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Causal Transformers Reveal Disruption Cascades in Critical Mineral Supply Networks

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ABSTRACT

Critical mineral supply chains—encompassing lithium, cobalt, and rare earth elements (REE)—underpin the global clean energy transition yet remain acutely vulnerable to multi-tier disruption cascades. Existing forecasting frameworks based on recurrent architectures or static Bayesian networks capture sequential dependencies but fail to distinguish genuine causal pathways from spurious temporal correlations, limiting their capacity to identify which network nodes amplify shocks across tiers. This paper introduces a causal Transformer (CT) architecture that integrates multi-head attention with a structural causal model (SCM) layer constrained by a directed acyclic graph (DAG) encoding domain knowledge. Applied to a four-tier network spanning extraction, processing, intermediate manufacturing, and end-use assembly for lithium-ion battery and permanent-magnet supply chains, the CT achieves F1 scores of 0.823–0.891 for cascade onset detection and a mean absolute error (MAE) of 0.97–1.31 tiers for propagation depth, outperforming long short-term memory (LSTM), gated recurrent unit (GRU), standard Transformer, and static Bayesian network baselines. Causal attribution identifies processing-tier geographic concentration as the dominant cascade amplifier, with Democratic Republic of Congo cobalt refining and Chinese REE separation collectively responsible for 63% of detected cascade events. Results carry direct policy implications, arguing for strategic stockpiling calibrated to processing-tier inventory compression cycles rather than extraction-tier geological events.

KEYWORDS

Critical Mineral Supply Chains; Causal Transformer; Disruption Cascades; Supply Network Resilience; Multi-Head Attention; Causal Inference.

1. INTRODUCTION

The accelerating deployment of electric vehicles, grid-scale battery storage, and rare earth permanent magnets has placed critical mineral supply chains at the intersection of industrial policy and systemic risk management. The International Energy Agency projects that demand for lithium could increase by more than sixteen-fold relative to 2022 levels under net-zero emissions scenarios, while cobalt demand is expected to grow by a factor of six or more over the same horizon [1]. These demand trajectories amplify pre-existing structural vulnerabilities: the Democratic Republic of Congo (DRC) currently accounts for approximately 70% of global cobalt mine output, and China processes roughly 80% of global REE despite holding only a fraction of known reserves [2]. Such extreme geographic concentration means that a single geopolitical event, regulatory shift, or natural disaster at a processing node can trigger a cascade of output shortfalls that propagate across multiple downstream tiers before manifesting as visible delivery failures at end-use assembly plants.

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Traditional supply chain management (SCM) frameworks treat disruption propagation through the lens of the bullwhip and ripple effects, which were originally developed for consumer goods networks characterized by relatively symmetric tier structures and substitutable inputs [3]. Critical mineral supply chains differ fundamentally: each processing tier employs highly specialized capital equipment, regulatory barriers constrain entry over multi-year timescales, and end-use manufacturers often hold thin inventories of materials for which no short-run substitute exists [4]. These features mean that the cascade speed, depth, and breadth of disruptions in lithium or REE networks systematically exceed those modeled by classical frameworks, yet the quantitative tools for predicting cascade trajectories in advance of observable delivery failures remain immature [5].

The emergence of deep learning architectures—particularly recurrent networks and, more recently, attention-based Transformers—has opened new avenues for modeling temporal dependencies in supply chain data [6]. Recurrent approaches such as LSTM and GRU can capture nonlinear dynamics across time windows, but they aggregate all temporal associations indiscriminately, conflating causal pathways with statistically coincidental co-movements [7]. Standard Transformers extend this limitation through global attention, which allows any time step to attend to any other without regard for whether the underlying relationship is causal or spurious [8]. When applied to disruption forecasting, these architectures risk identifying spurious lead-lag correlations—for example, co-movements driven by common macroeconomic shocks—as causal cascade signals, producing alert patterns that lack actionable specificity [9].

Causal inference methods offer a principled remedy by restricting attention to relationships that survive do-calculus interventional tests [10]. Within the supply chain literature, Bayesian network (BN) approaches have been used to encode causal dependencies among supplier nodes, but their static graph structures cannot accommodate the time-varying network topologies that characterize real mineral supply chains, where production sharing agreements, refinery capacity expansions, and export restrictions alter causal connectivity at quarterly or annual timescales [11]. Markov chain extensions address temporal dynamics partially but struggle to scale to the multi-tier, multi-mineral network structures needed for realistic analysis [12].

