

Scalable Cloud Data Pipelines for Supply Chain Analytics and Decision Support

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Abstract

Supply chain organizations increasingly draw on cloud-based data pipelines to ingest information from suppliers, logistics providers, and retail partners at a scale and velocity that on-premises infrastructure struggles to match, and they increasingly layer predictive analytics — demand forecasting, disruption-risk scoring — on top of that ingested data to support operational decisions. Each of these capabilities has a substantial literature of its own, but a gap persists between them: a cloud-native ingestion pipeline built for throughput and elasticity typically does not preserve the provenance of each data point back to the specific supplier, shipment, or network tier it came from, while predictive analytics for disruption risk and demand forecasting is most useful to a decision-maker precisely when its output can be traced back to the originating part of the network that is driving a forecast or an alert. Without that traceable link, a cloud pipeline can scale ingestion effectively while still leaving a decision-maker unable to act on a risk alert with confidence about where in the network the underlying signal originated. This paper proposes SCOPE (Supply Chain Observability and Prediction Engine), an architecture in which an elastic cloud ingestion and streaming layer, a predictive risk-and-demand analytics layer, and a traceable decision-support layer are coordinated by a provenance-linked analytics coordinator that tags every prediction and alert with the specific network node, tier, or shipment driving it. Following a design-science research approach, SCOPE is illustrated, not empirically validated, through a comparative capability table, a short case scenario, and two illustrative figures, with every quantitative value explicitly labeled as an illustrative estimate rather than measured production data. The paper situates SCOPE against the literature on cloud-native and stream-processing infrastructure, big-data analytics for logistics and supply chain management, supply chain risk and digital-twin research, demand forecasting, and blockchain- and IoT-based traceability, and discusses the architecture's practical implications, assumptions, and limitations.

Keywords: Supply Chain Analytics, Cloud Computing, Data Pipelines, Decision Support, Demand Forecasting, Supply Chain Risk, Traceability, Digital Twin

Introduction

Modern supply chains generate data continuously across every tier of their network — supplier shipments, manufacturing throughput, logistics telemetry, retail point-of-sale signals — and cloud-based data pipelines have become the standard mechanism for ingesting and processing this data at the scale and velocity a multi-tier global network produces, drawing on stream-processing models capable of balancing correctness, latency, and cost for massive-scale, out-of-order data[1] and the stateful processing guarantees that keep such a pipeline consistent as data arrives continuously[2],

running on the elastic, containerized infrastructure the cloud-native computing literature describes[3]. Wang, Gunasekaran, Ngai, and Papadopoulos's[4] foundational review of big-data analytics in logistics and supply chain management documents that this ingestion capability has, in turn, enabled a substantial expansion in the analytics organizations can build on top of it, from descriptive reporting toward genuinely predictive capability[1-9].

Two such predictive capabilities have matured considerably in recent years. Seyedan and Mafakheri's[5] review of predictive big-data analytics for supply chain demand forecasting documents a growing set of machine-learning and statistical methods capable of forecasting demand from the same high-volume, multi-source data a cloud pipeline ingests. Ivanov, Dolgui, and Sokolov[6] document the related and increasingly urgent problem of disruption-risk analytics, introducing the ripple effect — the way a disruption at one supply chain node propagates and amplifies across downstream tiers — as a phenomenon digital technology and Industry 4.0 infrastructure can help detect and analyze, provided the underlying data pipeline captures enough network structure to trace a ripple back to its origin. Ivanov and Dolgui[7] extend this line of research with the digital supply chain twin, a continuously updated digital representation of the physical network capable of simulating disruption propagation, which depends on exactly the kind of network-aware, provenance-preserving data pipeline this paper's architecture develops.

This is the specific gap this paper addresses: a cloud data pipeline optimized purely for ingestion throughput and elasticity can scale to the data volume a global supply chain produces without necessarily preserving the structural link between a given data point and the specific supplier, shipment, or network tier it originated from, and a predictive analytics layer built on top of such a pipeline inherits that same gap. A decision-maker reviewing a disruption-risk alert or a demand forecast is best served not merely by the prediction itself but by a traceable account of which part of the network is driving it, a requirement the traceability literature addresses directly for product-level provenance — Queiroz, Telles, and Bonilla's[8] systematic review of blockchain and supply chain management integration documents blockchain-based mechanisms for maintaining an immutable, traceable record of a product's movement through a supply chain, and Tsang, Choy, Wu, Ho, and Lam[9] demonstrate a blockchain-driven IoT architecture for food traceability specifically — but this traceability literature was developed largely independently of the cloud-native ingestion and predictive-analytics literatures reviewed above, leaving no existing architecture that connects elastic ingestion, predictive risk and demand analytics, and traceable decision support around one coordinated data pipeline[10-16].

