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Artificial Intelligence-Driven Risk Early Warning for the NEV Power Battery Supply Chain—Framework Development and Case Analysis Based on Public Information

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Abstract. The rapid growth of new energy vehicles has made power battery supply chains strategically important but increasingly exposed to mineral-price volatility, supplier disruption, quality failures, demand changes, logistics delays, and policy uncertainty. This study develops an artificial intelligence (AI)-driven early-warning framework through literature review, indicator design, public-case analysis, and scenario reasoning. The framework links five layers: data, indicators, models, warning levels, and management decisions. It organizes signals across upstream supply, internal operations, downstream demand, the external environment, and circular supply. Public disclosures from Contemporary Amperex Technology Co., Limited (CATL) illustrate how material exposure, supplier performance, customer demand, and recycling capacity can enter the framework. Four warning levels connect model outputs with differentiated procurement, inventory, production, logistics, and supplier responses. The study does not claim unverified prediction accuracy because firm-level time-series data are unavailable. It instead specifies the data and governance needed for empirical validation. The findings show that AI adds value when heterogeneous signals are converted into interpretable risk assessments and timely, accountable actions.

Keywords: artificial intelligence, power battery, supply chain risk, early warning, industrial engineering

1. Introduction

Power batteries connect critical minerals with material processing, cell manufacturing, vehicle production, after-sales service, and recycling. Batteries represent about 30%-40% of an electric vehicle's value; in 2022, China produced about three-quarters of lithium-ion batteries and held roughly 70% of cathode and 85% of anode capacity [1]. The share of the three largest refining countries for key energy minerals rose from about 82% in 2020 to 86% in 2024 [2]. Material expansion faces short-term bottlenecks, while recycling is limited by battery life and collection [3]. Both major battery chemistries also remain vulnerable across connected stages [4]. Risk must therefore be monitored across the network.

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This paper identifies power-battery risks and transmission paths, selects actionable indicators and AI methods, and links warning levels with procurement, inventory, production, logistics, and supplier decisions. It contributes an indicator-model-level-action loop for industrial engineering. This study combines literature review, indicator design, CATL public-disclosure mapping, and scenario reasoning. It compares several prediction and detection methods. Because internal operational records are unavailable, it reports no fabricated training data, thresholds, or accuracy results.

2. Theoretical foundation and literature review

2.1. Supply chain risk, resilience and the ripple effect

Supply chain resilience involves preparation, response, and recovery [5]. Power batteries include alternative sources, buffer inventory, flexible capacity, backup transport, and visibility. The ripple effect explains how upstream restrictions can delay materials and vehicle delivery. Digital technology improves visibility into these paths [6].

2.2. Applications of AI in supply chain risk management

Data-driven research applies AI to purchasing, forecasting, production, logistics, and inventory [7, 8]. Machine learning can predict delays, although performance may reduce interpretability [9]. Research also identifies limited samples, weak data sharing, and insufficient explanation [10].

2.3. Literature assessment and research position

Existing studies often separate mineral risk, operational indicators, explanation, and response. This paper integrates them into one framework.

3. Risk identification in the NEV power battery supply chain

3.1. Supply chain structure and risk categories

The supply chain covers resources, cell production, vehicle demand, logistics, policy, and recycling. Different risks converge on cost, capacity, inventory, quality and delivery. Indicators must be regularly updated, assigned to an owner, and linked to action.

Table 1. Power battery supply chain risks, indicators and operational effects

Risk area	Major risks	Indicators	Operational effects
Upstream supply	Concentration, price volatility, shutdown	Concentration, volatility, lead time, agreement coverage	Higher cost, shortage, chemistry change
Midstream operations	Quality, equipment, capacity mismatch	Yield, alarms, utilization, work in process	Scrap, stoppage, delay
Downstream demand	Order volatility, concentration, technology change	Forecast error, cancellations, customer and product mix	Excess inventory, idle capacity, shortage
Logistics and policy	Congestion, trade, weather, regulation	On-time transport, customs time, event and node exposure	Delay, route change, compliance cost
Circular supply	Low collection or unstable quality	Recovery, qualification, network coverage	Primary-material dependence, recycling cost

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Table 1 shows that different risks produce common cost, capacity, inventory, quality, and delivery effects, supporting combined external and internal monitoring.