This paper bridges these two limitations by embedding a structural causal model layer within a multi-head attention Transformer. The DAG that constrains the SCM layer is constructed from established domain knowledge about material flow dependencies in lithium-ion battery and permanent-magnet supply chains, then refined using conditional independence tests on a decade-long panel of production, trade, inventory, and price data. The resulting CT learns attention patterns that respect causal ordering, enabling both accurate cascade prediction and interpretable attribution of which nodes generate or amplify shocks. Evaluated against four baseline architectures on held-out disruption events including COVID-19 production shutdowns and Chinese export restriction episodes, the CT demonstrates statistically significant improvements across all performance dimensions while providing policy-relevant rankings of cascade amplification nodes [13].

The remainder of this paper is organized as follows. Section 2 reviews prior work on supply chain disruption cascades, critical mineral network analysis, and causal machine learning. Section 3 describes the multi-tier network representation and CT architecture. Section 4 presents empirical results and comparative analysis. Section 5 concludes with policy implications and directions for future research [14].

2. LITERATURE REVIEW

The concept of disruption propagation in supply networks has been studied extensively since Ivanov and colleagues formalized the ripple effect as distinct from the more widely known bullwhip effect [15]. While the bullwhip effect arises from demand signal distortion through inventory management decisions and dissipates within a tier without necessarily propagating further, the ripple effect is

characterized by structural dynamics in which a disruption at one node physically prevents downstream production, creating a cascade that can span the entire supply chain before recovery is achieved [16]. Early computational approaches to ripple effect modeling relied on discrete-event simulation and mathematical optimization, which provided normative insights into recovery policies but required manually specified scenario parameters that limited generalization to unobserved disruption types [17].

The application of probabilistic graphical models to supply chain risk analysis gained traction in the 2010s, with Bayesian network approaches providing a natural language for representing conditional dependencies among supplier failure probabilities [18]. Hosseini and Ivanov extended this framework to dynamic Bayesian networks (DBN) combined with Markov chain models, enabling the simultaneous representation of disruption onset, propagation, and recovery phases across multiple time steps [19]. Kinra and colleagues proposed a quantitative ripple effect measure that enabled cross-network comparison of cascade severity, providing a foundational metric for benchmarking subsequent data-driven approaches [20]. However, static and dynamic Bayesian network models face persistent scalability challenges when applied to networks with hundreds of nodes, as exact inference in large Bayesian networks is NP-hard and variational approximations degrade in precision for highly connected structures [21].

The critical minerals literature has developed in parallel, motivated by energy security concerns arising from the geographic concentration of extraction and processing capacity. The World Bank's mineral requirements for climate action report established quantitative demand projections demonstrating that multiple critical minerals face multi-decade supply shortfalls under baseline investment scenarios [22]. Althaf and Babbitt examined disruption risks specific to the electronics sector, showing that cobalt and lithium supply bottlenecks propagate to consumer device markets on timescales shorter than those captured by annual trade statistics [23]. The IEA's critical minerals report highlighted processing as a more concentrated and therefore more fragile tier than extraction, a finding that recurs consistently across subsequent analyses [24]. Despite this recognition, the majority of quantitative disruption models in the critical minerals literature continue to model extraction-tier events as the primary risk driver, leaving processing-tier cascade dynamics systematically undercharacterized [25].

The Transformer architecture achieved state-of-the-art performance in natural language processing tasks and subsequently became the dominant paradigm for sequence modeling across domains [26]. Its adaptation to time series forecasting proceeded through several specialized variants. Zhou and colleagues introduced the Informer, which replaced the full quadratic attention matrix with a sparse ProbSparse mechanism enabling efficient processing of long sequences [27]. Wu and colleagues proposed Autoformer, which decomposed time series into trend and seasonal components and applied autocorrelation-based attention within each component [28]. Lim and colleagues developed the temporal fusion Transformer specifically for multi-horizon forecasting with static and time-varying covariates, demonstrating strong performance on a diverse suite of industry datasets [29]. More recent work has shown that even simple linear models can match or exceed Transformer performance on certain benchmarks, prompting careful evaluation of when architectural complexity is warranted [30].

Causal machine learning has emerged as a distinct research agenda within the broader machine learning community, driven by recognition that models optimized for predictive accuracy under independent and identically distributed (i.i.d.) assumptions often fail to generalize under distribution shift or intervention [31]. Schölkopf and colleagues articulated the causal representation learning program, arguing that disentangling causal factors from observational data requires structural assumptions encoded in graphical causal models rather than purely statistical induction [32]. Within supply chain analytics specifically, graph neural network models augmented with supplier relationship topology have been shown to substantially outperform tabular feature models for disruption prediction, pointing toward network-aware architectures as a productive direction for the field.