This paper addresses that gap by developing SCOPE (Supply Chain Observability and Prediction Engine): an architecture in which an elastic cloud ingestion and streaming layer, a predictive risk-and-demand analytics layer, and a traceable decision-support layer are coordinated by a provenance-linked analytics coordinator that tags every prediction and alert with the specific network node, tier, or shipment driving it, consistent with Power and Sharda's[10] model-fidelity principle that a decision-support interface's value depends on faithfully representing the model and data underlying its recommendations. The remainder of the paper reviews the literature on cloud-native and stream-processing infrastructure, big-data analytics for logistics and supply chain management, supply chain risk and digital-twin research, demand forecasting, and blockchain- and IoT-based traceability, describes the design-science methodology used to construct and illustrate the architecture, presents the architecture alongside a comparative table, a short case scenario, and

two illustrative figures, and discusses the architecture's practical implications, assumptions, and limitations before concluding.

Literature Review

Cloud-Native and Stream-Processing Infrastructure

Akidau et al.[1] formalize the Dataflow Model, a correctness framework balancing completeness, latency, and cost for processing massive-scale, unbounded, out-of-order data, establishing the theoretical foundation a global supply chain's continuously arriving, multi-source data stream requires. Carbone et al.[2] describe the stateful stream-processing model that lets a pipeline maintain consistent, fault-tolerant state as this data arrives continuously from many sources at once. Deng et al.[3] survey the cloud-native computing paradigm that provides the elastic, containerized operational substrate such a pipeline typically runs on, allowing ingestion capacity to scale with the data volume a global, multi-tier network produces. This literature establishes the infrastructure SCOPE's ingestion layer assumes rather than re-derives; none of it addresses what structural information about the originating network node should be preserved as data moves through the pipeline, which is the specific gap addressed below[17-23].

Big-Data Analytics for Logistics and Supply Chain Management

Wang, Gunasekaran, Ngai, and Papadopoulos[4] provide a foundational review of big-data analytics applications in logistics and supply chain management, documenting a substantial expansion in analytics capability — from descriptive reporting toward predictive and prescriptive applications — once cloud-scale data ingestion became practical for multi-tier supply chain data. This review establishes the broad analytics landscape this paper's predictive layer operates within, while identifying the specific translation of raw ingested data into decision-relevant, traceable insight as an area the review characterizes as requiring further development beyond ingestion and reporting capability alone.

Supply Chain Risk, Resilience, and Digital-Twin Research

Ivanov, Dolgui, and Sokolov[6] introduce the ripple effect as a central concept in supply chain risk analytics: a disruption at one node propagates and amplifies across downstream tiers, and digital technology can help detect and analyze this propagation, provided the underlying data captures enough network structure to trace a ripple to its origin. Ivanov and Dolgui[7] extend this work with the digital supply chain twin, a continuously updated digital representation of the physical network capable of simulating disruption propagation and supporting resilience planning; the digital twin concept depends directly on a data pipeline that preserves network-node provenance, which this literature assumes as an input rather than itself develops.

Demand Forecasting and Decision-Support Fidelity

Seyedan and Mafakheri[5] review predictive big-data analytics methods for supply chain demand forecasting, documenting a growing set of machine-learning and statistical techniques capable of forecasting demand from high-volume, multi-source supply chain data, while noting that translating a forecast into an actionable operational decision depends on the decision-maker's ability to understand what is driving it. Power and Sharda[10] establish, more generally, that a decision-support interface's practical value rests on the decision-maker being able to trust that what

the interface shows faithfully represents the model and data generating its recommendations — a requirement this paper's architecture extends specifically to require traceability back to the originating network node or shipment, not merely fidelity to the model's internal logic.