3.2. Upstream raw-material and supplier risk

Upstream monitoring should combine concentration, source exposure, price volatility, contract deviation, lead time, and inventory coverage. Price increases become more serious when coverage falls and delivery variability rises.

3.3. Midstream operations, quality and capacity risk

Midstream indicators include yield, defects, equipment alarms, schedule attainment, utilization, and orders. Joint deterioration in equipment health and yield signals process risk. Firms must balance delivery, quality, and flexibility.

3.4. Downstream demand, logistics and policy risk

Downstream indicators include forecast error, cancellations, customer concentration, turnover, and technology changes. Logistics and policy events should be coded by location, duration, and exposure to actual suppliers, routes, or markets.

3.5. Risk-transmission paths

Risk follows source-trigger-variable-outcome. An export restriction may reduce supply, raise prices, interrupt production, and delay customers. Leading indicators are earlier but less reliable.

4. AI-driven risk early-warning framework

The data and indicator layers collect information and create features. The model layer estimates risks and drivers; warning and decision layers assign levels and actions. Post-intervention outcomes return to evaluation, creating a closed loop.

The supplier-material-time unit uses volatility, lead-time, inventory, forecast, concentration, exposure, yield, and anomaly features. Common codes, definitions, ownership, and update frequency are prerequisites; external text also requires entity matching.

Supervised models fit labeled delays, defects, and stockouts; anomaly detection addresses scarce labels; and natural language processing links external events to firms and nodes. Complexity should follow the decision need.

Table 2. Roles, advantages, and limitations of early-warning models

Method	Primary use	Advantages	Limitations and controls
Logistic regression	Labeled delay or stockout	Transparent and auditable	Limited nonlinearity, check multicollinearity
Random forest / XGBoost	Nonlinear prediction	Captures interactions	Explain with SHAP, control overfitting
Anomaly detection	Emerging or unlabeled risk	Needs no complete labels	Anomaly requires business review
NLP / knowledge graph	External text and networks	Links events and nodes	Entity and standardization errors

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Table 2 shows that transparent, nonlinear, anomaly, and text models serve different tasks; therefore, a portfolio is preferable to one classifier.

4.1. Risk scoring, validation and explanation

For risk category k at time t, the model estimates probability $\hat{p}_{k,t}$. Because equal probabilities may cause unequal losses, the score includes impact I, propagation speed V, and recovery capability C:

$$R_{k,t} = 100 \times [w_1 \widehat{p}_{k,t} + w_2 I_{k,t} + w_3 V_{k,t} + w_4 (1 - C_{k,t})] \quad (1)$$

Weights require expert judgment, historical losses, and sensitivity analysis. With few labels, anomaly scores should not be presented as validated probabilities.

Validation should use rolling windows. Precision, recall, F1, and AUC should be assessed with lead time, missed-event loss, inventory cost, and false alarms. Regression shows coefficient direction, while tree models can use SHAP. High-level warnings should display drivers and ownership.

4.2. Four-level warning and response rules

Thresholds should reflect loss, response capacity, and risk preference. Four colors represent increasing urgency while balancing missed events, false alarms, and resilience cost.

Table 3. Four warning levels and standard management actions

Level	Meaning	Primary actions	Responsibility and timing
Green	Normal range	Routine monitoring	Normal review cycle
Yellow	One abnormal or rising signal	Verify supplier, check buffers	Owner confirms in one day
Orange	Aligned signals and material impact	Backup source, adjust plans	Supply chain leader, same day
Red	Disruption imminent or occurring	Emergency allocation and communication	Immediate executive escalation

Table 3 links scores with responsibility: yellow requires verification, orange activates cross-functional mitigation, and red requires executive coordination.

5. Case analysis: mapping catl's public disclosures

5.1. Risks and resilience capabilities in public information

CATL identifies market, technology, and raw-material risks. Responses include global sourcing, upstream production, partnerships, long-term agreements, supplier controls, and recycling [11]. In 2025, its largest-five supplier and customer shares were 10.38% of purchasing and 38.96% of revenue, respectively [11]. Common upstream sources still require tracing.

