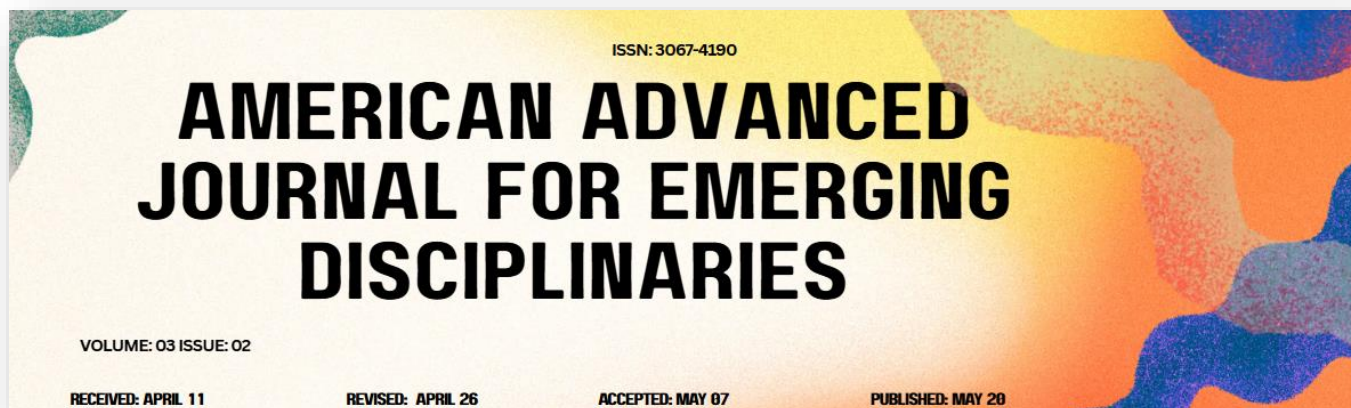




## Risk-Aware Product Intelligence for Enterprise Technology Adoption

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**Abstract**— Today’s competitive environment requires organizations to continuously strengthen their technology infrastructure while simultaneously minimizing technology-related risk. Product intelligence helps ease the burden of selecting new technology, yet most business functions lack the data, analytical capability, and market knowledge needed to evaluate third-party products and services on their own. As a result, organizations often turn to external vendors or suppliers for help with evaluations. Proper governance of product intelligence supports more effective knowledge-gathering throughout the technology adoption process. By applying a governance framework that manages both product intelligence and risk assessment, decision-makers can make better-informed technology adoption choices—ones that reflect the organization’s existing risk profile within its unique operating environment.

Technology-procurement decisions are inherently challenging for several reasons: they involve investments that occur only periodically, making the decision unfamiliar each time it arises; they require technology-specific expertise that business functions may lack; they often rely on data of uncertain quality; and they unfold through processes involving multiple decision rights, adding further complexity. A well-structured product-intelligence function can ease these challenges, especially when paired with a governance framework that ensures the decision-making process is handled in a risk-aware manner. The proposed governance framework achieves this by clarifying roles and responsibilities for technology evaluation, defining decision rights for technology-related assessments, embedding product-intelligence policies directly into evaluation processes, and establishing an organizational risk profile that enables more accurate technology evaluations.

**Keywords**—Decision Governance, Product Evaluation, Product Intelligence, Procurement Analytics, Risk Assessment, Risk-Aware Decision Making, Technology Adoption, Technology Evaluation, Technology Governance, Technology Procurement, Technology Risk Management, Third-Party Risk, Vendor Assessment, Vendor Governance.

### I. INTRODUCTION

Enterprises continually explore market-ready information technologies to support product innovation, process enhancement, and operational efficiency. Nonetheless, failure rates for such initiatives remain unacceptably high. Decision-makers apply several principles, frameworks, and methodologies to mitigate the risk of technology triggers, with varying levels of rigour. Often, the risk-aware decision process lags behind product-intelligence supply chains, which can compromise governance over key resources and capabilities.

