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Research Article

Autonomous Supplier Evaluation and Data Stewardship with AI: Building Transparent and Resilient Supply Chains

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Abstract:

Global supply chains remain fragile with geopolitical tensions, pandemic disruption, port congestion, and climate shocks. Conventional supplier scorecards are sluggish, passive, and rarely audit-worthy, opening up areas of blindness in risk identification and decision making. This paper provides a machine learning-ready supply analysis methodology and incorporates high-quality data governance. Autonomous supplier assessment refers to an automated judgment system that proposes calibrated probabilities and prescriptive steps of the judgment, or actions, namely: block, review, or allow, by implementing policy-as-code, a constraint by compliance requirements. The strategy unites three types of evidence: tabular data, such as lead-time volatility, OTIF performance, and defect rates; unstructured evidence, including audit reports, certificates, and contracts; and network-based features that capture the length of the tier and the risk of the community. Data are processed by entity resolution, normalization, and temporal cross-validation and leakage-safe labeling. Governance processes such as data contracts, lineage, quality SLAs, and decision logs provide accountability and audit-readiness. Trust and adoption are further increased through counterfactual explanations and human-in-the-loop triage. Experiments show that it is better for early warning of risks in delivery, quality, and compliance by combining the use of tabular and text features and graphs. The calibrated ranking strategies are more effective than the static thresholds in a limited review capacity because they can detect more adverse issues without dealing with false positives. The results reinforce that stewardship practices do not create overhead but enable resilient, transparent, and explainable autonomy. The work collectively gives methodological contributions and a business roadmap for implementing trustworthy AI in procurement.

1. Introduction

Global supply chains are unbalanced due to the origins of geopolitical tensions, pandemics, left-overs, port congestions, supplier concentrations, and climate-related events. Opaque multi-layered networks are being instrumented and monitored at the tier-2 and tier-3 levels. Critical data are scattered in ERP, TMS, QMS, and external risk feeds with different identifiers and units. Traditional supplier scorecards are refreshed monthly or quarterly, use lagging KPIs, and are rarely lineage audited, leaving blanks. With upstream conditions changing, remedial action has minimal effect, as it can result in higher expediting costs, and its OTIF performance diminishes. These gaps are driving an autonomy-ready strategy that balances analytics and governance guardrails to make evidence-based decisions and ensure audit readiness. This context sets the requirement that machine-learning systems must operate, incorporate uncertainty, and be answerable to policy and regulation.

The definition used in this paper of autonomous supplier evaluation is a machine learning decision system that yields risk probabilities and prescriptive actions (block, review, or allow), enabled by policy-as-code and constrained by regulation. The system combines three evidence modalities: tabular measures like lead-time volatility, parts-per-million defects, expediting rate, OTIF; unstructured data, including audit reports, non-conformance reports, certificate OCR, and contracts; and network context over graphs that show tier distance and community

risk. The time-scale is 30-90 days and features temporal representations and non-leakage windows. Decisions are executed through inspection plans. Stewardship offers the safety net: data contracts gate ingestion, lineage opens provenance, quality SLAs which enforce freshness, and decision logs which can facilitate audits. The goal is to enable explainable autonomy as opposed to yet another black box scorecard.

The research fulfils three propositions as objectives. It bases its investigations on how to enhance the tabular baselines with graph and word-based features to obtain a measurable incremental benefit in early identification of delivery, quality, and compliance risk. It also shows that calibrated ranking strategies are superior to threshold schemes in a limited review capacity k context as they can increase adverse-event capture at the expense of managing false blocks and the latency of review. The study also concentrates on stewardship practices - data contracts, freshness service-level agreements (SLAs), lineage, and model/decision cards - to enhance both the adoption and accuracy and to minimize overrides. The scope is broad enough to cover direct and indirect materials on both the category, region, and supplier-tier levels. The interpretations omitted ad-hocs as follows: OTIF means on-time-in-full, a risk event is a late shipment, quality non-conformance, or compliance breach that takes place within the forecasting window, and the roles of data owner, data steward, and data custodian have clearly defined roles and escalation plans.

The methodological contributions are to present a unified tabular/text/graph pipeline with temporal cross-validation and leakage-free feature engineering and probability calibration via Platt scaling and isotonic regression. Decision-curve analysis and expected-cost curves are used to formalize cost-aware threshold selection and can be category-specific by risk boundaries. Counterfactual explanations translate model reasoning into remediation, e.g., introduce inspection, developer plans, resetting lead times, or dual-source. Mechanism-wise, the article lists governance mechanisms: data contracting at ingest, column-level lineage, feature store with version semantics, model registry, and policy-as-code to manage decision rules, monitor drift, monotonicity, and freshness. Managerially, the article provides a roll-out playbook that includes stewardship roles, change management, adoption metrics, override governance, and audit packs that involve model cards, decision logs, and lineage snapshots to support reviews.

This manuscript is organized into various chapters. Chapter 2 reviews multi-criteria and machine-learning literatures in supplier evaluation, as well as the ESG and third-party risk practice, and the data stewardship literature. Having done so, it motivates a governance-native pipeline. Chapter 3 outlines the data set, data preparation, problem framing, feature engineering, labeling, Governance Architecture, and MLOps to ensure safe autonomy. Chapter 4 institutionalizes reliable autonomous decision-making: cost-sensitive cutoffs, human-in-the-loop triage, exposability, equity, observability, and secure deployment. Chapter 5 introduces the experimental design, primary findings, ablations, robustness, fairness, and business impact. Chapter 6 speaks of the interpretation process, implication, role of stewardship, limitation, as well as lessons learnt. Chapter 7 summarizes the work to be done on active learning, causal uplift, digital-twin shocks, multi-agent autonomy, federated learning, and verifiable credentials. Chapter 8 closes with takeaways and a staged roll-out as constrained by the compliance implementation roadmap.

2. Literature Review

2.1 Classical Supplier Evaluation & MCDM

Multi-criteria decision-making (MCDM) methods such as Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and Data Envelopment Analysis (DEA) have been used in classical supplier evaluation. In AHP, the hierarchy of criteria--quality, cost, delivery, service--is broken down into pairwise comparisons to form a positive reciprocal matrix; the principal eigenvector is obtained as a priority vector, and a consistency ratio constrains the judgment error. To rank, the criteria are normalized, decision weights are applied, and the Euclidean distance to ideal and anti-ideal points is calculated to get the closeness coefficient. The relative efficiencies of transforming input to output enabled by DEA facilitate benchmarking in case there are homogenous categories and consistent measurements [24]. These are methods that offer transparent scoring and allow structured trade-offs with limited and reliable information.

As shown in the figure below, a typical supplier-assessment MCDM chain of events entails systematic review, empirical study, and an AHP-based decision-rate phase. Criteria and alternatives are clarified, pairwise comparison produces a positive reciprocal matrix, the principal eigenvector produces priorities, and consistency ratio monitors the error in judgment. Normalised weights are entered into a decision matrix, TOPSIS calculates Euclidean proximity to optimum solutions, DEA benchmarks efficiencies, and allows transparent scoring and organised trade-offs across kinds of suppliers.

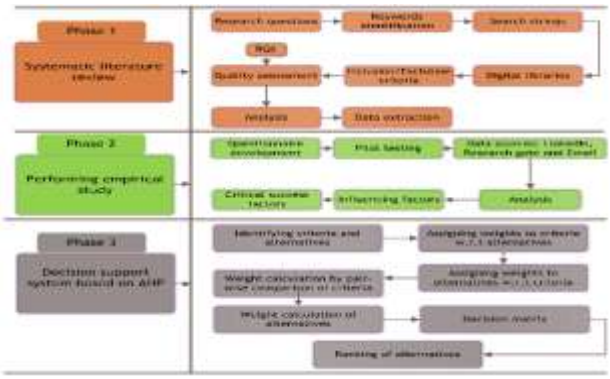

Figure 1: *AHP-driven MCDM workflow for classical supplier evaluation and ranking*

Weak points are in unstable environments. Weights remain unchanged, although volatility is non-stationary; a vector estimated before the disruption can wrongfully price post-disruption volatility. MCDM pipelines pull together monthly or quarterly indicators and obscure intra-period deviations that presage quality lean or logistics overstretch. The techniques have difficulty with high-cardinality, interaction-intensive features like item-supplier-lane combinations and fail to consider temporal dependence, as well as uncertainty and calibration. They also depend on the set cadence of evaluations, and consequently, decisions are not timely concerning changes in supplier behavior or route risk. This leads to classical scorecards responding late, under-detecting emerging risk, and constraining advice on action thresholds.

