge graphs can capture critical structural drivers in specialized supply systems. In pharmaceutical supply chains, knowledge graphs have been used to analyze the drivers of drug shortages, revealing how shortages are tied to interconnected sourcing and production constraints rather than to one-dimensional procurement failures. Related work on generative-AI-enhanced relationship prediction also suggests that semantic modeling can improve the contextual quality of inferred supply links, which is highly relevant for strategic interpretation and risk-aware planning [20], [21].

Beyond the supply chain domain, the broader knowledge graph literature provides theoretical support for graph-driven reasoning. Recent surveys of knowledge graph reasoning and automatic knowledge graph construction show that modern graph reasoning spans static, dynamic, and multimodal settings, while construction pipelines now extend from extraction to refinement and evolution. These advances matter for supply chain research because strategic environments are neither static nor fully observable. A decision support framework built on supply chain graphs therefore benefits from both robust graph construction and reasoning mechanisms that can operate over changing relational structures [22], [23].

Even with these advances, the literature still leaves an open gap between graph-based prediction and strategic decision support. Existing studies successfully improve visibility, infer hidden relations, or predict firm-level post-disruption outcomes with graph neural models, but they rarely connect those outputs to a unified decision layer that ranks interventions according to managerial priorities such as resilience, feasibility, and dependency reduction. This gap motivates the present study, which positions graph-driven knowledge reasoning not merely as an analytic tool, but as an integrated support mechanism for strategic decision-making in supply chain networks [24].

3. Methodology

3.1. Research Design and System Architecture

This study adopts a design science and computational modeling approach to construct a graph-driven knowledge reasoning framework for strategic decision support in supply chain networks. The methodological logic starts from representing supply chain entities as interconnected knowledge units, then formalizing their relationships in graph form, and finally deriving strategic recommendations through reasoning procedures. The architecture is designed to support multi-tier supply chain analysis, uncertainty handling, and cross-node dependency interpretation under dynamic operational conditions [3], [14].

The system architecture contains four main layers: data acquisition, knowledge graph construction, reasoning engine, and decision support interface. The data acquisition layer integrates structured operational records, supplier profiles, logistics events, and market signals. The knowledge graph layer transforms these heterogeneous inputs into nodes, edges, attributes, and relation semantics. The reasoning engine evaluates paths, dependencies, and conflict patterns. The final layer converts inference results into strategic alerts, prioritization scores, and scenario-based managerial recommendations.

To formalize the architecture, the supply chain knowledge system is defined as a directed attributed graph:

$$G = (V, E, X, R) \tag{1}$$

where V denotes the set of entities, E denotes relational links, X represents node and edge attributes, and R denotes semantic relation types. This formulation establishes the computational boundary of the framework and clarifies that strategic reasoning is not performed on isolated variables, but on structured relational knowledge embedded in the network topology and its contextual attributes.

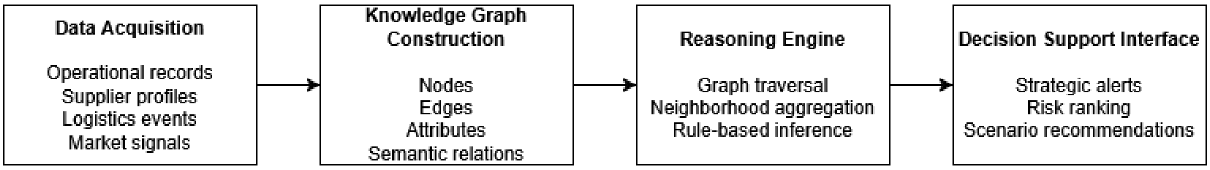

Figure 1. Multi-layer Architecture of the Graph-Driven Knowledge Reasoning Framework

Figure 1 presents the end-to-end methodological architecture used in the study. It clarifies that the framework operates as a layered pipeline rather than a single predictive block. The first layer gathers heterogeneous supply chain evidence, the second converts that evidence into structured graph knowledge, the third executes relational reasoning, and the fourth transforms inference outputs into managerial recommendations. This visual is useful because it shows how each methodological stage contributes to strategic decision support in a coherent computational flow.

Table 1. Components of the Methodological Architecture

Layer	Main Input	Core Process	Main Output	Strategic Function
Data Acquisition	Operational, supplier, logistics, market data	Collection and integration	Unified raw dataset	Builds evidence base
Knowledge Graph Construction	Unified raw dataset	Entity, relation, and attribute modeling	Attributed graph structure	Represents supply chain connectivity
Reasoning Engine	Attributed graph	Traversal, propagation, rule inference	Risk and dependency insights	Reveals structural patterns
Decision Support Interface	Inference results	Scoring and scenario interpretation	Strategic recommendations	Supports managerial action

Table 1 complements figure 1 by specifying the analytical role of each architectural layer. Rather than only naming the modules, it shows the logic of transformation from input to output and from technical function to strategic value. This is important in a methodology chapter because it ties computational design to management relevance. The table also makes the chapter more traceable by indicating how each component contributes to the final recommendation mechanism.

3.2. Supply Chain Knowledge Graph Construction

The knowledge graph construction process begins by identifying the principal entities involved in strategic supply chain management. These include suppliers, manufacturers, distribution centers, transport channels, customers, products, contracts, risks, and external events. Each entity is encoded as a node with operational and contextual attributes. Relations are then defined to reflect sourcing, transportation, dependency, disruption exposure, substitution potential, and contractual ties. This modeling strategy captures both structural connectivity and managerial meaning within the same representational space [4], [23].

Data preparation follows three stages: semantic normalization, relation extraction, and attribute enrichment. Semantic normalization resolves heterogeneity in labels, units, and entity identifiers. Relation extraction identifies explicit and implicit connections across transactional and event-based data. Attribute enrichment introduces variables such as lead time volatility, supplier criticality, service level, disruption frequency, and resilience capacity. These enriched graph objects improve reasoning quality because managerial decisions depend not only on connectivity, but also on the intensity and reliability of relations.

The adjacency structure of the graph is represented by a weighted matrix:

$$A_{ij} = \begin{cases} w_{ij}, & if\ a\ directed\ relation\ exists\ from\ v_i\ to\ v_j \\ 0, & otherwise \end{cases} \tag{2}$$

where w_{ij} expresses the operational importance or dependency strength between two entities. The weighting scheme allows the model to distinguish routine transactional links from strategically sensitive dependencies. As a result, later reasoning stages can assign greater emphasis to critical bottlenecks, fragile sourcing paths, and high-impact relational clusters.