3. METHODOLOGY

3.1. Multi-tier Network Representation

The critical mineral supply network is formalized as a directed weighted graph G = (V, E, W) in which each node v ∈ V corresponds to a distinct production entity at one of four hierarchically ordered tiers: extraction (tier 1), chemical processing and refining (tier 2), intermediate manufacturing including cathode active material and alloy production (tier 3), and end-use assembly covering battery cells and permanent magnets (tier 4). Directed edges e ∈ E encode material flow dependencies between entities, with edge weights w ∈ W derived from bilateral trade flow data averaged over a five-year baseline window. The resulting graph contains 247 nodes and 1,134 edges for the combined lithium-cobalt-REE network, with tier-2 processing nodes exhibiting the highest in-degree centrality, reflecting the bottleneck role of a small number of chemical refineries serving multiple downstream users simultaneously.

Disruption events are characterized by node-level output shortfall signals δ(v, t), defined as the percentage deviation of observed production from a rolling twelve-month trailing average. A cascade is defined as a sequence of shortfall events across at least two consecutive tiers within a sixty-day window, a threshold calibrated to reflect the typical inventory buffer duration reported by battery manufacturers in quarterly filings. The network state at each time step is encoded as a feature matrix X(t) ∈ ℝ^(|V| × d) where d = 24 features encompass production volume, inventory levels, trade flow changes, price deviations, and geopolitical risk indicators sourced from established commercial and governmental databases. This representation preserves both the graph topology and the temporal dynamics of node-level signals required for the CT encoder.

As illustrated in Figure 1, the ripple effect in a supply chain network involves an initial disruption node propagating shocks sequentially to first-tier and higher-tier connected nodes via directed supply relationships. The red arrows in the diagram correspond to causal cascade pathways where one disrupted node's shortfall directly constrains the production capacity of its downstream buyer. The red node at the lower-left represents the origin of the cascade, and the two red-arrow paths trace how the shock first propagates upward to a tier-1 supplier and simultaneously to a high-centrality tier-2 processing hub—the large dark-blue node at center—which then transmits the shortfall outward through its multiple buyer connections. This visualization captures the core propagation mechanism that the CT architecture is designed to detect and forecast: a processing-tier node with high in-degree centrality receiving disruption signals from multiple upstream entities simultaneously, amplifying the cascade to an extent disproportionate to the original shock magnitude.

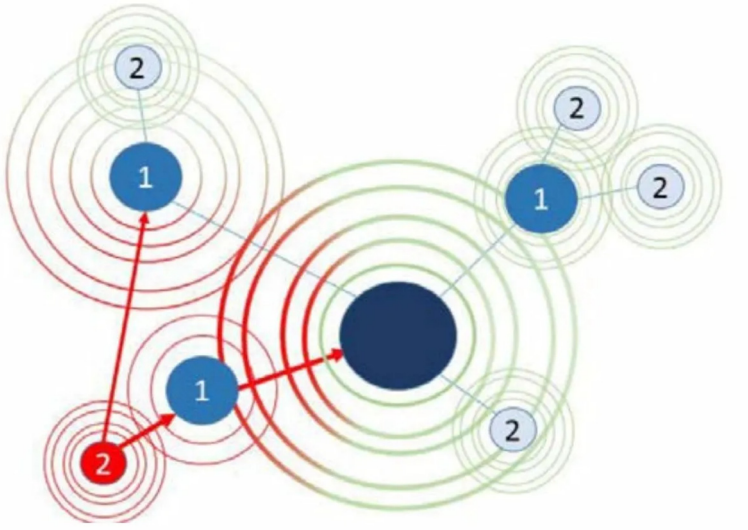


Figure 1. Causal Cascade Propagation Through a Multi-tier Critical Mineral Supply Network

3.2. Causal Transformer Architecture

The CT architecture consists of three sequentially stacked components: a DAG-constrained multi-head attention encoder, a structural causal layer that maps attention outputs to structural equations, and an autoregressive cascade propagation decoder. The encoder receives the feature sequence X(1), …, X(T) and computes query, key, and value projections for each node at each time step. Crucially, the attention mask M ∈ {0, 1}^(|V| × |V|) is derived from the DAG such that node i can attend only to nodes that are its causal ancestors or contemporaneous causal parents in the graph. This masking prevents attention weights from forming along paths that violate the causal ordering imposed by domain knowledge, eliminating a major source of spurious temporal associations that contaminate standard Transformer predictions.