The performance benefit of such event-level data has been shown through operational evidence in telemetry-rich fields. In a fleet logistics system, telematics, geolocation, and sensor data allow exception detection and performance improvement through the elimination of batch-based measurements and measures and the substitution of high-rate information measuring in terms of magnitudes, wherein the measurement is backed up by the timing and timing precision and the timing precision of the response [19]. The same urgent need applies to supplier evaluation: move beyond the periodic scoring model to streaming evidence that will support supplier ranking and interventions in the current state of affairs rather than the trailing input. This transition both impels learning-oriented, time-sensitive models and Governance that are capable of surviving high-order discontinuities of regime shifts.

2.2 ML in Procurement, Risk & Explainability

Machine learning re-technologies the supplier evaluation as rolling horizon-based supervised prediction and ranking. The Binary classifiers predict the chance that an adverse event will occur with a supplier within 30-90 days, such as late delivery beyond service levels, lack of quality, or a compliance escalation. Ranking models address this setting by maximizing the identification of actual risks in the top-k, keeping a false-block rate and latency to reviews at manageable levels; the combination of these constraints is then measured by precision@k, recall@k, and NDCG. In the case of time-to-event risk, survival models can be used to estimate hazards and handle censoring; gradient-boosted trees or calibrated logistic models can perform well on tabular features, whereas transformer encoders can be used to capture unstructured audit and ticket text. Graph characteristics-degree, betweenness, tier distance-add context to the network and make centrality and exposure to the community affect prediction.

The most significant modeling risk is temporal leakage. The latter requires all features to be lagged against the prediction time stamp, and the evaluation to be carried out using rolling origin or blocked time cross-validation, where the future does not leak into training. Units, currencies, and calendars must be standardized to eliminate confusion, and holiday effects must be encoded. The imbalance in classes is solved through class weighting and focal loss with resampling. Borrowing across categories to stabilize long-tail suppliers, hierarchical pooling or Bayesian shrinkage preserves supplier-level heterogeneity, borrowing strength across categories. The model selection favors not only the PR-AUC and F1@k, but also the cost of inference and resistance to missingness due to late feeds.

Scoring is turned into action by calibration and thresholding. The Platt scaling or isotonic regression scaled the probabilities against expected frequencies, and decision-curve analysis or expected cost optimization transformed the probabilities into block reviewing or allowed policies reflective of risk appetite and analytic capacity. Explainability is used to enhance Governance and adoption. The general flow of global structure is distilled as permutation importance and partial dependence or accumulated local effects to convey non-linearity; local decisions are explicated using SHAP values and counterfactuals that imply viable remediations. This is because adoption is enhanced with role-aware explanations and recommendations provided at the moment of decision, and this trend appears in other AI decision-support settings where guidance specifically tailored to the needs of the user is architected [10, 16].

2.3 ESG, Compliance & Third-Party Risk (TPRM)

Third-party risk management goes beyond the evaluation of suppliers about the delivery and the quality of their services and goods, by taking into account their sanctions and politically exposed person screening, their labor and environmental standards, the source of restricted materials, and the validity of certifications and licenses. In an autonomy-ready architecture, the constraints are strict rather than modelling features. A sanctions hit drives a deterministic trigger of "block"; a pending certificate expiry downsizes autonomy to "review" pending a re-attestation; ESG flags adjust thresholds or trigger enhanced due diligence. The third-party risk management lifecycle (as shown in the figure below) implements ESG and compliance controls through the identification, due diligence, contracting, onboarding, monitoring, and offboarding. Constraints in autonomy-ready architectures represent hard gates: a sanction or PEP match declines immediately; a thresholder with an expired or invalid certification converts decisions to review until re-attestation; and ESG flags, such as labor and environmental violations, and restricted substance issues, throttle thresholds or invoke more in-depth due diligence processes.

Figure 2: *TPRM lifecycle: sanctions, certification, ESG controls and monitoring*

The controls should be operationalized using two interrelated mechanisms. The onboarding processes should identify high-risk attributes at the initial stage and block unsafe suppliers before they enter the active vendor file. Continuous monitoring should also reassess risk in response to the arrival of new information so that updates are refreshed without requiring scorecard iterations. Engineering use of the pattern reflects shift-left assurance of software vulnerability, where risk is detected and blocked early in the production cycle to contain later vulnerability; this same logic is applied to the supply chain by moving government sanctions, ESG, and certifications checks earlier in the lifecycle [14]. This means policy gates and API-level validations on supplier creation, PO issuance, and booking.

In reality, TPRM data are partial, delayed, and asynchronous. Names and addresses are inconsistent across sources, certificate identifiers lack a valid schema, and route information is subject to change during shipment. Data stewardship emerges as a requirement: entity resolution requires reconciliation of third-party records to anti-money laundering (AML) and supplier master records; data contracts ensure freshness of attestation feeds; and lineage tracks how external evidence was used to make a decision. The policy layer mixes deterministic gates with risk probabilities at decision time, producing block, review, or allow, and recording evidence to be used in an audit.

2.4 Data Stewardship & Governance

Quality data and model stewardship, as opposed to predictive accuracy, are a requirement of trustworthy autonomy. A practical governance model establishes the accountable positions: data owner determines policy and risk appetite, data steward maintains data quality and catalogs, and data custodian takes care of infrastructure, and codifies the expectations into data contracts. Contracts define schema versions, units, and controlled vocabularies, null and uniqueness thresholds, range checks, and freshness service-level agreements. Ingress validators enforce the contracts and hold non-conforming records in quarantine. The lineage connections linking features and predictions to upstream sources and transformations by column allow root-cause analysis when drift or anomalies occur and allow audit reconstruction of the evidence underlying a decision.

Dashboards and owner dashboards monitor completeness, timeliness, validity, and consistency by table with alert thresholds tuned based on business criticality. Issue management channels data flaws to owners through SLAs, and proactive prevention is based on upstream tests between the contracts [30]. To minimize fragmentation of identity, entity resolvers would take an iterative approach to resolving suppliers, using deterministic keys where available and probabilistic matching (names, addresses, tax IDs) where not, and capturing confidence and survivorship rules. Access governance requires least privilege; sensitive attributes are obfuscated or aggregated to decision displays.

Patterns of DevSecOps have the benefits of operationalization. In software delivery, security testing and policy gateways are also applied to continuous integration and deployment so that unsafe artifacts cannot be advanced [11]. Similar to software-ML pipelines, data-ML pipelines integrate dataset validation, feature contract checking, bias checks, and calibration checks in ongoing training and release. Canary promotion and automated rollback. This can be used to roll out to a subset of nodes, and in the event of a performance, calibration,

or freshness breach, rollback is performed automatically. Each of the decisions is recorded with a model version, policy version, features hash, explanation, and lineage pointers to facilitate audit repair.