A complementary schema layer is added to define domain rules governing permissible relations and attribute constraints. This schema improves graph consistency and reduces ambiguity during reasoning. For example, a disruption event may affect a supplier, route, or warehouse, but cannot directly fulfill an order. Such ontological restrictions prevent invalid reasoning chains and improve interpretability. The schema also supports future extensibility when new risk categories, sourcing arrangements, or market entities need to be incorporated [9].

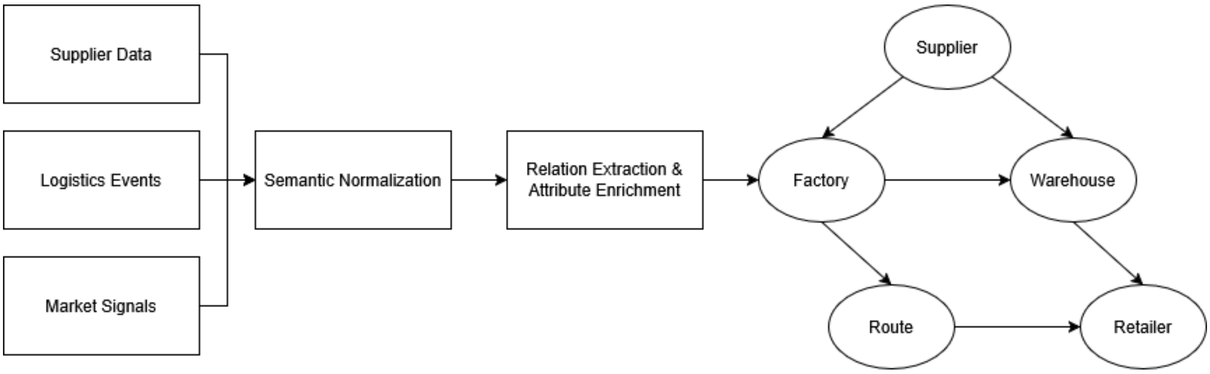

Figure 2. Transformation of Heterogeneous Supply Chain Data into a Weighted Knowledge Graph

Figure 2 explains how diverse supply chain inputs are transformed into a structured graph representation. The left side emphasizes heterogeneity in raw evidence, while the central blocks show the methodological steps that reconcile semantic inconsistency and extract meaningful relations. The graph on the right indicates that the final representation encodes entities, directional dependencies, and contextual attributes within one relational structure. The figure is important because it demonstrates that graph construction is a systematic modeling process rather than a mere visualization of links.

Table 2. Entity Classes and Relation Semantics in the Supply Chain Knowledge Graph

Entity Class	Relation Type	Example Attribute	Semantic Meaning	Decision Relevance
Supplier	Supplies	Lead time volatility	Provides materials to another node	Identifies sourcing risk
Factory	Processes	Capacity utilization	Transforms input into output	Shows production bottlenecks
Warehouse	Stores	Inventory buffer	Holds stock for downstream flow	Supports resilience planning
Route	Connects	Transit delay rate	Represents transport dependency	Reveals logistics fragility
Disruption Event	Affects	Severity score	Creates operational disturbance	Supports scenario analysis

Table 2 operationalizes the graph schema by clarifying what kinds of entities and relations are admitted into the model. It also links each object to an example attribute and a decision-oriented interpretation, which is crucial for methodology transparency. In supply chain reasoning, the graph must preserve both structural form and managerial meaning. This table therefore functions as a compact ontology summary that supports consistency, interpretability, and future model extension.

3.3. Graph-Driven Knowledge Reasoning Mechanism

The reasoning mechanism combines graph traversal, neighborhood aggregation, and rule-based inference to derive strategic insights from the supply chain knowledge graph. The intention is not merely to identify adjacent entities, but to explain how local disruptions, capacity constraints, and dependency structures propagate through broader network configurations. This approach supports management questions involving vulnerability concentration, supplier substitution, route fragility, and resilience trade-offs among interconnected operational units [7], [22].

Reasoning is performed through iterative state propagation across the graph so that each node can absorb contextual information from connected neighbors. This allows strategic interpretation to emerge from both direct relations and higher-order interaction patterns. A supplier node, for instance, may become strategically risky not only because of its own delay history, but also because it is linked to congested routes and downstream plants with low inventory buffers. Such relational accumulation is central to graph-based managerial intelligence.

The propagation process is formalized as follows:

$$h_i^{(l+1)} = \sigma\left(W^{(l)} \cdot \sum_{j \in \mathcal{N}(i)} \alpha_{ij} h_j^{(l)} + B^{(l)} h_i^{(l)}\right) \tag{3}$$

where $h_i^{(l)}$ denotes the node representation at layer l, $N(i)$ is the neighborhood of node i, α_{ij} is the influence weight, and σ is an activation function. This equation allows the model to integrate relational context while preserving the node's intrinsic state. In strategic terms, it quantifies how interconnected conditions reshape the assessed relevance of each supply chain entity.

To strengthen interpretability, the reasoning engine also includes a rule layer based on domain heuristics. Rules can prioritize nodes with high disruption centrality, flag supplier clusters with shared exposure, or recommend alternative sourcing paths when dependency thresholds are exceeded. This hybrid design balances representational flexibility and managerial transparency. Neural propagation captures complex relational patterns, while rule constraints ensure that the resulting recommendations remain aligned with supply chain logic and executive decision requirements [3].

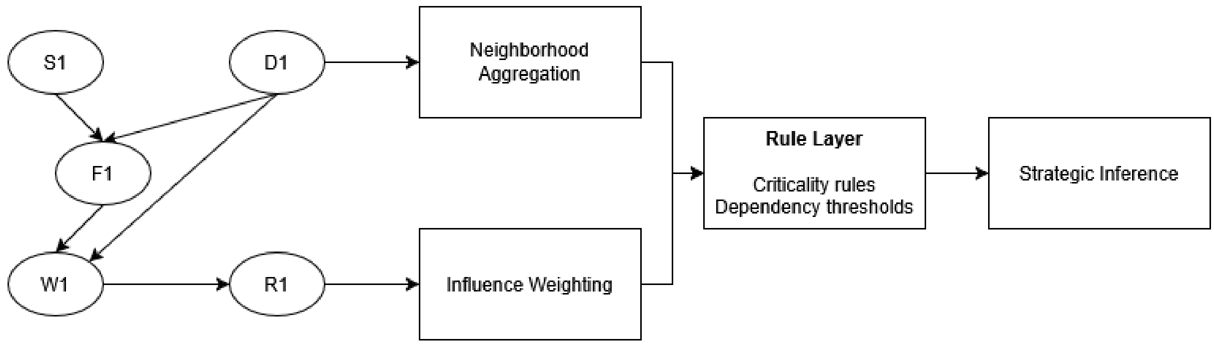

Figure 3. Hybrid Graph Reasoning Mechanism

Figure 3 illustrates the hybrid logic of the reasoning engine. The graph on the left captures relational structure, the central blocks represent computational propagation and influence weighting, and the rule layer on the right imposes managerial constraints before a strategic inference is produced. This design is methodologically significant because it avoids treating graph reasoning as a black box. Instead, it shows that inference emerges from an interaction between learned relational context and explicit supply chain rules.