Blockchain- and IoT-Based Traceability

Queiroz, Telles, and Bonilla[8] systematically review blockchain and supply chain management integration, documenting blockchain-based mechanisms for maintaining an immutable, traceable record of a product's movement through a multi-tier supply chain. Tsang, Choy, Wu, Ho, and Lam[9] demonstrate a blockchain-driven Internet-of-Things architecture for food traceability specifically, combining IoT sensor data with a consensus mechanism to maintain a verifiable chain of custody. This literature establishes mature traceability mechanisms at the level of an individual product or shipment, but was developed largely independently of the cloud-native ingestion and predictive-analytics literatures reviewed above, leaving no existing architecture that connects elastic ingestion, predictive analytics, and traceable decision support around one coordinated pipeline. SCOPE is this paper's response to that gap.

Methodology

Research Approach

This paper follows a design-science research approach: it develops an architecture — SCOPE — intended to address a practical problem (coordinating elastic cloud ingestion, predictive risk-and-demand analytics, and traceable decision support around a single provenance-linked data pipeline), and it evaluates that architecture against the cumulative findings of the peer-reviewed literature rather than against a production deployment, because no such deployment of this specific architecture yet exists to study. The comparative table and figures in the Results section are accordingly illustrative constructions, explicitly labeled as such, built to be directionally consistent with the cited literature's findings rather than presented as measured outcomes.

Development of the Architecture

SCOPE was developed by identifying what an elastic cloud ingestion pipeline[1][2][3] would need to preserve in order to support the network-aware predictive analytics the supply chain risk and digital-twin literature calls for[6][7] and the demand-forecasting literature documents[5], without sacrificing the ingestion throughput that literature establishes as achievable. A provenance-linked analytics coordinator was introduced specifically to tag every ingested data point, and every prediction or alert the analytics layer subsequently generates, with the specific network node, tier, or shipment it is traceable to, drawing on the chain-of-custody mechanisms the traceability literature establishes[8][9] but applying them to the analytics pipeline's own predictions and alerts rather than only to physical product movement. This design directly operationalizes Power and Sharda's[10] model-fidelity principle for decision support, extended to require fidelity to data provenance as well as to model logic.

Construction of Illustrative Evaluation Data

Because no production SCOPE deployment exists to measure, the quantitative content of the Results section was constructed through explicit, reasoned estimation. Construction began from a directional finding reported in the cited literature — Ivanov et al.'s[6] finding that ripple-effect

propagation can be traced given adequate network-structure data, or Seyedan and Mafakheri's[5] finding that forecast actionability depends on decision-maker understanding of the forecast's drivers — and built illustrative values directionally consistent with that finding at a plausible order of magnitude. Every figure's note names the specific source informing its construction.

Framing of the Disruption-Tracing Scenario

The illustrative case scenario and the time-to-trace figure in the Results section are framed around a disruption originating at a single upstream supplier that ripples through several downstream tiers before reaching a decision-maker's dashboard, consistent with the ripple-effect concept Ivanov et al.[6] establish; this framing was chosen specifically because it is the setting in which provenance-linked traceability most directly affects a decision-maker's ability to act, rather than a setting in which a prediction is consumed without reference to its network origin.

Scope and Assumptions

This paper assumes an organization deploying cloud-based supply chain analytics already has, or can obtain, data-sharing agreements with its network partners sufficient to support the multi-tier ingestion SCOPE's architecture depends on; it does not itself address the contractual or data-governance negotiations such agreements require. It is scoped to the coordination of elastic ingestion, predictive analytics, and provenance-linked decision support; it does not address the choice of a specific forecasting algorithm or a specific blockchain consensus mechanism, both of which the cited literature already treats extensively. All quantitative results in the Results section are illustrative estimates grounded in the literature rather than measurements.

Results

Architecture Overview: SCOPE

SCOPE organizes supply chain analytics around a cloud analytics layer that sits beneath, and continuously ingests from, every tier of the physical supply chain network it observes, rather than treating the network's structure as external context the pipeline discards after ingestion. Data flows from Tier-2 suppliers, Tier-1 suppliers, manufacturing, distribution centers, and retail nodes into an elastic ingestion and streaming layer built on the stateful, scalable infrastructure established above[1][2][3]. A predictive risk-and-demand analytics layer consumes this ingested data to generate disruption-risk alerts and demand forecasts, drawing on the ripple-effect and digital-twin research[6][7] and the forecasting methods Seyedan and Mafakheri[5] document. Throughout both layers, the provenance-linked analytics coordinator tags every data point, prediction, and alert with its originating network node, applying the traceability mechanisms established above[8][9] to the analytics pipeline itself. The resulting traceable predictions and alerts reach a decision-support dashboard built around the model-and-data fidelity principle Power and Sharda[10] establish, and a disruption flagged at the dashboard can be traced back to its originating node directly, rather than leaving the decision-maker to reconstruct that link manually.