These observations contribute to a model for governance-driven product intelligence that supplies reliable, predictive, actionable, and usable intelligence on entry technology-related products. Such product intelligence enables risk-aware selection, non-elimination, and use decisions. Applications in enterprise technology-related product procurement require expansion of existing concepts, frameworks, and methodologies to realise product-intelligence workflows within cloud-based and conventional enterprise technology environments. Specifically, the evolving governing product-intelligence model outlines a governance framework for process, a data supply-chain architecture, and a risk-aware evaluation methodology that quantifies assurance and performance risks across technology triggers.

### II. THEORETICAL FOUNDATIONS

Conceptual foundations for the governance-driven product intelligence model guiding risk-aware technology

adoption are developed. Product intelligence, governance, risk, assurance, data provenance and integrity, transparency, and decision rights are defined. Two theoretical lenses — key elements of governance theory and leading risk management frameworks, such as the Australian/New Zealand standard — alongside concepts and models for decision-making under uncertainty, underpin the work. Relationships among core constructs, supporting assumptions, and boundary conditions are presented.

In a broad sense, product intelligence encompasses knowledge about a product that informs and supports its continuous improvement, enhances the fulfillment of stakeholders' expectations, or clarifies whether the product is a suitable choice for a particular organization. In the present context, product intelligence refers to the knowledge generated by the collection, integration, and analysis of relevant data sourced from diverse internal and external origins and substantiated by evidenced-based controls and assurance. Such information provides product-related insights for stakeholders during the procurement decision-making process and throughout the product life cycle, thus improving the trustworthiness of product-related decisions and operations across different exercising domains and constituencies.

### A. Mathematical Formulation

This section formalizes the governance-driven product intelligence model into eleven measurable constructs spanning risk scoring, data trust, governance maturity, decision confidence, and cost impact. Unless stated otherwise, indexed scores are normalized to the interval [0, 100], and the subscript  $n$  denotes a score divided by 100 for use inside bounded (e.g., logistic) expressions.

$$CTRS = w_S R_S + w_O R_O + w_F R_F + w_C R_C + w_{\{Sec\}} R_{\{Sec\}} \quad (1)$$

Eq. (1) defines the Composite Technology Risk Score (CTRS) as a weighted sum of the five risk dimensions of Section II-C, with weights  $w_i$  drawn from Table I and  $\sum w_i = 1$ . Lower CTRS indicates lower aggregate exposure.

$$R_i = (1 / k_i) \sum_{j=1}^{k_i} w_{ij} s_{ij} \quad (2)$$

Eq. (2) computes each dimension score  $R_i$  by aggregating  $k_i$  normalized metrics  $s_{ij}$  (0–100) using metric-level weights  $w_{ij}$ , allowing each dimension to draw on multiple

underlying indicators (e.g., strategic alignment index and roadmap-fit score for the strategic dimension).

$$DPTS = \gamma_1 C + \gamma_2 A + \gamma_3 L + \gamma_4 (1 - U) \quad (3)$$

Eq. (3) defines the Data Provenance Trust Score (DPTS) from completeness  $C$ , accuracy  $A$ , lineage depth  $L$ , and unresolved-provenance ratio  $U$ , with  $\sum \gamma = 1$ . DPTS is computed per data-source category and reported in Fig. 4 and Table IV.

$$GMI = (100 / 5) \sum_{d=1}^5 M_d, M_d \in [0, 5] \quad (4)$$

Eq. (4) defines the Governance Maturity Index (GMI) as the mean of five governance-dimension maturity levels  $M_d$  — role clarity, decision-rights definition, policy embedding, escalation efficacy, and assurance integration — scaled to a 0–100 range.

$$PIQI = \beta_1 DPTS + \beta_2 TIQ + \beta_3 COV + \beta_4 ACT \quad (5)$$

Eq. (5) defines the Product Intelligence Quality Index (PIQI) from DPTS, timeliness (TIQ), source coverage (COV), and actionability (ACT), with  $\sum \beta = 1$ .