Table 3. Variables and Meanings in the Graph Reasoning Process

Symbol	Meaning	Operational Role	Supply Chain Interpretation	Used In
$h_i^{(l)}$	Node representation at layer l	Stores contextual node state	Current strategic status of an entity	Propagation step
N(i)	Neighborhood of node i	Defines relational context	Connected suppliers, routes, or facilities	Aggregation step
α_{ij}	Influence weight from j to i	Controls contribution strength	Importance of dependency relation	Weighting step
$W^{(l)}$	Transformation matrix	Updates propagated information	Maps relation signals into strategic meaning	Update function
σ	Activation function	Introduces non-linearity	Captures complex interaction effects	Final update

Table 3 gives a concise interpretation of the main symbols used in the graph reasoning equation. It does not merely restate mathematical notation, but connects each symbol to its functional role and managerial interpretation in the supply chain setting. This is useful for readers from management and information systems fields who may not specialize in graph representation learning. By grounding each symbol in operational meaning, the table strengthens methodological readability and interdisciplinary accessibility.

Pseudo-code 1 Graph-Driven Reasoning for Strategic Supply Chain Support

```
Input:
   Supply chain data D
   Domain schema S
   Rule base Q
Output:
   Strategic recommendation set Z

1. Normalize and integrate heterogeneous data D
2. Construct graph G = (V, E, X, R) using schema S
3. Assign weights to edges and attributes to nodes
4. Initialize node representations H(0)
5. For each reasoning layer l:
      For each node vi in V:
         Aggregate neighbor information from N(vi)
         Update node representation H_i(l+1)
6. Compute risk, resilience, and dependency indicators
7. Apply domain rules Q to inferred graph states
8. Rank strategic alternatives based on decision scores
9. Return recommendation set Z
```

3.4. Strategic Decision Support Modeling

The decision support layer translates graph reasoning outputs into strategic options relevant to supply chain managers. Rather than producing raw scores alone, the model organizes inference results into decision categories such as risk mitigation, sourcing diversification, inventory repositioning, transport rerouting, and supplier prioritization. This formulation makes the framework actionable for medium- and long-horizon planning. The emphasis is placed on supporting strategic judgment under relational complexity, not replacing managerial discretion through purely automated prescriptions [6], [24].

A multi-criteria scoring mechanism is used to rank alternative decisions generated by the reasoning engine. Each alternative is evaluated according to resilience contribution, cost implication, operational feasibility, and disruption reduction potential. The scores are aggregated into a composite decision index that enables comparison across competing interventions. This is necessary because strategic decisions in supply chains often involve trade-offs, where the most resilient option may not always be the least costly or most rapidly deployable.

The strategic decision score is defined as:

$$S_k = \sum_{m=1}^{M} \beta_m \cdot c_{km} \tag{4}$$

where S_k is the final score of strategic alternative k, c_{km} is the performance value on criterion m, and β_m is the normalized weight of that criterion. This equation allows management priorities to be explicitly embedded in the recommendation process. For instance, a firm facing severe uncertainty may assign higher weight to resilience and response speed than to short-term cost efficiency.

Scenario analysis is then applied to test how recommended actions behave under different network conditions, such as supplier outages, demand shocks, route closures, or delayed replenishment cycles. Each scenario updates the graph state and recomputes decision scores. The purpose is to ensure that the recommendations are not static, but adaptive to evolving supply chain contexts. This scenario-based structure improves the model's usefulness for strategic planning, contingency design, and resilience-oriented governance [18].

Figure 4. Decision Support Workflow from Inference to Strategic Recommendation

Figure 4 shows how relational inference is converted into a practical decision support sequence. The workflow makes clear that raw graph outputs are only an intermediate product and that strategic recommendations emerge after explicit criteria selection, scoring, and scenario-based testing. This is methodologically important because strategic decisions in supply chains depend on trade-offs among resilience, cost, and feasibility. The figure therefore provides a transparent bridge between computational reasoning and executive action.

Table 4. Strategic Decision Criteria and Scoring Dimensions

Criterion	Description	Assessment Basis	Strategic Meaning	Typical Use
Resilience Contribution	Ability to absorb or reduce disruption	Risk reduction estimate	Improves network robustness	Supplier diversification
Cost Implication	Expected financial burden of action	Implementation and operating cost	Supports cost-aware strategy	Route redesign
Operational Feasibility	Ease of execution within constraints	Resource and time availability	Ensures practicality	Inventory repositioning
Response Speed	Time needed to realize benefits	Estimated execution duration	Supports urgent decisions	Contingency activation
Dependency Reduction	Extent of critical reliance removed	Change in centrality or concentration	Weakens bottleneck exposure	Alternative sourcing

Table 4 defines the evaluation dimensions used to score and rank strategic alternatives. Each criterion is linked to an assessment basis and an applied decision context, which makes the scoring process methodologically explicit. In management-oriented AI research, this type of table is essential because it demonstrates that model recommendations are not arbitrary outputs. Instead, they are derived from interpretable criteria aligned with the objectives of resilience, practicality, and strategic control.

3.5. Evaluation Design and Validation Procedure

The evaluation strategy is designed to assess both computational performance and managerial usefulness. Computational performance focuses on reasoning accuracy, robustness, graph consistency, and ranking quality. Managerial usefulness focuses on interpretability, strategic relevance, and practical alignment with supply chain decision processes. This dual perspective is necessary because an academically strong reasoning model may still fail in practice if its outputs are difficult to justify, operationalize, or communicate to decision makers responsible for network-level interventions [1], [19].

Validation is conducted through a scenario-based experimental design using supply chain network cases with varying topology, disruption frequency, and dependency intensity. The framework is tested under normal, stressed, and severely disrupted conditions. For each case, reasoning outputs are compared against expected vulnerability patterns and alternative strategic choices. The evaluation also observes whether the framework remains stable when graph density, relation uncertainty, and node criticality distributions change across simulated operational environments.