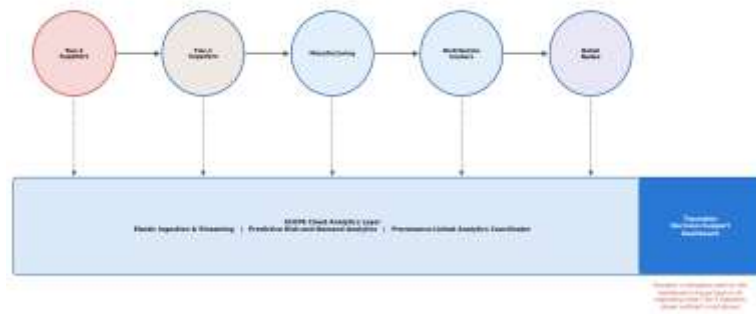


Figure 1. SCOPE (Supply Chain Observability and Prediction Engine): a supply chain network architecture showing every network tier feeding a shared cloud analytics layer that produces traceable alerts at a decision-support dashboard.

Table 1. Illustrative capability comparison across supply chain analytics approaches.

Dimension	Siloed Per-Tier Reporting	Cloud Ingestion Without Provenance Linking	SCOPE
Ingestion scalability across network tiers	Weak; each tier reports independently	Strong; elastic cloud ingestion at scale	Strong; elastic ingestion preserved
Traceability of alerts to originating network node	Strong within a single tier; weak across tiers	Weak; provenance typically discarded after ingestion	Strong; every alert tagged to its origin
Disruption ripple-effect visibility	Weak; no cross-tier view	Moderate; data available but not structurally linked	Strong; network structure preserved throughout
Decision-maker trust in forecasts and alerts	Moderate; limited data, well understood locally	Weak; high data volume but low explainable provenance	Strong; traceable provenance supports trust

Illustrative Case Scenario

Consider a hypothetical multinational manufacturer whose Tier-2 raw-material supplier experiences a sudden production stoppage. Under siloed per-tier reporting, the stoppage is visible to the immediate Tier-1 supplier but takes days to surface as an unexplained delay further downstream. Under cloud ingestion without provenance linking, the downstream delay is visible almost immediately in aggregate shipment data, but the decision-support dashboard shows only a generalized risk score with no clear link back to the originating Tier-2 stoppage, leaving the decision-maker to investigate manually. Under SCOPE, the provenance-linked analytics coordinator traces the downstream delay directly back to the Tier-2 stoppage the moment the risk-scoring model flags it, surfacing the specific originating node on the decision-support dashboard

rather than a generalized alert. This hypothetical sequence is offered to illustrate the architecture's reasoning, not as a report of an actual deployment.

Illustrative Capability Scores Across Supply Chain Analytics Approaches

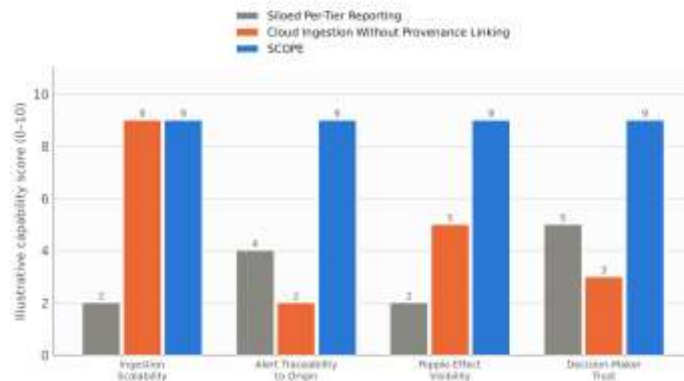


Figure 2. Illustrative capability scores (0-10 scale) for siloed per-tier reporting, cloud ingestion without provenance linking, and SCOPE.

Note. These capability scores are illustrative estimates constructed for this paper's comparative framework rather than the product of a scored evaluation instrument; they were shaped by the ripple-effect findings Ivanov et al. (2019) report and the decision-support fidelity principle Power and Sharda (2007) establish, and should be read as a reasoning aid rather than a benchmark.