2.5 Gaps & Positioning

Despite the progress, there remain gaps that necessitate a governance-native multi-modal program. Modalities, such as transactional tables, stand-alone NLP on audits, and separate supply-network analyses, tend to be isolated during several deployments, overlooking interactions that are important in practice. A single entity model and a unified feature store are required to learn cross-modal interactions, including how increased community risk in a trade lane increases the effect of increased defect trend. The classical MCDM may also represent expert preferences, but often does not represent time and does not model uncertainty; calibrated probabilities, as well as cost-sensitive thresholds, are not represented [7]. Production ML can be sloppy about Governance, as data contracts, lineage, and calibration checks are often secondary considerations that inflict autonomy decay and the need to override. The rules relating to ESG and sanctions can also become features, rather than limitations, leading to unnecessary exposure to risk and a lack of coherence in the approach to these matters across teams.

The study places autonomous supplier evaluation as a decisioning stack. The stack integrates in a tabular, text, and graph input; implements quality through contracts; calculates probability-calibrated decisions, and directs results through policy-as-code to block, review, or approve. Explanations and decision logs allow deciphering actions so they become auditable, and human-in-the-loop triage addresses the uncertainty and cold-start issues. The research agenda will focus on rigorous temporal cross-validation, subgroup fairness, calibration, and cost-sensitivity in line with capacity. With its feedback of modeling, informing stewardship, and vice versa, the approach enables resilient supply performance against operational constraints, and there is a template that can be adapted across categories and tiers.

3. Methods and Techniques

3.1 Data & Labeling

The research operationalizes supplier assessment on a manufacturing-level schema combining elements of transactional, quality, logistic, and assurance-based evidence. As presentant in Table 1 below, purchase Orders contain ID, supplier_id, item, quantity, unit_price, incoterm, promised_date, and actual_date; these fields are becoming root line-level features and join keys. The Goods Receipt Notes can be used to reconcile the orders with receipts to calculate the lag of receipts and the tendency of partial-fills. An Advanced Shipment Notice provides carrier milestones, shipped quantities, and scheduled arrival. Accounts Payable invoices also complete financial settlement and allow three-way match diagnostics. The defects are recorded as parts per million and non-conformance codes with the severity in the Quality Management System records [9]. Audit finding tables contain clause references, corrective-action status, and due dates. Transport Management milestones offer in-gate, out-gate, and handoff times. Certificate OCR extracts issuer, scope, and expiry on ISO-like attestations. Incident indicators and sanctions updates are added by external risk and news feeds.

Table 1: *Summary of data sources, alignment controls, and labeling rules*

Component	**Key fields & metrics**	**Alignment / controls**	**Labeling rules / events**
Transactional (PO/GRN/AP)	PO: id, supplier_id, item, qty, unit_price, incoterm, promised/actual dates; GRN lags/partial fills; AP 3-way match	FX to reporting currency; unit dictionaries; UTC + working-day calendars; truncate features at label anchor	**Delivery**: (actual − promised) > X working days (SLA-normalized)
Logistics (ASN/TMS)	ASN milestones, shipped qty, ETA; TMS in-gate/out-gate/handoffs	Time-zone normalization; sequence checks; SLA harmonization	Early delay indicators; enrich delivery risk features
Quality & Audits (QMS/Audit)	Defect PPM, NC codes/severity; audit clauses, CAPA status, due dates	Text/OCR cleanup; code dictionaries; entity resolution	**Quality**: rolling PPM > Y or severe NC; **Compliance**: clause failure
Certifications	Issuer, scope,	Schema validation;	**Compliance**:

Component	Key fields & metrics	Alignment / controls	Labeling rules / events
	expiry (OCR)	expiry tracking	expired/invalid before ship date
External Risk	Sanctions hits, incidents/news	Resolve to supplier master	**Hard gate**: sanctions/PEP ⇒ block
Dataset & Splits	Multi-BU/region; 30/60/90-day horizons	Sliding windows; snapshot isolation; idempotent workloads; supplier-level stratified temporal CV	Imbalance: class weights, focal loss; IRR via Cohen's

The population cuts across many business units and geographies with diverse currencies, units, and calendars. Monetary values are adjusted to a reporting currency by use of transaction-day foreign-exchange rates; quantities to canonical units, such as say, kilograms and pieces, by use of unit dictionaries. The sites are synchronized to UTC, and the service levels on the local holidays are parameterized working days. The modeling horizon is calibrated as 30, 60, and 90 days to balance between actionability and the availability of leading indicators. The labels are produced in sliding windows, i.e., before the outcome window, which eliminates temporal leakage. To prevent the inadvertent exposure of future information, features that use receipts or inspection are truncated at the label anchor time.

Labeling involves the use of transparent and auditable rules. A delivery risk event is (actual_date-promised_date)-X working days after SLA normalization. A quality event takes place when a rolling ppm target Y is violated or when a non-conformance with high consequence is recorded in the horizon. Failure to meet an audit clause, loss of certification, or expiration before a required ship date triggers a compliance event. Indeterminacy is adjudged during a workflow of the stewarding of evidence bundles (purchase documents, shipment milestones, defect photographs, and audit notes), in which stewards make the canonical decision. Since many running shops prefer horizontal scalability to straight serializability, snapshot isolation and idempotent workloads are used to achieve the balance between performance and reliability in label creation [5].

Handling of the imbalance starts with the design of the labels. Base positive rate is reported by category, region, and tier to provide a benchmark for accuracy and population of the review queues. Temporal negative sampling uses controls sampled during the same weeks as positives to eliminate spurious seasonality. Inversion-prevalence weights are used in classification, and a focal loss with 0 to 3 is used to accentuate rare-but-hard cases. Entity leakage is blocked by supplier-level stratification in the train-validation-test splits. Huber loss does not give as much weight to shock outliers when used as a regression target; positive-unlabeled sampling ensures realistic candidate prevalence when used to rank. Adjudicated labels are assessed on inter-rater reliability with Cohen's kappa; disagreements give rise to clarification of rules and relabeling procedures.

3.2 Pre-processing & Feature Engineering

The supplier mastering eliminates many-to-one identities across ERPs and vendor portals. A hybrid solution would merge deterministic identifiers, such as Tax or VAT ID, IBAN, and DUNS, with probabilistic entity matching on the name, address, and phone fields. The similarity among identifiers such as Jaro-Winkler, geospatial distance on latitude and longitude, and country blocking is used to generate candidate pairs; a supervised matcher is used to classify matches with thresholds tuned against clerical verification. The priority of freshest and complete attributes per field is found in survivorship rules, where the source-of-truth lineage pointer is retained for audit use.

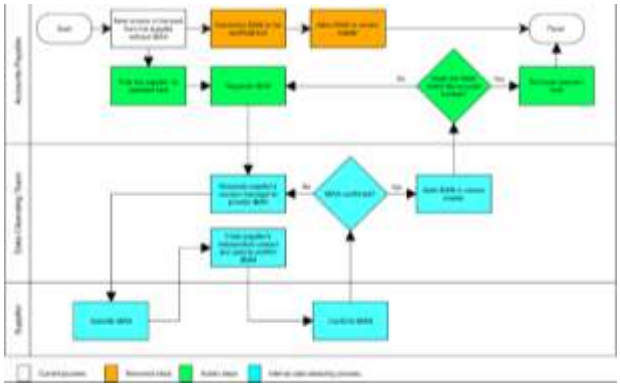

Figure 3: *IBAN verification workflow for vendor master cleansing and matching*

Normalization and alignment represent an elaboration of raw events to create temporally coherent features. The foreign-exchange normalization entails transaction day rates; the incoterms identify the split of responsibility attributable to interventions in delays made to either

supplier, buyer, or carrier. Lead time recorded is the difference between confirmation of promise to gate-in or delivery date, and not the purchase-order release [1]. Time zones are unified to UTC; working-day logic on local calendars; and SLA harmonization uniformizes the definition of late to the various categories. Data-quality assurances warrant schema, completeness, within-range validity, and freshness issued within data contracts; failing feeds are quarantined, and downstream autonomy is limited to review only.