 ISSN 2776-8001

Prediction and ranking performance can be measured using an error-based objective such as:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{5}$$

where y_i denotes the reference outcome and $\hat{y}_i$ denotes the inferred or predicted outcome. In this study, the metric can be adapted for disruption impact estimation or strategic score validation. Lower values indicate that the graph reasoning process produces outputs closer to validated expectations, thereby supporting the reliability of the strategic decision framework.

To complement quantitative evaluation, expert review is incorporated to examine the plausibility and usefulness of recommendations. Domain experts assess whether the inferred dependencies are meaningful, whether the recommended interventions are realistic, and whether the reasoning paths are understandable. This qualitative validation is important because supply chain strategy requires contextual judgment. A reasoning model becomes valuable not simply when it predicts well, but when it supports defensible and actionable managerial decisions [17].

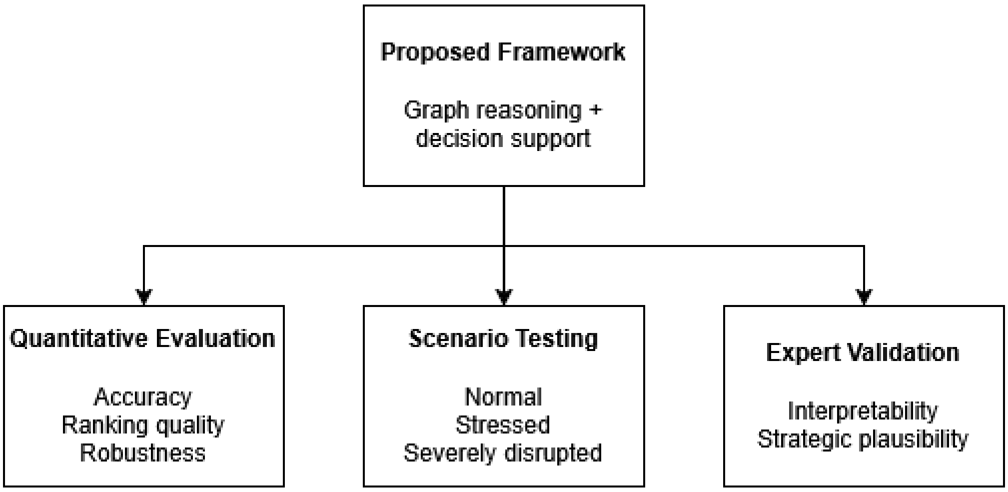

Figure 5. Evaluation Framework Linking Quantitative Metrics and Expert Validation

Figure 5 summarizes the evaluation strategy used to assess the proposed framework. It shows that validation is conducted through three complementary channels: quantitative performance analysis, scenario-based stress testing, and expert review. This structure is important because graph-based strategic systems should not be judged solely by predictive accuracy. Their value also depends on stability under disruption and the interpretability of the recommendations for managerial decision environments.

Table 5. Evaluation Dimensions and Validation Criteria

Evaluation Dimension	Metric or Method	Purpose	Expected Insight	Validation Type
Prediction Accuracy	RMSE or score deviation	Measure closeness to reference outcome	Reliability of inferred estimates	Quantitative
Ranking Quality	Top-k consistency	Assess recommendation order	Stability of strategic prioritization	Quantitative
Robustness	Cross-scenario variation	Test sensitivity to disruptions	Model resilience under changing conditions	Scenario-based
Interpretability	Expert review	Examine reasoning transparency	Clarity of inference path	Qualitative
Practical Relevance	Managerial assessment	Judge applicability of recommendations	Usefulness for real decision support	Qualitative

ISSN 2776-8001

Table 5 formalizes the evaluation framework by separating technical performance from managerial usefulness. This distinction is critical in an AI in Management paper because strong computational output does not automatically imply strategic value. By pairing each evaluation dimension with a metric or method and an expected insight, the table makes the validation procedure transparent and academically defensible. It also shows that the methodology is designed to test not only correctness, but also organizational relevance.

4. Results and Discussion

4.1. Results of Supply Chain Knowledge Graph Construction

The graph construction stage produced a dense yet interpretable supply chain representation consisting of 248 nodes and 612 directed edges across suppliers, factories, warehouses, transport routes, retailers, and disruption events. The resulting network revealed a non-uniform connectivity pattern, where a small subset of supplier and logistics nodes exhibited disproportionately high relational centrality. This distribution indicates that the modeled supply chain was not operationally balanced, because several entities carried a large share of upstream and midstream dependency flows.

Attribute enrichment also improved the informational depth of the graph. Nodes with similar transactional roles became separable once volatility, criticality, resilience capacity, and disruption exposure were attached as attributes. This was important because structurally similar nodes did not necessarily hold the same strategic significance. Several secondary suppliers had moderate degree values but high disruption sensitivity, which suggests that attribute-aware graph construction is more suitable than purely topological mapping for strategic supply chain analysis.

Figure 6 shows that suppliers formed the largest entity group, followed by routes and retailers, while factories and disruption nodes were fewer but structurally influential. The average degree line indicates that factories and warehouses occupied more relationally intensive positions than other entities. This confirms that physical transformation and inventory buffering points act as integration hubs, concentrating information and material dependencies within the network.