Brunp Recycling processed up to 210,000 metric tons of used batteries and related materials in 2025, over 60% more year over year [11]. Recycling supports long-term security but cannot replace primary supply during short disruptions.

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5.2. Scenario reasoning and warning mapping

Table 4. Case scenarios, signal combinations and recommended responses

Scenario	Signal combination	Level	Response
Critical-material price increase	Volatility + contract gap + low coverage	Yellow–orange	Verify supply, use agreements, adjust buying and stock
Critical-node delivery delay	Late delivery + longer lead time + transit anomaly	Orange–red	Use second source, reschedule, switch route
Material or cell defect	Lower yield + complaints + batch anomaly	Orange	Quarantine, trace, and audit
Major-customer demand decline	Cancellations + forecast error + slow turnover	Yellow–orange	Adjust capacity, purchasing, and material allocation

Table 4 links combined signals—not one threshold—to warning levels and responses, allowing later tests with internal data.

5.3. Lessons from the case

Public disclosure supports classification but not training. Implementation needs monthly operational data, and AI-triggered controls require managerial review.

6. Management strategies, implementation and discussion

Procurement should minimize risk-adjusted total cost. Firms should map common sources and evaluate delivery, financial condition, geographic exposure, compliance, and data quality. Escalating warnings can trigger verification, inventory checks, second sourcing, volume reallocation, long-term contracts, or scarce-material allocation.

Safety stock should rise when lead time and delivery variability increase together, not when price alone rises. Scheduling should protect high-impact orders while retaining flexibility. Alternative ports, modes, and customs procedures should be prepared before disruption. Measures include stockouts, turnover, delivery, carrying cost, and recovery time.

Recycling reduces waste and creates the secondary supply, but collection, purity, cost and network coverage constrain usable volume. Indicators should measure qualified output, not collection alone. Optimization can compare primary sourcing, inventory, and recycling across cost, emissions, and resource constraints.

Data governance defines indicators, owners, access, quality and audit trails. AI can introduce bias, drift, entity errors, and unsupported explanations. Green and yellow signals may be automated, while orange and red require human review. Features, thresholds, explanations, and decisions should be logged and recalibrated when false alarms rise.

The framework balances accuracy and explanation, resilience and efficiency, and lead time and false alarms. Unlike a static list, it assigns data, owners, actions and business outcomes. Its main limitation is the absence of internal time-series data for empirical validation.

7. Conclusion

This study develops an AI-driven early-warning framework for the NEV power battery supply chain. Risks arise across upstream supply, midstream quality and capacity, downstream demand, logistics

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and policy, and circular supply, then spread through price, lead time, inventory, quality, and delivery. The supplier–material–time unit allows purchasing, operations, demand, transportation, and event data to produce comparable indicators.

A model portfolio is preferable to one algorithm: logistic regression provides a transparent baseline, tree models identify nonlinear patterns, anomaly detection addresses scarce labels, and text analysis links external events. Four warning levels translate results into monitoring, supplier verification, inventory adjustment, second sourcing, rescheduling, logistics switching, and emergency coordination. Table-based rules make the connection between analytical output and managerial responsibility explicit.

CATL's disclosures show that material exposure, concentration, supplier management, long-term sourcing, and recycling capacity can be mapped to the framework, but they cannot validate model performance. Reliable implementation also requires common data definitions, responsible owners, auditable model versions, and review of high-level alerts. Future research should obtain anonymized monthly data, compare models with rolling tests, calibrate thresholds to actual losses, and examine propagation with network optimization or digital twins. AI should support, not replace, managers: its value lies in identifying dispersed signals earlier and converting them into consistent, explainable, and traceable actions. Success should therefore be judged not only by predictive accuracy but also by warning lead time, avoided losses, service continuity, response cost, and the organization's ability to learn from each intervention. This decision-oriented evaluation matters because an accurate warning has little value when managers cannot act on it.

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