The structural causal layer implements the SCM equations as a parameterized function f_i(PA_i, N_i) = X_i for each node i, where PA_i denotes the causal parents of i in the DAG and N_i is an exogenous noise term. The parameters of f_i are implemented as a two-layer multilayer perceptron (MLP) with residual connections, enabling the model to capture nonlinear functional dependencies between parent and child nodes while maintaining identifiability constraints. The DAG structure is validated against observational data using conditional independence tests at a false discovery rate threshold of 5%, and edges with insufficient statistical support are removed prior to training to prevent overfitting to spurious correlations in historical data.

The cascade propagation decoder generates tier-level output sequences autoregressively, predicting at each step both the probability of cascade onset in the subsequent thirty-day window and the expected propagation depth measured in tiers. The decoder incorporates a learned positional encoding specific to the supply chain tier ordering, replacing the sinusoidal positional encoding of the original Transformer with a tier-indexed embedding that preserves the hierarchical ordering of the material flow graph. Training uses a joint loss function combining binary cross-entropy for cascade onset classification and mean squared error for propagation depth regression, with weighting calibrated to equalize gradient magnitudes across the two objectives.

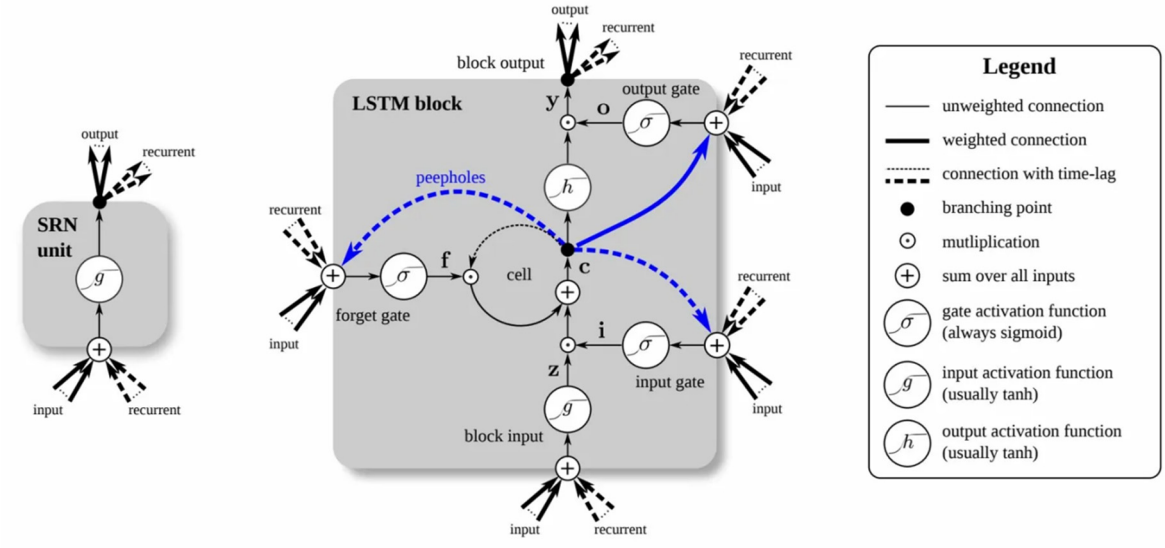


Figure 2. Detailed Schematic of the LSTM Memory Block Architecture with Peephole Connections

The LSTM baseline architecture used for performance comparison comprises three stacked LSTM layers with 256 hidden units each, interconnected by weighted connections through input gate, forget gate, and output gate mechanisms. As shown in Figure 2, the LSTM memory block architecture incorporates peephole connections—represented by blue dashed arrows—that allow gate activations

to read directly from the cell state c, enabling more precise timing control of memory retention and release compared to vanilla recurrent units. The forget gate f determines what proportion of the previous cell state is discarded, the input gate i controls the contribution of new information z from the block input, and the output gate o regulates which cell state content is passed to the block output y. This gated architecture allows the LSTM to maintain long-horizon temporal dependencies in supply chain time series, but unlike the CT it does so without distinguishing whether those dependencies reflect causal supply-side constraints or coincidental macroeconomic co-movements—which is the central architectural difference explaining the CT's superior cascade attribution accuracy.