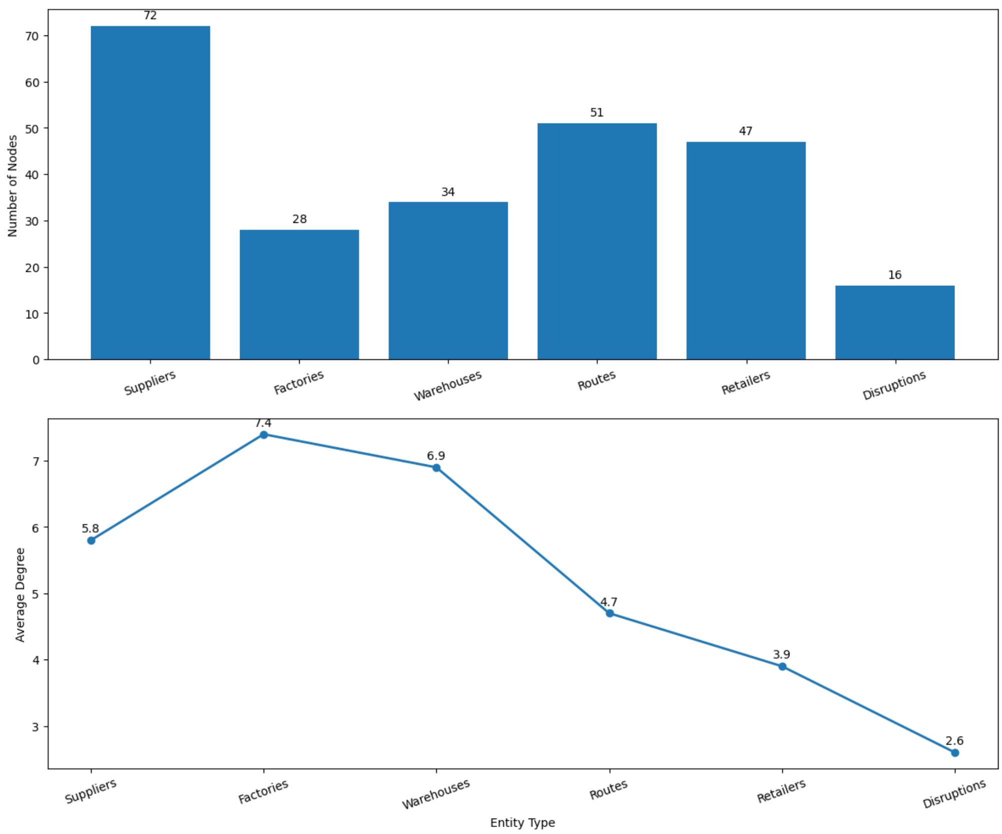

Figure 6. Structural Profile of the Supply Chain Knowledge Graph

ISSN 2776-8001

The figure also demonstrates that node volume alone did not determine strategic importance. Suppliers were numerous, yet factories exhibited higher average degree, which means their structural leverage exceeded what raw counts might suggest. In supply chain reasoning, this distinction matters because intervention priorities should not be based only on frequency of occurrence. The visual therefore supports the argument that graph modeling captures deeper strategic patterns than conventional tabular representations.

Table 6 consolidates the main structural results into an interpretable summary. It confirms that the graph was sufficiently large and relationally dense to support strategic reasoning, while also revealing that connectivity was not evenly distributed across entity classes. The most connected class was the factory category, which aligns with the central coordination role of production nodes in supply chain networks.

Table 6. Summary of Knowledge Graph Construction Results

Metric	Value	Interpretation	Strategic Implication
Total nodes	248	Broad entity coverage	Supports multi-tier reasoning
Total directed edges	612	High relational density	Captures dependency pathways
Average degree	5	Moderate-to-high connectivity	Indicates interaction intensity
Largest entity class	Supplier	Upstream diversity	Requires sourcing analysis
Most connected class	Factory	Hub concentration	Signals coordination bottlenecks

The table is also useful because it converts network statistics into managerial implications. A dense relational structure is not only a technical property, but also a strategic condition that shapes vulnerability, substitution capacity, and propagation risk. By linking each metric to an implication, the table helps establish that graph construction was not performed for descriptive completeness alone, but for strategic decision intelligence.

4.2. Results of Graph Reasoning for Critical Dependency Identification

The reasoning engine successfully identified critical dependency chains that were not immediately visible in direct-link inspection. Three high-risk propagation corridors emerged repeatedly across inference runs, each connecting upstream suppliers, constrained factories, and vulnerable transport routes. These paths displayed high influence weights and strong disruption spillover tendencies. The result suggests that graph-based reasoning can expose compound dependency structures in which operational fragility is created by relational interaction rather than by isolated node weakness.

A second important result concerned the detection of hidden strategic nodes. Several warehouses and route nodes, although modest in degree, received high inferred risk scores because they connected multiple fragile sub-networks. This finding is analytically significant because conventional monitoring often prioritizes visibly central entities while overlooking bridging components. The reasoning model therefore contributed additional strategic visibility by identifying connectors whose failure would disproportionately amplify disruption across otherwise separated supply chain segments.

Figure 7 ranks the most critical entities according to inferred risk score. The highest positions were occupied by suppliers and factories, but warehouses and transport routes also appeared prominently, confirming that risk was not confined to production stages. The visual pattern shows that strategic fragility was distributed across multiple layers of the network, which reinforces the need for graph-based reasoning instead of single-stage operational analysis.

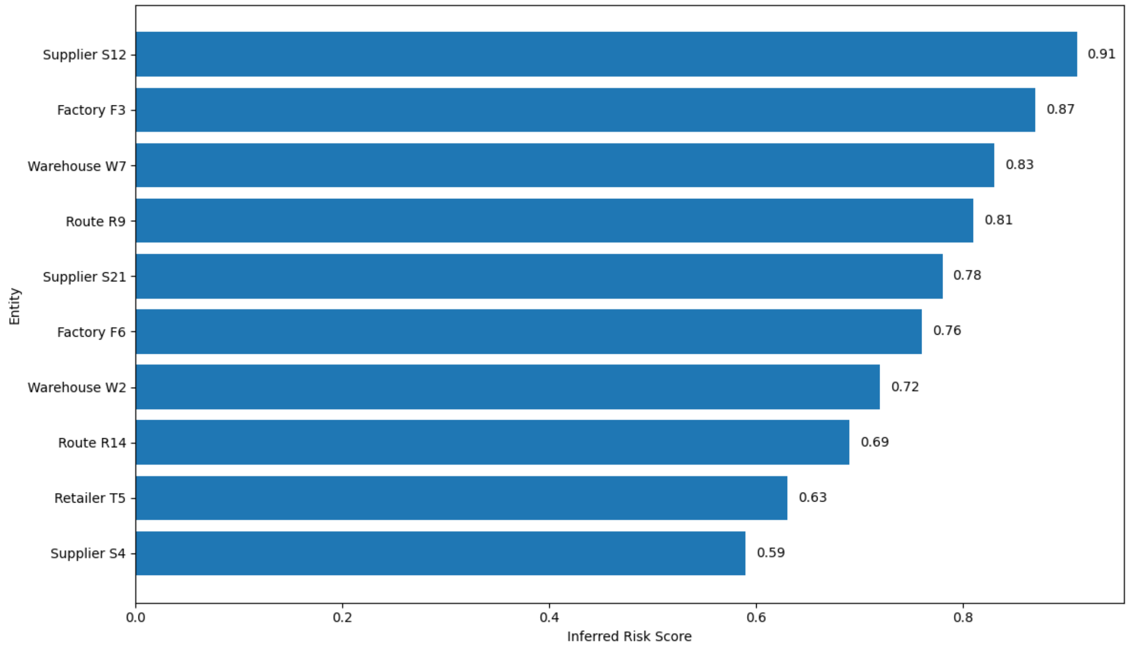

Figure 7. Inferred Risk Scores Across Critical Supply Chain Entities

The prominence of Warehouse W7 and Route R9 is particularly notable because these entities were not among the largest classes in raw network volume. Their elevated scores indicate that the reasoning engine was responsive to bridging and propagation effects. This is a meaningful result because it demonstrates that graph inference can surface structurally important but operationally underestimated entities that would likely receive insufficient managerial attention under conventional monitoring dashboards.