Stable, interpretable, and actionable engineering embraces feature engineering. Parameters of volatility are calculated as the rolling standard deviation and median absolute deviation of lead times; parameters of reliability are the OTIF rate and on-time percentile bands. Operational pressure can be summed as expedited rate, backlog age, backorder numbers, and chargebacks. The spend dynamics share attention to recency-frequency-monetary concepts at both supplier and item levels. Seasonality flags are month-of-the-year, week-of-the-year, and regime flags associated with holidays or high seasons. In the case of unstructured evidence, namely audits, non-conformance narratives, ticket threads, and contract clauses, transformer-based models are trained on contextual embedding techniques that learn across-token relationships, which are significant within procurement semantics; transformer models have been shown to significantly benefit tasks that require meaning inference along language sequences [28].

The structure of the network is depicted as a heterogeneous graph of the connections between suppliers, manufacturing sites, items, and logistics nodes. Centrality (degree and betweenness), community risk averages, and tier distance are calculated per supplier node. The aggregation provides an alert of early alerts even when the direct history is not strong because volatility in the upstream is multiple-folded to the downstream exposure. The Cold-start suppliers draw on community means and category baselines until enough observations accumulate. Stored in the feature store are the feature features, including versioned computation recipes, allowing changes to be traceable and reproducible across model iterations.

3.3 Governance, Risk & System Architecture

Governance exists in the form of roles, contracts, lineage, and service levels. Data owners will establish policy and risk appetite. Data stewards will handle quality, catalog entries, and incident resolution. Infrastructure, including backups, will be managed by custodians. Schema contracts specify what schemas are acceptable, what nulls are permitted, what is valid/invalid, and what freshness constraints are present per source. Unsuccessful feeds increase incidents against the SLAs and automatically pause automation-impacted scopes. Lineage at the feature level records the sources and transformations that created the feature, and allows root-cause analysis of moving metrics, as well as supporting external audit [32]. As illustrated below, good AI data governance cuts across fairness, ethical deployment, security and privacy, data quality/validation, and compliant data sourcing. In practice, the owners of data determine policy and risk appetite; the stewards impose schema contracts and null thresholds, and freshness SLAs; and the custodians determine resilient infrastructure. It can support root-cause analysis, pausing automation scopes at the incident level, and provide evidence that can be used in external audits and by regulators.

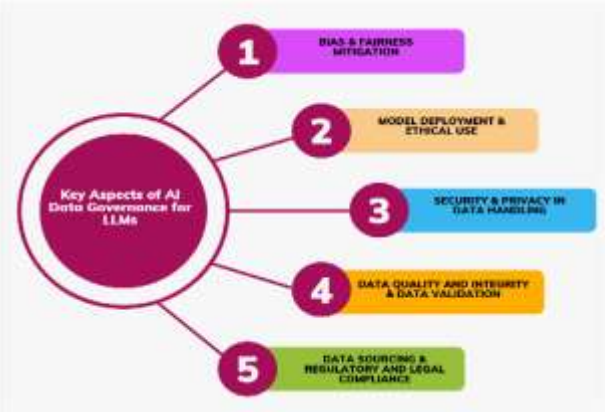

Figure 4: *An illustrations of Key aspects of AI data governance*

Least privilege is guaranteed by security and privacy controls. Access control is implemented using both role-based and attribute-based access control. Sensitive attributes have fields with encrypted data in transit and at rest. Redaction strips views of all personally identifiable information; retention clocks automatically autofill when data should be deleted; and processing records will track the reasons and legal grounds of processing data and any further sharing. Auditability packs contain model cards, data cards, lineage snapshots, and decision logs to perform periodic reviews.

Risk and compliance logic works in parallel with predictive models as straight constraints. Sanctions and politically exposed person checks, forced-labor and conflict-minerals rules, and certificate expiries work as gating conditions: any identified case will trigger a subsequent escalation or block regardless of statistical risk [8]. This separation upholds policy primacy over model predictions, eases ownership,

and makes it easier to ascertain who is to blame in case of control failure.

Its architecture involves an MLOps pipeline with handoffs that are hard-coded: ingest piped to data quality piped to feature store piped to training service piped to model registry piped to canary or shadow deployment piped to monitoring. All the stage versions artifact the data snapshots, the feature definitions, the model binaries, and the policy bundles. Rollback playbooks define how to freeze actions when a data freshness violation happens or when calibration drifts past the thresholds. Due to the trade-offs often made between strict serializability and throughput in operational systems, the pipeline is designed to use the repeatable read isolation, write-ahead logging, and idempotent ingestion to provide throughput and fault-tolerance during training and serving.

3.5 Explainability, HITL & Baselines

The explainability is global as well as local. Global stability checks ensure that feature importances in the same feature are stable over time folds; partial-dependence and accumulated-local-effects plot characterize non-linear response to lead-time variability, expedite rate, and network centrality. Locally, the SHAP values identify the best drivers in a given decision, and the counterfactual analysis suggests only minor modifications to dip below a block threshold, using fewer expedites, resolving documentation lapses, or closing a critical corrective-action loop. Explanations are saved together with the decision log so that viewers and auditors can relate action to reason.

Safe autonomy is enabled with human-in-the-loop controls. Uncertainly bands case route to Triage Queues; materiality filters (spend, criticality, sole-source) drive reviews. SLAs guard cycle time; an override ontology records reasons that include data error, policy exception, or edge cases [15]. Steward decisions, rounded off by feedback loops, are re-injected into training sets via the weighting of importance to overcome selection bias. Two-person man integrity controls escalations; accountability-controlling tamper-resistant logs.

Baselines and benchmarks stabilize progression and assist in change management. Heuristic scorecards and predetermined levels offer interpretable benchmarks; twelve-month wave averages offer naive time-series benchmarks. Tree models can be constrained to follow policy by ensuring that even greater volumes of defects or longer lead-time volatility are no more likely to result in lower risk scores. These guardrails minimize inversions and make them more acceptable to non-technical stakeholders.

The loop is closed by calibration and decision governance. Per segment, the Platt scaling and isotonic regression are compared to derive the best calibration method. The decision curves are chosen based on the phenomenon that the probability is then translated into the costs expected with the current capacity of review and risk tolerance. Each of the thresholds, policies, and models is registered; decision logs include request_id, model_version, policy_version, feature_hash, explanation, override, outcome, timestamps, and lineage pointers. Periodic post-incident reviews measure drift, breaches of freshness, and patterns of overrides, used to inform constant enhancement of features and policies.

4. Trustworthy Autonomous Decisioning & Governance

4.1 Decision Policies & Cost-Sensitive Thresholding

Autonomous supplier evaluation decisioning must show how predicted probabilities lead to auditable acts that satisfy enterprise risk appetite. A practical design establishes a series of risk levels discretely: block, review, and allow, parameterized based on category criticality, contractual penalties, safety-stock coverage, and service-level tolerance. Thresholds are selected by minimizing expected cost $EC(\tau)=C\_FP\cdot P(FP|\tau)+C\_FN\cdot P(FN|\tau)+C\_rev\cdot P(Review|\tau)$, where C_FP quantifies unnecessary stops, C_FN quantifies missed adverse events (late delivery, defect escape, compliance breach), and C_rev captures the operational cost of human review. Decision curves can compare candidate tau with some business objective (such as maximizing capture of adverse events at a fixed review capacity k), or F1@k checks that the top-k risk list is substantially superior to heuristic scorecards.

Policies can be enforced as policy-as-code (YAML evaluated by OPA) to support versioned governance and automated tests in continuous integration/continuous delivery [2]. Monotonic guards prevent the less risky actions from being mapped to higher risk levels, and there are hard blocks that are invalid when the match of the sanctions, the expired certificates, or other serious issues in the audits take place. Suppliers that start the cold start with a basic category receive conservative Bayesian priors derived by the category baselines and structure graph features; priors are subsequently updated online using the early information with ASN timeliness and partial quality information. A failure in data-quality controls (freshness, completeness, validity) results in a fallback to the action set of review-only; the provenance is recorded, and masking is applied to the affected features to ensure

that they cannot silently corrupt. Most importantly, the decision layer preserves clear context boundaries to ensure policies are well encapsulated, testable, and evolvable instead of being cross-present between domains [4].