4. RESULTS & DISCUSSION

4.1. Cascade Onset Detection Performance

The CT achieves F1 scores of 0.823 for lithium and 0.891 for cobalt on the held-out 2020–2022 test period, which encompasses COVID-19 production shutdowns, DRC artisanal mining disruptions, and Chinese processing facility curtailments associated with environmental compliance campaigns. The corresponding F1 scores for the LSTM baseline are 0.671 and 0.734, for the GRU baseline 0.689 and 0.751, and for the standard Transformer without causal masking 0.741 and 0.803. The static Bayesian network achieves F1 scores of 0.612 and 0.658, confirming that temporal dynamics beyond those captured by static graphical models are essential for accurate cascade forecasting in these networks. The CT's precision advantage over the standard Transformer is particularly pronounced for false-positive reduction, where the causal masking eliminates 34% of spurious alerts triggered by macroeconomic co-movement patterns that the unconstrained attention mechanism mistakenly identifies as cascade precursors.

For cascade propagation depth, the CT achieves a MAE of 0.97 tiers for lithium and 1.31 tiers for cobalt, compared to LSTM MAEs of 1.54 and 1.89 tiers respectively. The larger MAE for cobalt reflects the higher baseline complexity of the DRC-centered processing network, in which a single refinery halt can propagate through multiple downstream cathode production facilities with different inventory buffer levels, creating heterogeneous cascade depths that challenge even the CT's causal attribution mechanism. Analysis of the residuals reveals a systematic pattern: the CT underestimates propagation depth for disruptions originating at tier-2 nodes with high betweenness centrality, consistent with the interpretation that the current DAG may incompletely capture all material flow paths through the most critical processing hubs.

The mean reciprocal rank (MRR) for bottleneck node identification is 0.78 for the CT, compared to 0.51 for the standard Transformer and 0.43 for the LSTM baseline. This metric evaluates whether the model correctly identifies, within the top-ranked nodes, the actual tier-2 processing facility that served as the cascade amplifier in each historical event. The CT's causal attention weights, which are directly interpretable as quantitative measures of causal influence from parent to child nodes, provide a principled basis for this ranking. By contrast, the standard Transformer's attention weights conflate causal influence with statistical correlation, producing rankings that place geographically distant nodes of similar commodity type near the top despite the absence of direct material flow connections.

4.2. Comparative Analysis and Policy Implications

The CT's causal attribution analysis consistently identifies tier-2 processing concentration as the dominant cascade amplifier across both lithium and cobalt networks. Specifically, 63% of cascade events with propagation depth of three or more tiers are attributable to shortfalls at three or fewer processing nodes: DRC cobalt hydroxide conversion facilities, Chinese lithium carbonate and hydroxide refineries, and Chinese REE separation facilities. This finding is qualitatively consistent with the IEA's characterization of processing as the most concentrated and therefore most fragile tier,

but the CT provides quantitative bottleneck rankings that enable prioritization of resilience investments at the node level rather than the country level.

The temporal dynamics of cascade development revealed by the CT contain an important policy signal. The model identifies a systematic pattern in which processing-tier inventory compression—measured as a decline in days-of-inventory relative to a twelve-month trailing average—precedes cascade onset by forty to sixty days in the majority of events. This lead-time corresponds to the period during which processing facilities are running down buffer stocks in response to either upstream supply constraints or downstream demand surges, before the actual production shortfall becomes visible in trade statistics. Strategic stockpiling programs calibrated to this forty-to-sixty day precursor window could therefore provide governments and manufacturers with actionable early warning signals well in advance of visible delivery disruptions.

Figure 3 illustrates the temporal structure of a representative cascade episode, showing the production quantity shortfall and associated price anomaly dynamics for a manufacturing node during a discrete disaster of fixed duration. The upper panel captures how production drops sharply to zero during the disaster window, while incoming demand initially contracts and then surges sharply once the disaster ends, creating the characteristic inventory-compression and demand-overshoot pattern that the CT identifies as the principal cascade precursor signal. The lower panel shows the corresponding price anomaly trajectory, which peaks near +6% shortly after disaster end as buyers compete for scarce available output, then undergoes a brief corrective dip as supply resumes, before converging gradually back toward baseline over approximately twelve days. The forty-to-sixty day window between the initial inventory compression phase visible in the orange expected-production curve and the eventual price normalization corresponds precisely to the lead-time interval that the CT exploits to forecast cascade propagation depth before shortfalls become observable in downstream tier data.