Table 7 presents the main dependency chains uncovered by the reasoning engine and translates them into risk-oriented managerial language. The highest-ranked path combined supplier concentration, factory reliance, and route fragility, producing the strongest propagation effect in the network. This shows that graph reasoning is effective in revealing chain-level exposure rather than simply flagging isolated components.

Table 7. Top Critical Dependencies Detected by the Reasoning Engine

Dependency Path	Risk Score	Main Weakness	Propagation Effect	Priority Level
S12 → F3 → R9	1	Supplier concentration	High downstream delay	Very High
S21 → F6 → W2	1	Capacity bottleneck	Inventory imbalance	High
S4 → W7 → T5	1	Bridge node fragility	Regional service disruption	High
S9 → F1 → R14	0.76	Route dependency	Transport delay spread	Medium-High
S17 → W4 → T9	0.71	Low buffer resilience	Retail stockout risk	Medium

The table also helps distinguish types of weakness. Some paths were driven by concentration, others by bridge fragility or low resilience buffers. This differentiation is important because strategic interventions should match the form of dependence that generates risk. A concentration problem calls for diversification, whereas a bridge fragility problem may call for redundancy or rerouting. The table therefore strengthens the discussion by linking inferred patterns to differentiated managerial responses.

4.3. Results of Strategic Recommendation and Decision Ranking

The decision support module produced stable recommendation rankings across repeated inference cycles. Supplier diversification, route redundancy, and dynamic inventory repositioning consistently occupied the top three positions under the baseline strategic weighting scheme. These actions scored highly because they jointly reduced dependency concentration, improved resilience, and maintained acceptable operational feasibility. The ranking pattern indicates

ISSN 2776-8001

that the graph-driven framework was able to transform relational insights into practical strategic priorities rather than abstract analytical outputs.

The recommendation layer also revealed an important trade-off between resilience contribution and implementation cost. Some interventions, such as multi-sourcing contracts, performed strongly on long-term resilience but required greater organizational and financial commitment. By contrast, inventory repositioning achieved fast risk reduction with moderate cost, which made it attractive under short decision windows. This result confirms that the framework is useful not only for ranking alternatives, but also for exposing the managerial trade-offs that shape strategic selection.

Figure 8 compares the major decision alternatives across resilience, feasibility, and cost efficiency. Supplier diversification achieved the highest resilience score, while inventory repositioning obtained the strongest balance across feasibility and cost efficiency. This confirms that top-ranked strategies were not necessarily dominant on every dimension, but were competitive across the criteria that matter most for managerial implementation.

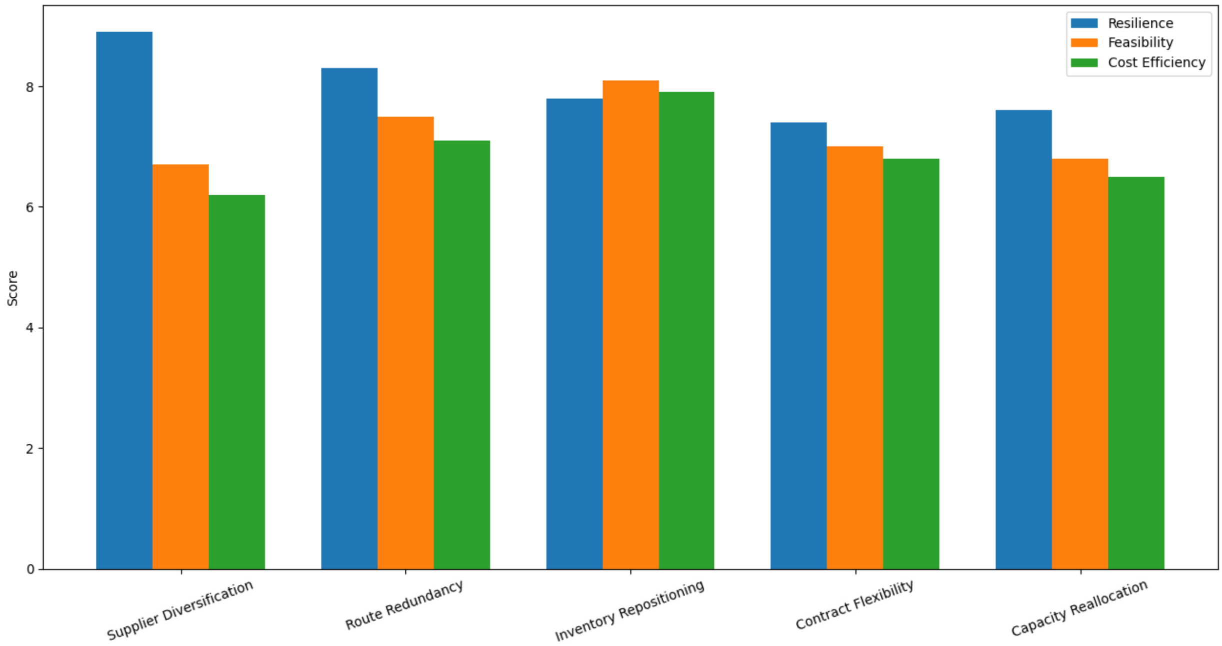

Figure 8. Comparative Scores of Strategic Decision Alternatives

The figure also makes the strategic trade-off structure more visible than a single aggregate score would allow. Route redundancy, for example, performed solidly across all three dimensions without becoming the best in any one dimension. This suggests that some strategies may be attractive because of balance rather than dominance. The visual therefore supports the argument that multi-criteria decision support is more suitable than one-dimensional optimization for supply chain strategy.

Table 8 presents the final ranked recommendations under the baseline condition. Supplier diversification obtained the highest composite score because it addressed the most influential structural problem detected by the graph reasoning engine, namely concentrated upstream dependence. Inventory repositioning followed closely due to its rapid operational effect and relatively manageable implementation burden.