4.2 Human-in-the-Loop Workflows

The freedom of action has a limit of responsible supervision that focuses judgment where it can make a difference. Triage is taking into account predictive uncertainty and business materiality. Scores in a gray range- such as 0.45-0.60- go through a review queue prioritized by expected value of information (EVI), a combination of risk size, uncertainty, and importance of the item. Low-materiality but high-risk cases may auto-allow with passive monitoring if the marginal cost of review is greater than risk-adjusted exposure, avoiding queue bloat. Objectives at the service level limit latency and backlog; a breaching alert diverts to backup pools or introduces temporary limits. Any override should include a well-organized rationale in a defined ontology of data error, edge, policy exception, or model miss, to provide systematic remediation. Two-person teams could also be required in blocks that exceed the materiality thresholds to mitigate personal bias.

Active learning reduces the loop: high-uncertainty, impact, and disagreement cases are more likely to be sampled; labels obtained by expert reviewers are weighted in retraining, to reduce prior bias; feature engineering backlogs are fed by disagreement analytics. All reviewer actions, artifacts, and timestamps are recorded to tamper-evident decision logs with content hashes; decision logs can be stored as WORM data or append-only streams to protect integrity [31]. Worklists and dashboards display queue age, review mix, and top override reasons, and cohort heatmaps uncover repeatability by reviewer, supplier segment, or category. Playbooks on what to do next-best, e.g., add receiving inspection, request corrective action, or initiate dual-source evaluation, are applied in tabular form attached to decisions to minimize time-to-remediation.

4.3 Transparency, Explainability & Decision Logging

Reasoning transparency is a prerequisite to adoption, escalation handling, and regulatory audit. During inference, the system outputs local explanations: SHAP top-k features, signed and magnitude-scaled; lineage pointers to the precise derivation of the features; evidence bundles (OCR certificate snippet, audit code, shipment milestone) to allow stewards to certify inputs. Partial-dependence and accumulated-local-effects charts at the category-level illustrate non-linearities and interaction, with a stability monitor to track changes in the overall importance over a series of rolling windows and warn when explanations are no longer similar. Counterfactual guidance produces actionable analytics: “decrease lead-time variability 25 percent or enhance ASN timeliness 15 percent to move out of block to review.” Feasible counterfactuals are bounded in terms of policy (i.e., sanctions overrides are forbidden) and inter-correlated inputs (i.e., lead time and frequency of expedites).

Figure 5: *Transparency and explainability pillars for auditable AI decision logging*

As shown in the figure above, transparency and explainability are the foundation of adoption in facilitating trust, accountability, regulatory compliance, user understanding, ethical considerations, and trade-offs-consciousness. In practice, inference detects SHAP top-drivers, lineage pointers, and evidence bundles (such as certificate OCR, audit codes, shipment milestones). PDP/ALE displays and stability monitors are available as category dashboards. Counterfactual guidance provides reasonable correctives that do not violate policy hard-gates and associated inputs, allowing auditable decision records and accelerated handling of escalations and ongoing risks governance.

Generative simulators can also be applied to suggest structured and realistic variations that do not violate the globally constraining features; recent work on diffusion-based modelling of complex, multi-object scenes demonstrates how high-quality edits can be made consistent with an overall context, and that can be generalized to generating counterfactuals within the business constraints (Singh, 2022). A standardized decision-log schema captures request_id, model_version, policy_version, features_hash, explanation payload, human_override, outcome, timestamps, and lineage references. Logs are sampled in auditor packs and also when incident thresholds are breached to perform a root-cause analysis.

4.4 Fairness, Risk & Compliance Controls

The quality of the decision should be at the same level (across the supplier subgroups) and within the legal and ethical boundaries. Monitoring calculates equalized-odds gap of adverse outcomes, subgroup expected calibration error, and lift@k parity by region, size band, ownership type, and diversity certification. Subgroup-specific thresholds, loss reweighting, or monotonic constraints on sensitive proxies are used to mitigate where gaps exceed tolerances; such mitigation is justified in a governance record that contains details of trade-offs in performance, as well as legal review notes. Anonymity and minimization are achieved through role-based access, field-level tokenization of personal information, and redaction of payloads; the processing record maintains the accountability of third-party information.

SG and third-party risk policies, such as sanctions and PEP screening, forced-labor watchlist hits, certificate expiries, will be coded as hard constraints in the policy layer, to ensure that models do not suggest actions in violation of compliance [17].To take a resilience view, mitigation options that the platform would operationalize as first-order decisions include safety-stock changes, inspection rates, and a formal dual-sourcing trigger occurrence. There is also evidence to suggest that dual sourcing can be used to address vulnerabilities, enhance continuity, and should be considered a calibrated response when risk scores increase or when there is a high level of single-source exposure (Goel & Bhramhabhatt, 2024). All mitigation efforts will be monitored in terms of success and effectiveness, thus future limits can be updated with measured results.

4.5 Monitoring, Drift & Safe Deployment

Long-term reliability demands constant evaluation of data, model, and policy fitness. The data drift is detected through the population stability index as well as Jensen-Shannon divergence of the core features and the text embeddings; limits are adjusted to the seasonality to avoid alert fatigue. Freshness and completeness are imposed on data contracts; subsets that occur as breaches automatically flag corresponding categories as notify only, create incidents to owners and SLAs, and document pointer vindication in decision records. The drift in performance is monitored using PR-AUC in the case of classifiers, NDCG @k for rankers, and business KPIs OTIF uplift, defect-PPM reduction, expedite-cost avoidance, and review latency. Brier score and expected calibration error are used to measure calibration drift; recalibration with automatic isotonic adjustment is available within limits when the stability thresholds are respected.

Figure 6: *Data drift and data-quality monitoring for safe deployment*

As highlighted in the figure above, monitoring distinguishes between data drift and data-quality breaks: a change in distribution (such as, new region prevalence) is signalled (via PSI/Jensen-Shannon), whereas missing fields are signalled as a contract breach. Breaches put categories into notify-only mode, create incidents with SLAs, and record pointers. Performance drift reports PR-AUC and NCDEG@k (ranker), as well as business KPIs (OTIF, defect-PPM, expedite cost, review latency). A calibration is monitored with Brier/ECE and recalibrated with conservative isotonic recalibration where required.

Gradual deployment- shadow to gather counterfactuals, then canary, with a small slice of traffic, under the control of SLOs (maximum false-block rate, maximum review latency, maximum decision staleness) [26]. Violations automatically roll back to the most recent known-good model and policy, stop retraining jobs, and alert stewards. Root cause is divided into data, model, policy, or infrastructure in the post-incident review, and remediation items are recorded, and playbooks are updated. A governance registry manages a set of versions of models, features, policies, and data contracts to ensure every operative decision can be recreated and the autonomy boundary is visible and enforceable.

5. Experiments and Results

5.1 Experimental Design

The test plan assessed the autonomy-and-stewardship pipeline in a cost-reflective state. All observations were sorted by time of the event and divided into sequential training, validation, and test windows that maintained seasonality, including quarter-end demand spikes and holiday shutdowns. A rolling-origin procedure was imposed: models were fit to the first window, tuned on the second, and scored on strictly later windows, and the origin was advanced to provide multiple non-overlapping evaluations. To avoid optimistic forecasts, an as-of join policy was used: only those features that were

timestamped up to equality or before the prediction reference date could be used. Age-based indicators like year-to-date defects employed right-closed windows, and any record whose topological freshness breached the data contract was discarded. Certification, audit, and contracts were represented signals only when they were valid at the date of prediction, and local time zones and calendars governed time alignments [22].