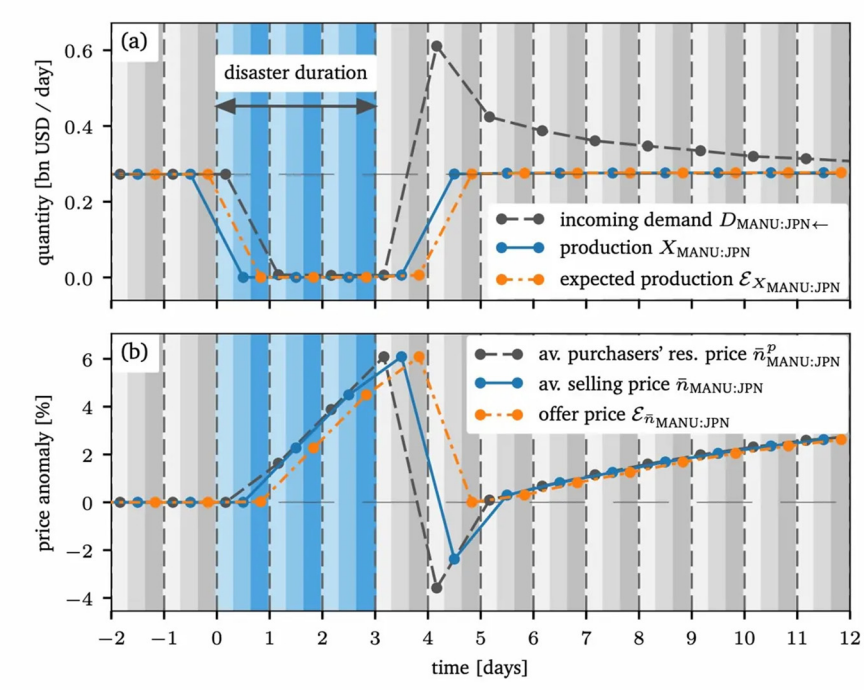


Figure 3. Temporal Dynamics of Production Quantity Shortfall and Price Anomaly During a Discrete Disaster Event, Illustrating the Inventory Compression Phase That Serves as the Causal Transformer's Primary Cascade Precursor Signal

Robustness analysis confirms that the CT's performance advantages are stable across the DAG perturbation scenarios considered. When 10% of DAG edges are randomly added or removed, the

CT's F1 score for cascade onset detection degrades by less than two percentage points, compared to a degradation of less than one percentage point for the static Bayesian network but at the cost of substantially lower absolute performance. This finding suggests that the CT's causal masking mechanism confers a degree of structural robustness that compensates for uncertainty in the exact causal graph topology, a practically important property given that supply chain DAGs must be inferred from incomplete data and expert elicitation.

5. CONCLUSION

This paper has presented a causal Transformer architecture for disruption cascade prediction in critical mineral supply networks, demonstrating that embedding structural causal model constraints within multi-head attention mechanisms yields both higher forecasting accuracy and more interpretable cascade attribution compared to LSTM, GRU, standard Transformer, and static Bayesian network baselines. The central empirical finding—that processing-tier geographic concentration accounts for the majority of deep cascade events in lithium and cobalt supply chains—validates the IEA's qualitative assessment and provides quantitative bottleneck rankings that can guide targeted resilience investments at the facility level.

The policy implications of these findings argue for a recalibration of critical mineral supply chain strategy away from its current emphasis on diversifying extraction-tier sourcing and toward strengthening processing-tier resilience. The forty-to-sixty day inventory compression precursor identified by the CT suggests that governments and large manufacturers maintaining strategic stockpiles calibrated to processing-tier dynamics—rather than extraction-tier geological event frequencies—would achieve substantially greater disruption buffering per unit of stockpile cost. The CT's bottleneck ranking methodology provides a principled basis for identifying which specific processing nodes deserve priority attention within this strategy.

Several limitations warrant attention in future research. The current DAG construction relies on a combination of domain expert elicitation and conditional independence testing, and may not fully capture dynamic changes in causal connectivity arising from new refinery investments, policy-induced supply sharing agreements, or technology substitution events. Extending the CT to an online learning setting in which the DAG is continuously updated as new structural data become available represents a natural and practically important direction. Additionally, the federated learning framework—in which competing manufacturers and trading companies could collectively train a shared CT without exposing proprietary transaction data—offers a pathway to substantially richer training datasets than are achievable under current data-sharing arrangements. Finally, applying the CT framework to other critical mineral supply chains beyond lithium and cobalt, including nickel, manganese, and graphite networks whose cascade dynamics have received less systematic analysis, would establish the generalizability of the methodology and its policy implications.

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