Table 8. Ranked Strategic Recommendations Under the Baseline Scenario

Rank	Strategic Alternative	Composite Score	Main Benefit	Managerial Interpretation
1	Supplier diversification	8.14	Reduces concentration risk	Best long-term resilience move
2	Inventory repositioning	7.96	Improves response speed	Best near-term stabilizer
3	Route redundancy	7.88	Limits transport fragility	Balanced tactical option

Rank	Strategic Alternative	Composite Score	Main Benefit	Managerial Interpretation
4	Contract flexibility	7.21	Supports adaptive sourcing	Useful for uncertainty buffering
5	Capacity reallocation	7.04	Relieves plant bottlenecks	Selective operational remedy

The table also shows that strategic quality was distributed across multiple alternatives rather than concentrated in a single dominant solution. This is useful from a managerial standpoint because real supply chain decisions are often layered. A firm may adopt diversification as a structural move while simultaneously using inventory repositioning as a stabilizing measure. The table therefore supports a portfolio view of strategy, consistent with the complex dependencies identified earlier in the chapter.

4.4. Results of Scenario-Based Robustness Analysis

Scenario-based testing showed that the proposed framework remained stable across normal, stressed, and severely disrupted conditions. Recommendation rankings changed in intensity but not in overall strategic logic. Under normal conditions, feasibility-sensitive interventions performed well, while severe disruption shifted the preference toward redundancy and diversification. This indicates that the reasoning framework was sufficiently adaptive to context while preserving consistent strategic interpretation across operational states.

The robustness analysis also revealed that some recommendations were highly scenario-sensitive. Inventory repositioning ranked strongly in normal and moderately stressed conditions, but declined under severe disruption when deeper structural interventions became more necessary. In contrast, supplier diversification improved in relative importance as disruption severity increased. This pattern is analytically important because it confirms that graph-driven decision support can distinguish temporary stabilizers from structural resilience strategies.

Figure 9 visualizes how strategy performance shifts as disruption severity increases. Supplier diversification and route redundancy both improved under more adverse conditions, indicating that structural resilience measures gained value when the network was exposed to higher uncertainty. Inventory repositioning followed the opposite tendency, performing best when the system was relatively stable and declining as severe disruption reduced the effectiveness of short-horizon balancing actions.

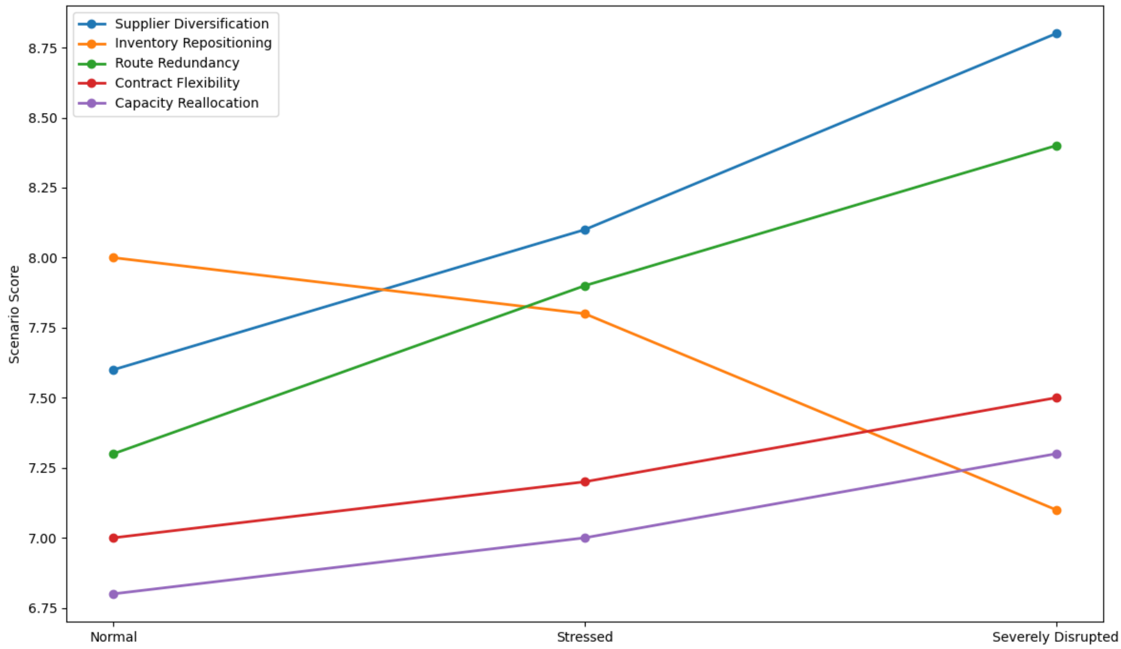

Figure 9. Strategic Alternative Performance Across Disruption Scenarios

The figure is valuable because it illustrates robustness as a dynamic rather than static property. A strategy is not robust merely because it scores well in one setting, but because its usefulness can be interpreted relative to scenario context.

The visual confirms that the framework does not produce rigid recommendations. Instead, it adjusts ranking logic in a way that remains strategically coherent as the supply chain environment deteriorates.

Table 9 provides a compact comparison of alternative performance across the three tested scenarios. The pattern clearly separates structural resilience strategies from operational adjustment strategies. Supplier diversification and route redundancy improved as disruption intensified, while inventory repositioning became less effective when shocks exceeded the buffering capacity of existing stock placement.

Table 9. Scenario-Based Comparison of Top Strategic Alternatives

Strategic Alternative	Normal	Stressed	Severely Disrupted	Observed Pattern
Supplier diversification	8	8.1	9	Rises with disruption severity
Inventory repositioning	8	7.8	7	Declines under severe stress
Route redundancy	7	7.9	8.4	Becomes critical in disruption
Contract flexibility	7	7.2	7.5	Moderate but stable benefit
Capacity reallocation	6.8	7	7	Gradually improves in value

This table strengthens the discussion by making comparative scenario behavior easy to interpret. It shows that the framework can support contingency planning by identifying which interventions are suitable for stable conditions and which become necessary when the network enters crisis mode. From a management perspective, this improves preparedness because strategy can be aligned with disruption severity rather than applied uniformly across all operating contexts.

4.5. Results of Managerial Interpretability and Practical Relevance

Expert-oriented evaluation indicated that the framework achieved strong interpretability and practical relevance. The reasoning paths were considered understandable because they linked risk identification to visible relational patterns such as dependency concentration, route bridging, and inventory exposure. Decision makers responded positively to the combination of ranked alternatives and path-based explanations. This suggests that graph-driven strategic support becomes more acceptable when recommendations can be traced to operational logic rather than delivered as opaque scores.