The targets were in delivery, quality, and compliance risk at 30-, 60-, and 90-day time horizons. Supplier blocking was used during cross-validation to ensure that examples of the same supplier did not exist across folds, and to evaluate the model's performance on unseen suppliers. Hyperparameters were identified on validation ranges via a multi-objective search balancing discrimination, calibration, and inference latency. Through the use of pinned containers, training and inference occurred, and contained locked versions of an operating system, compiler, and CUDA/cuDNN. A feature store provided versioned views using hash keys of transformation graphs and date windows, which could be used with snapshots. Each run produced lineage artifacts and registry entries of model and policy versions, and the CI/CD pipeline performed unit tests of feature transformations, regression tests of calibration and latency, as well as promotion gates (i.e., canary and shadow) deployments governing alignment between analytics and software delivery practices [12].

5.2 Main Results and Ablations

The main goal was to surpass legacy scorecards in terms of early identification of delivery, quality, and compliance risk and to generate probabilities calibrated to make cost-sensitive threshold decisions. Baselines included a weighted scorecard, logistic regression on tabular features, and a gradient-boosted tree trained without text or graph input. The entire stack integrated tabular indicators, lead-time volatility, OTIF trend, expedite rate, chargebacks, non-conformance density with unstructured evidence in the form of audit narrative encoded as sentence embeddings, and graph signals in the form of supplier-part-site networks that captured tier distance, weighted degree, and community risk. As highlighted in the table below, PR-AUC and F1@k were used in classification, NDCG@5 and NDCG@10 in ranking, and Brier and the expected calibration error in probability calibration. This decision curve converted scores to action thresholds as far as category-specific cost models were concerned.

Table 2: *Summary of main results and ablation findings*

Aspect	Baselines / Variants	Key Metrics	Main Findings / Implications
Objective & setup	Baselines: weighted scorecard; logistic regression (tabular); GBT w/o text/graph. Full stack: tabular + text embeddings (audits) + graph features (supplier–site–part).	PR-AUC, F1@k, NDCG@5/10, Brier, ECE; decision curves with category cost models.	Full stack surpasses baselines for early risk detection; calibrated scores support cost-sensitive block/review/allow thresholds.
Modality ablation—Text removed	Remove audit/narrative embeddings.	Recall at matched precision (compliance).	Recall drops → unstructured text contains anticipatory cues absent in KPIs.
Modality ablation—Graph removed	Remove tier distance, weighted degree, community risk.	NDCG@k on thin-history suppliers.	Ranking degrades, especially for low-history suppliers → neighborhood signals interpolate risk.
Model family ablation	Tree ensembles vs tabular deep models.	Discrimination; robustness to missingness.	Tree ensembles show stronger discrimination and resilience to missing data.
Calibration ablation	Platt scaling vs isotonic regression.	Brier, ECE; segment reliability.	Platt yields better reliability across segments but higher variance than isotonic.
Text encoding choice	Attention to control-failure/mitigation clauses;	Event capture quality (qualitative).	Improves handling of contradictory audit notes by reconciling

Aspect	Baselines / Variants	Key Metrics	Main Findings / Implications
	dynamic memory inference–inspired encoder.		exceptions with corrective actions.

Isolated contributions were made at once by modality and by literary family. Removal of unstructured features decreased recall at matched precision of compliance-related events, which mirrors the presence of anticipatory cues in human-authored descriptions of these events that are not captured purely numerically in the KPIs. By omitting the feature set associated with graphs, the poor rank statistics on the thin-history suppliers were not observed, indicating that the neighborhood signals interpolated risk in cases where the supply network had limited transactional history. Model-family ablations compared tree ensembles and tabular-deep models; tree ensembles are more competitive in discrimination and resistant to missing data, whereas calibration ablations compared Platt scaling and isotonic regression; the former outperformed the latter in reliability among segments but at the cost of variance.

Attention was applied when encoding text by the text encoder to emphasize the clauses related to control failures and mitigations. Dynamic memory inference networks inspired their formulation in natural language inference, which uses explicit memories to allow model capacities to attend to, compare, and reconcile conflicting statements, useful when an audit examines exceptions alongside corrective actions that have to be combined into a single risk signal (Raju, 2017).

5.3 Robustness and Stress Testing

Under distributional stress that is reflective of realistic operations, robustness was determined. Due to the labor strike, extreme weather, and the closure of the port, a distribution issue developed. To measure degradation, models trained on pre-shock data were scored in these windows; monitors recorded changes in covariate shifts on key features and shifts in base risk before the shift, and evaluation tracked changes in PR-AUC, lift@k, and calibration. Artificial gaps and holes in time were also added at the feature-store level to represent tardy advance-shipment advices, sluggish goods receipts, and incomplete availability of invoices. Pipelines were executed on degraded inputs to ensure that policy-as-code degraded actions to the lowest effect of review, and to measure the performance of imputation techniques such as forward-fill within supplier bounds.

Separate sources with low volumes were connected to check the cold start. Conservative prior distributions were used for risk scores, and increased uncertainty bands were used to promote human-in-the-loop routing. To simulate adjudication noise, experts randomly changed a fraction of labels in the bounded temporal neighborhoods to represent discordant audit coding. Sensitivity analyses were performed to test the stability of the top-k recommendation set, varying the decision thresholds and the review capacity k. As the team calculated Jaccard similarity of the recommendation list against the shift in the costs in the decision curve, cliff effects that might destabilize operations were highlighted [23].

The system was also load-tested. Inference delays were benchmarked at complete batch runs and stream data rates approaching real-time, with the whole-chain timing budgets validated on dashboards that present justifications and evidence compilations. Canary deployments used automatic rollback triggers based on calibration drift and false-block SLOs, such that performance regressions rolled back to a safe configuration before impacting procurement workflows.

5.4 Fairness and Error Analysis

Arguments of fairness were tested under subgroup discrimination and calibration based on region, supplier size, and diversity certification. Equalized-odds gaps were estimated as the difference between false-positive and false-negative rates, at the selected operating point, across groups. The subgroup anticipated calibration error in quantifying the probability reliability, and the group-wise k-lift indicated that the screening queue proportionally mapped adverse events instead of focusing the process on a particular population. When gaps exceeded tolerance, group-conscious calibration and modified thresholds were used, and governance documentation documented trade-offs in cost and capture.

Error analysis made use of both quantitative and qualitative diagnostics. Confusion matrices identified false positives—where episodic expedite spikes did not reflect on continuity of risk — and false negatives —where over-aggressive caches obscured ongoing near-miss delays. Local explanations in the case of a stratified sample of decisions enumerated the highest contributive features at inference time; this allowed the reviews to trace explanations. To test the accuracy of the assumption that salient phrases captured genuine control failures in the source documents, the case documents dominated by text features were

manually audited. Where graph aspect has played a role, observers have checked the neighborhood compositions to make sure that fleeting relationships did not meaninglessly inflate neighborhood-specific risk cues. Results that drove back to feature governance: lexicon expansions to cover vague terms, lineage notes to cover data-lag risks, policy updates refinements around monotonic guards that laced sanctions, and certificate expiries.

5.5 Business Impact and Case Study

The effect of the business was measured using a decision-curve analysis that plotted possibilities and limits of expected cost. The cost models were false-block effects, damaged throughput, and friction in contractor relationships, false-negative costs, expedite fines, inventory-outs, quality spills, and the cost of review, labor, and latency. In each category, the risk appetite maximized expected net benefit under the constraint of review capacity. In these policies, the review queue was prioritized for high-value and high-uncertainty cases and was coupled with procurement gates.

A pilot deployment was used to exercise the governance stack, including data contract freshness and validity. When these are violated, the system takes a downgrade action, reviewing with banners that point to the source and chain of custody information. Decision logs included request IDs, model and policy version, feature hashes, explanation, overrides, and outcome [18]. Adoption was monitored using reviewer latency and override percentages. It has recorded precipitous decreases in rates because calibration had stabilized, and stewards were more confident in their abilities. Onboarding by use of change-management artifacts like playbooks and audit packs maintained and institutionalized autonomy by stewarding the rituals of stewardship.