Siloed per-tier reporting scores weakly on ingestion scalability and ripple-effect visibility because it lacks a cross-tier view, though it scores moderately on traceability and trust within its own limited scope; cloud ingestion without provenance linking inverts this pattern, scaling well but losing the node-level traceability that supports decision-maker trust; SCOPE is positioned, by design, to combine the strengths of both because its provenance-linked coordinator was built specifically to preserve traceability while scaling ingestion across every network tier.

Illustrative Time to Trace a Disruption to Its Originating Node Over a Six-Month Deployment

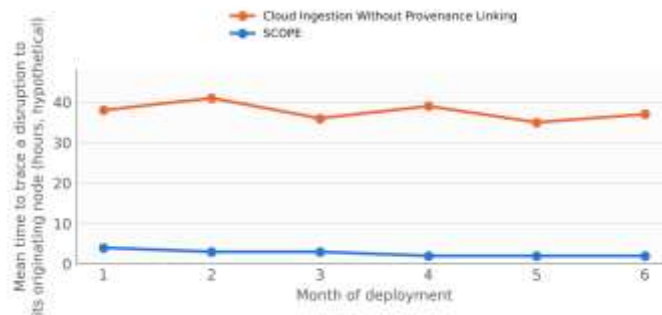


Figure 3. Hypothetical mean time to trace a disruption alert to its originating network node (hours), by approach, over a six-month deployment.

Note. This is a hypothetical, illustrative trajectory rather than measured incident data; the approach without provenance linking maintains a persistently long manual tracing time because aggregate risk scores carry no structural link back to the originating node, consistent with the traceability gap Queiroz et al. (2019) document for supply chains lacking an integrated provenance mechanism, while SCOPE's consistently short tracing time reflects alerts being pre-tagged with their originating node at generation time.

Discussion

Implications for Practice

The architecture developed here suggests that an enterprise building cloud-based supply chain analytics should treat provenance linking as a first-class pipeline requirement rather than an afterthought layered onto an already-scaled ingestion system, since the comparison above illustrates that ingestion scalability alone does not translate into decision-maker trust or ripple-effect visibility without a structural link back to each prediction's originating network node.

Limitations

No production SCOPE deployment or measured tracing-time data informed this study; the table and figures above are explicitly illustrative constructions. The architecture's provenance-linked coordinator depends on data-sharing cooperation across every network tier it ingests from, an assumption the traceability literature treats as achievable through blockchain- or IoT-based mechanisms[8][9] but not as automatic, particularly across organizational boundaries with differing data-governance policies. The predictive analytics layer's effectiveness is bounded by the forecasting and risk-analytics techniques Seyedan and Mafakheri[5] and Ivanov et al.[6] describe, which the cited literature itself treats as an actively advancing area rather than a fixed ceiling.

Future Research

Empirical work instrumenting an actual multi-tier supply chain deployment using SCOPE's provenance-linked coordinator, compared against a matched deployment using conventional cloud ingestion without provenance linking, would directly test this paper's central claim. Research on the specific data-governance and interoperability mechanisms needed to extend provenance linking across organizational boundaries, and research quantifying how traceable alerts specifically affect decision-maker response time during an active disruption, would strengthen the architecture's practical guidance.

Conclusion

This paper has argued that cloud-based supply chain analytics has scaled ingestion and expanded predictive capability substantially[4][1][2][3][5], and that supply chain risk and digital-twin research has established the value of network-aware disruption analysis[6][7], but that a gap remains between a scaled ingestion pipeline and a decision-maker's ability to trace a prediction or alert back to the specific network node driving it, a gap the traceability literature addresses only at the level of individual product provenance[8][9] rather than for an analytics pipeline's own predictions. This paper has developed SCOPE as an architecture in which a provenance-linked analytics coordinator ties every prediction and alert to its originating network node, closing that gap as one coordinated system rather than leaving ingestion, analytics, and decision support independently assembled. The architecture was illustrated, not validated, through a comparative table, a case scenario, and two illustrative figures, with every quantitative value explicitly labeled as an estimate. Future empirical work instrumenting a real multi-tier deployment would be necessary before an organization could adopt SCOPE with confidence in its specific tracing-time and forecasting parameters, but the underlying argument — that provenance linking and predictive analytics should be designed into a supply chain data pipeline together rather than added separately rests on peer-reviewed evidence this paper has synthesized specifically for that coordination problem.

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