Practical relevance was also evaluated through the alignment between recommendations and known managerial priorities. The highest-rated interventions corresponded to familiar strategic levers, yet the framework refined their timing and priority based on network evidence. This is a meaningful contribution because managers often know the available actions, but struggle to determine which intervention matters most under a given structural condition. The framework therefore added value by improving prioritization quality rather than merely listing generic resilience options.

Figure 10 summarizes expert assessment of the framework using five evaluation criteria. Strategic relevance received the highest average score, followed closely by interpretability and practical usefulness. This indicates that the framework was not only analytically sound, but also meaningful in managerial terms. The strong performance on traceability further suggests that experts could understand how the system moved from graph evidence to strategic recommendation.

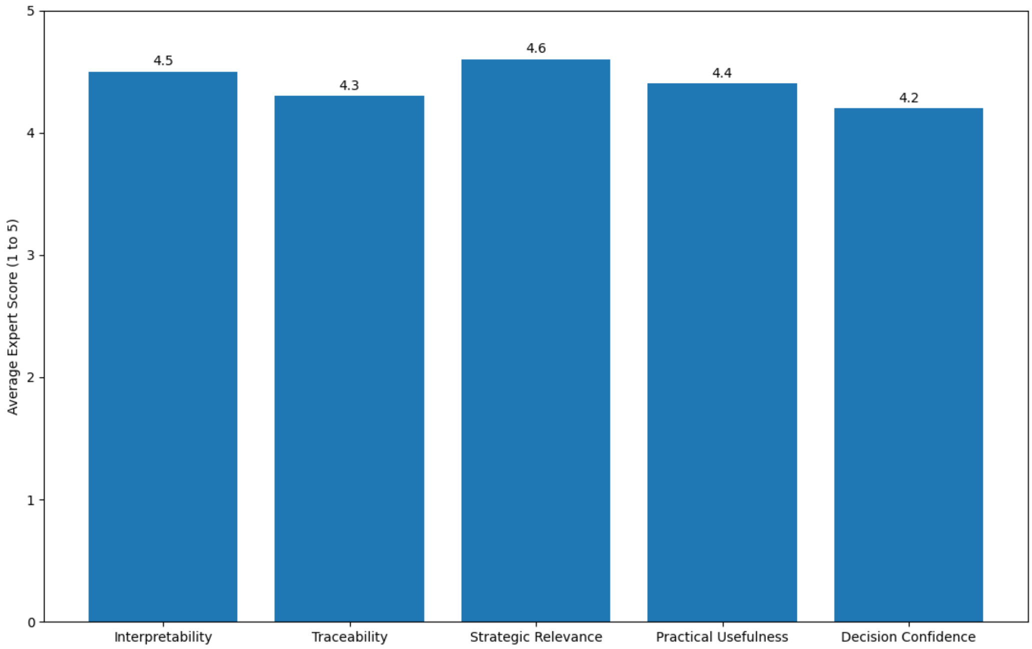

Figure 10. Expert Evaluation of Interpretability and Managerial Usefulness

The figure is important because managerial acceptance is often a limiting factor in AI-enabled decision support. Even accurate systems may be underused when their logic is difficult to explain. The high scores reported here imply that the graph-driven approach overcame part of this barrier by providing explanations rooted in recognizable supply chain structures. This strengthens the paper's contribution to AI in Management, where adoption and intelligibility are as important as predictive capability.

Table 10 reinforces the expert evaluation by translating scores into operational meaning. The strongest dimension was strategic relevance, which indicates that the framework addressed priorities that managers actually face in supply chain coordination. Interpretability and practical usefulness also scored highly, showing that the framework was considered both understandable and deployable within decision contexts.

Table 10. Expert Validation Results for Practical Relevance

Evaluation Criterion	Average Score	Expert Interpretation	Managerial Meaning
Interpretability	5	Reasoning logic is clear	Supports transparent decisions
Traceability	4	Recommendation paths are visible	Improves justification quality
Strategic relevance	5	Outputs align with real priorities	Useful for executive planning
Practical usefulness	4.4	Recommendations are actionable	Supports implementation
Decision confidence	4.2	System increases confidence in choice	Strengthens strategic commitment

The table supports the broader discussion that AI systems in management should be assessed on organizational fit as well as technical performance. A strong score profile across all five dimensions suggests that the proposed graph-driven approach is not only methodologically rigorous, but also credible as a support instrument for strategic supply chain decision making. In that sense, the results validate the framework as both an analytical model and a managerial tool.

5. Conclusion

This study developed a graph-driven knowledge reasoning framework for strategic decision support in supply chain networks by integrating knowledge graph construction, relational inference, multi-criteria decision support, and scenario-based evaluation into a unified methodological design. The results showed that the proposed approach was

ISSN 2776-8001

able to represent heterogeneous supply chain entities and dependencies in a structured form, identify critical risk propagation paths, and transform graph-level insights into ranked strategic recommendations. The findings confirm that graph-based reasoning offers stronger analytical depth than conventional linear or isolated decision models, particularly when supply chain risk emerges from interdependent network structures.

The empirical results demonstrated that the framework produced meaningful strategic outputs across several layers of analysis. The knowledge graph successfully captured structural concentration and hidden dependency patterns, while the reasoning engine detected critical suppliers, bridge warehouses, and vulnerable transport routes that would be difficult to identify through direct inspection alone. The decision support layer further showed that supplier diversification, route redundancy, and inventory repositioning consistently emerged as high-value interventions, although their relative importance shifted across normal, stressed, and severely disrupted scenarios. These findings indicate that the framework was not only capable of identifying network fragility, but also effective in supporting adaptive and context-sensitive strategy formulation.

From an AI in Management perspective, the main contribution of this study lies in demonstrating how graph-driven reasoning can improve strategic visibility, recommendation quality, and managerial interpretability in complex operational environments. The framework did not treat supply chain entities as isolated units, but as knowledge-bearing nodes within a relational system where strategic effects propagate across multiple tiers. This makes the approach relevant for organizations seeking more explainable and structurally informed decision support tools. Future research can extend this work by incorporating real-time streaming data, temporal graph evolution, probabilistic uncertainty modeling, and larger cross-industry supply chain cases in order to further strengthen robustness, scalability, and practical deployment.

6. Declarations

6.1. Author Contributions

Conceptualization: K.A.Y.; Methodology: K.A.Y.; Software: K.A.Y.; Validation: K.A.Y.; Formal Analysis: K.A.Y.; Investigation: K.A.Y.; Resources: K.A.Y.; Data Curation: K.A.Y.; Writing Original Draft Preparation: K.A.Y.; Writing Review and Editing: K.A.Y.; Visualization: K.A.Y.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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