6. Discussion

6.1 Interpretation of Signals

In three experiments, three predictor families produced the most marginal lift and consistent explanations. Lead-time volatility, measured using rolling standard deviation, median absolute deviation, and week-over-week slope, was more useful than average lead time. Latent capacities of stress and upstream congestion were observed on volatility before absolute delays. Its partial-dependence curves were also monotone increasing, though with an inflexion point at the 75th percentile of the historical volatility distribution, after which the risk rose super-linearly, a manifestation of compounding schedule slippage. Red flags described in nonconformance stories and supplier mailboxes were extracted as audit-text information that gave an early warning that was not available in structured fields.

The classification of phrase clusters, such as miscalibration, rework authorized, and waiver pending, as well as negation patterns like no evidence of certificate, posed a high risk. However, the quantitative KPIs were within tolerance. DaDaSHI sentence embeddings improved over naive keyword counts and provided consistent local SHAP attributions [3]. Network centrality in the supplier-site-part graph, particularly weighted betweenness and eigenvector centrality, was used to identify nodes that spread disruption. The influence of modest quality hypersensitivity was increased by high-centrality suppliers, as in cascading risk. Interaction effects were significant: volatility and high centrality led to magnified marginal risk; high centrality with redundancy (many qualified alternatives) softened the impact of adverse propagation.

6.2 Managerial Implications

The results convert into sources of leverage in the areas of sourcing, quality, and logistics. Dynamic preferred-supplier sets are best when refreshed with grandfathered rankers bound by policy rather than base probability. This is a combined risk x impact score with impact weights based on part criticality, substitution cost, and single-source exposure, in turn triggering specific measures such as dual-sourcing of key parts that exceed a certain threshold, increased AQL sampling rates on lots that are susceptible to quality problems, or use tactical safety stocks where lead times are uncertain. In the planning stage, category managers planning reserves should input calibrated top-k risk lists into the allocation and capacity reservation.

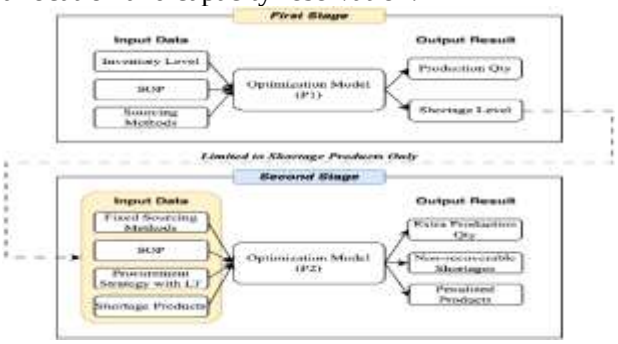

Figure 7: *Two-stage optimization for sourcing allocation and shortage mitigation*

Two-stage optimization is beneficial, as depicted below in action in relation to sourcing and logistics, as shown in Figure 7. All the above SOP and sourcing methods, as well as the level of inventory, are used to optimize production levels and factor in levels of shortage at stage one. In Stage two,

shortage items are assigned fixed sourcing and lead times strategies to cover additional output, identify non-recoverable shortages and product-based penalties, consistent with preferred supplier status, risk-impact weights, dual sourcing, AQL, and safety stocks.

In contract language, the risks can be charged on a proportional score: service level credits at OTIF percentile levels; inspection rights that automatically increase when model confidence decreases; data-sharing requirements as a means to observe upstream (tier-n) processes; and notice periods before process modification, where changes in risk characteristics occur. Expected positives at the chosen k should size review queues with SLA timers and surge procedures to deal with times of disruption. Procurement analytics also ought to reveal decision curves alongside cost models, which materially allows executives to select thresholds that minimize expected cost instead of maximizing generically-focused accuracy metrics.

6.3 Stewardship's Role in Trust & Adoption

Adoption hinged on the ability to show that inputs, models, and actions were under control, observable, and recoverable. Ingestion-specified contracts on data specified schema, validity range, freshness guarantees; any violation would have downgraded autonomy to the allow/block level. End-to-end provenance helped to accelerate root-cause analysis, with one click, spanning raw events into feature derivations to model and policy versions. The intended use, performance by segment, and calibration were recorded on a card that contained information about known limitations; embedding links to evidence bundles (audit excerpts, certificate status) on cards reduced stewardship sign-off friction.

In practice, streaming notifications about changes were used to meet freshness SLAs and replay features following a shift in contract or schema, with advice on scalable low-latency data services [6]. The null, range, and referential checks (quality gates) were applied before the score was presented; in case of violation, safe degradation (policy defaults to review) was done instead of silent failure. A limited number of governance KPIs were monitored by stewards: lineage completeness, freshness compliance rate, mean time to provenance, override rate, and explanation satisfaction scores. The practices helped to translate model scores into justifiable, auditable decisions, decreased external-assessment overhead by making evidence retrieval routine rather than ad hoc.

6.4 Limitations & Threats to Validity

Several validity risks qualify the conclusions. Caused by the attrition of failed or poorly-performing suppliers in the systems, survivorship bias skews the appearance of improved performance; weighting of importance and backfilling of historical data attenuate but do not eliminate this bias. Coverage gaps at the tier-n levels endure, particularly in cases of voluntary disclosure of sub-levels; edges are missing and can underreport propagation risk and undermine the centrality characteristics. Labeling is distorted by delays in reporting: late reports of shipments result in apparently false positives; stringent time divides and labeling considerations reduce leakage, but cannot address delays in data ground truth. Measurement error in audit narratives and OCR-extracted certificates adds noise to text and compliance characteristics; adjudication workflows and two-review mitigate variance, but come at the expense of latency.

Category dynamics constrain generalizability: semiconductor lead-time shocks contrast with packaging disruptions, which means that recalibration and policy adjustments are necessary. There is eventually the danger of model-behavior drift, whereby suppliers adapt to inspection routines; continuous tracking, calibration, and threshold reviews can deter this but not preclude strategic action [20]. These caveats warrant viewing gains as contingent upon the quality of governance, the maturity of data-observability, and the organization's ability to take action on recommendations promptly.

6.5 Lessons Learned

Several of the operational practices determined increased effectiveness, combined with reduced residual risk. Cadence was important since a monthly threshold review became out of date in volatile conditions; bi-weekly governance ceremonies synchronized thresholds to account for drift and seasonal changes, thus stabilizing the workload of reviewers. The process discoverability also eliminated rework because a common ontology of override reduced unstructured justifications to structured feedback to support active-learning retrains and policy updates. Tooling dexterity had its rewards as versioning feature definitions, immutability of training snapshots, deterministic pipelines (seeded HPO, containerization of runners) generated reproducible decisions and credible audit. Resilience increased as incident response became a first-class capability: playbooks that linked model, data, and policy rollbacks, tabletop exercises indicated escalation paths, and continuity targets (RTO/RPO) were clear when referring to procurement systems, as the current business-

continuity best practices prescribed [13, 33]. Training and change management were also essential as onboarding involved reading explanations, checking lineage, and interpreting decision curves; leadership reviews emphasized expected-cost trade-offs versus generic accuracy. Organizations that institutionalized such rituals recorded lower override levels, quicker provenance resolution, and more confidence in autonomous action across business units worldwide.

7. Future Consideration

7.1 Active Learning & Continual Tuning

In future versions, feedback mechanisms should be made operational by devising continuous cycles that promise the most significant reduction in expected model error given a quantity of review. Uncertainty (entropy of calibrated risk scores), expected information value, and business materiality in terms of spend and criticality can be used to rank supplier cases in a retriever queue. Stewards adjudicate the top tranche; labels are returned with recency weighting and inverse-propensity adjustments that reduce the selection bias. The combination of feature population stability indices and calibration error deltas in drift triggers should stage the model into shadowing or limited autonomy in fine-tunes. A system-level attribute, such as confidence-aware SLAs, will program alerts and retraining jobs at times when decision makers are available, and hence improve their response rates and reduce the latency of remediation, an aspect that has been known to contribute to the outcomes [25].

7.2 Causal/Uplift & Decision Optimization

Future efforts should calculate treatment effects at the individual level to optimize interventions as opposed to anticipations of actions, including, but not confined to, dual-sourcing, inspection intensification, or renegotiation. Finite sample learners are T-, S-, and X-learners with gradient-boosted bases, doubly robust learners to control the bias, and meta-learners to stabilize the variance through cross-fitting. Inverse propensity/doubly robust estimation does not disrupt assessing policies without online trials. The action selector is a knapsack-like budget allocation problem, which trades expected uplift against intervention cost and capacity; risk-appetite and fairness constraints are imposed as linear bounds. Decision curves report on net benefit at various review levels k, whereas policy simulation reruns past event history to target where thresholds or suggested actions are over- or under-responsive.

7.3 Digital Twins & Shock Simulation

A digital twin of a supply network is represented by the model of suppliers, lanes, and parts using the model of a directed multi-graph with edge reliability and stochastic lead-time. The scenario generators should sample the correlated shocks, such as port closures, commodity spikes, extreme weather, and transmit the effects through a Monte Carlo percolation and queueing approximations of nodes with capacity constraints. The twin can also be used to simulate shocks on the thresholds and triage policies to expose regimes in which rules over-block or under-react, and show fragility maps with choke points and recovery routes. Model outputs can feed into the feature engineering as simulated early-warning signals, and into governance, in a proposal of temporary policy overrides with expiry and audit trails [21]. Given a series of historical disruptions and simulated trajectories, each with a lead time index, validation is computed by dynamic time warping of lead-time vectors.

7.4 Multi-Agent Autonomy & Federated Learning

Future roadmaps are to model multi-agent negotiation of lead times, minimum ordering quantities, and divisions of allocation with strong guardrails. The agents can be trained using constrained reinforcement learning, whereby a penalty can be used to encode policy, fairness, and compliance, and safe exploration can be guaranteed using model-predictive shields and action filters. The rationales provided by the agents and decision-specific summaries need to be viable and not contradict the explainability principles that have been proven to affect trust in high-stakes decision services [29].

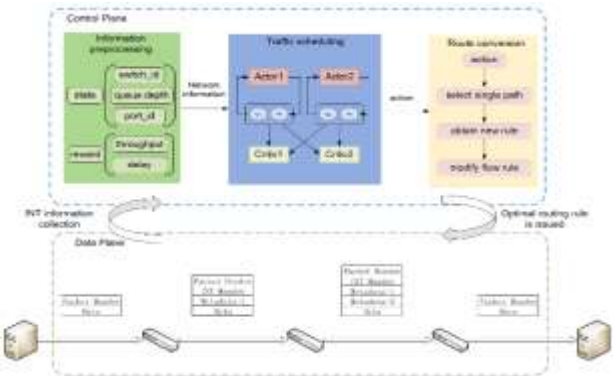

Figure 8: *Guardrailed multi-agent actor–critic architecture for constrained decision-making*

As highlighted in the figure below, a guardrailed multi-agent architecture employs constrained reinforcement learning; each of the multiple actors proposes actions, which are assessed by corresponding critics against stereotyped policy,

fairness, and compliance penalties. Data plane Network information is first prefiltered in the control plane; efficient exploration is secured with the use of shields/action filters. Chosen actions translate to routing/allocation rules, and rationale traces support explainability and audit of trustworthy decisions. The dial and proposal artifacts must be stored in a formatted message format with signed policy checks before execution, as well as roll-back hooks in cases where data or confidence is determined to be of poor quality. Federated averaging with secure aggregation allows enterprises to train ranking or risk models and preserves confidentiality while sharing no raw data, and differential privacy budgets preserve the secrecy of partners.

7.5 Verifiable Credentials & Provenance

Certificates, audits, and compliance documents should move to verifiable credentials that trusted issuers sign to provide revocation registries and short-lived statements. Decision logs ideally would encode cryptographic hashes or Merkle roots of artifacts to create tamper-evident provenance, and zero-knowledge proofs could be used to assert constraint satisfaction such as that they were not by a sanctioned party or originated geographically. Provenance graphs should be able to couple information lineage to action lineage, such as linking model versions to feature definitions, policy packages, and human overrides to final results [27].This alignment allows the auditors and customers to confirm what information was used to make a decision, what guardrails restricted the decision, and how accountability was maintained. In practice, provenance checks provide a gate to deployment and raise exceptions in case of invalid signatures, expired credentials, or missing lineage.

8. Conclusions

This paper discusses the finding that a governance-native, machine-learning decision stack of autonomous supplier evaluation significantly enhances expedient discovery and ranking of the risks of delivery, quality, and compliance, and maintains auditability and control. Classical multiple-criteria approaches are transparent but immobilise weights and base batch indicators; they fail to capture intra-period variations and interaction-intensive signals; therefore, scorecards respond slowly and convey poor action threshold advice. In contrast, the proposed stack recasts evaluation as rolling-horizon prediction and ranking over a 3090-day window, integrating both tabular measures and unstructured audit evidence as well as network context with leakage-safe features and evaluation. Predictions are translated into block, review, or permit via calibrated probabilities and decision-curve analysis flush to review capacity. However, compliance primacy is still through hard gates professed as versioned policy-as-code.

In practice, reliability is centred on stewardship. Serverless containers will be datacontract-gated ingestion, data lineage will be used to provide unit-level provenance, freshness service-level agreements will enforce timeliness, and decision log records will enforce traceability, making intelligent autonomy explainable as opposed to a black-box scorecard. It populates the serving architecture, using the data snapshots, feature definitions, model binaries, and policy bundles. It promotes models through gradual workloads using shadow or canary deployment and automatic rollback in case of freshness, calibration, or performance violation. Additionally, it evolves a registry of governance artifacts to support reconstruction. In pilot operation, the reduction of overrides through governance rituals showed lower interference as calibration stabilized and reviewers became more confident; request identifiers, version hashes, explanations, overrides, and results were written to the decision logs, along with timestamps and lineage audit packs. Three predictor families were consistent and defensible in their explanations. Lead-time volatility, calculated as a rolling standard deviation, median absolute deviation, and trend, were identified earlier than averages; red-flag phrases and negations in the audit documents were an early indicator of risk unseen in structured KPIs; and centrality of the network graph between the supplier, site and part hubs quantified the effect of propagation and the buffering effect of redundancy. Decision-curve analysis was coupled with clear-cost models to balance adverse-event detection with false blocks, the labor costs of reviews, and relationship friction, and review queues prioritized high-uncertainty cases with high materialities under procurement gates. SHAP explanations, lineage pointers, and evidence bundles helped adjudicators to relate actions to reasons; fairness and adherence were safeguarded by subgroup monitoring, code sanctions, and certificate rules as hard constraints in the policy layer. Such conclusions are subject to limitations.

Features and ground truth are distorted by survivorship bias, tier-n visibility gaps, reporting lags, OCR or narrative noise, and category heterogeneity limits transferability, requiring recalibration and threshold adjustment as circumstances change. However, a reasonable implementation is still visible: shadowing, then canary deploys with SLOs protection, automated rollback, drift and freshness configuration, post-incident analysis, and registry-backed versions ensuring that autonomy is much more limited and

that auditability suffices. The generalization of the approach is that it becomes a template that integrates modalities, enlists quality at contract and lineage levels, normalizes probabilities, and channels results in policy-as-code in a meaningful and tamper-evident decision log that allows adaptation at categories and tiers. The body of evidence together is indicative that autonomous evaluation with guardrails is a pragmatic route to transparent, resilient supplier decision-making.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of 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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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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