$$DCS = 1 / (1 + e^{\{-(\lambda_1 PIQI_n + \lambda_2 GMI_n - \lambda_3 CTRS_n)\}} \quad (6)$$

Eq. (6) defines the Decision Confidence Score (DCS) as a logistic function of normalized PIQI, GMI, and CTRS, bounding DCS to (0, 1). Confidence rises with intelligence quality and governance maturity and falls with aggregate risk exposure.

$$RATC = C_{\{base\}} (1 + \kappa \cdot CTRS_n) \quad (7)$$

Eq. (7) defines the Risk-Adjusted Technology Adoption Cost (RATC) as baseline procurement cost  $C_{base}$  inflated by a risk-loading coefficient  $\kappa$  applied to normalized CTRS.

$$E(t) = 1 \text{ if } CTRS(t) > \theta; 0 \text{ otherwise} \quad (8)$$

Eq. (8) defines the escalation indicator  $E(t)$ , which triggers governance-council review whenever the composite risk score exceeds threshold  $\theta$  ( $\theta = 50$  in Fig. 2).

$$ECE = (N_d / T_c) \cdot DCS_{\{avg\}} \quad (9)$$

Eq. (9) defines Evaluation Cycle Efficiency (ECE) as the throughput of completed decisions  $N_d$  per unit cycle time  $T_c$ , weighted by average decision confidence, so that faster but lower-confidence cycles are not rewarded disproportionately.

$$VRC = (1 / V) \sum_{v=1}^V w_v R_v \quad (10)$$

Eq. (10) defines Vendor Risk Contribution (VRC) as the weighted mean risk exposure across  $V$  vendors under concurrent evaluation, supporting portfolio-level escalation decisions.

$$NRR(t) = 1 - FP(t) / TE(t) \quad (11)$$

Eq. (11) defines the Escalation Noise-Reduction Rate (NRR) as one minus the ratio of false-positive escalations  $FP(t)$  to total escalations  $TE(t)$  at time  $t$ , tracked quarterly in Fig. 7.

$$GROI = (ARATC_{\{avoided\}} - Cost_{\{gov\}}) / Cost_{\{gov\}} \quad (12)$$

Eq. (12) defines Governance Return on Investment (GROI) as risk-adjusted cost avoided through governance relative to the cost of operating the governance function itself.

### III. GOVERNANCE FRAMEWORK FOR PRODUCT INTELLIGENCE

An overarching governance model directs data, analytics, and decision processes throughout the generation of product intelligence. Principal roles and accountabilities include an executive sponsor, a governance council, the technology product development team, the risk office, IT, compliance, and procurement. Clear decision rights and escalation paths, aligned policy clauses and standards, and compliance checks integrated into product intelligence workflows enable enterprise-wide transparency, risk management, and assurance.

The executive sponsor oversees the entire framework. A cross-functional governance council, comprising executive representatives from key functions, recommends approval, amendment, or disbandment of governance clauses, assesses a broad range of products, escalates critical issues, ensures that all clauses associated with the products are consistently applied, and enforces appropriate actions for recurrent non-compliance. The technology product development team, comprising business and IT stakeholders, generates

intelligence and guidance for a specific technology, ensuring both control and oversight. Its charter includes defining the product and its importance, describing key product decision domains and decision rights, providing a risk and assurance assessment, and producing supporting artefacts. The risk office operates independently of IT, assessing sales, service, support, consultancy, training, third-party and related technology product evaluations, vendors, and configuration management for risks not explicitly covered by a management board, council, or committee.

#### A. Experimental Results

Model A (ad-hoc, no formal governance), Model B (compliance-only oversight), Model C (risk assessment performed but organizationally siloed from procurement), and Model D (the proposed governance-driven product intelligence model, integrating risk, governance, and data provenance). Evaluation-cycle data were derived from the risk taxonomy, governance roles, and data-source categories described in Section II and instantiated using the equations of Section III.

Fig. 1. Risk Exposure by Dimension Across Adoption Models

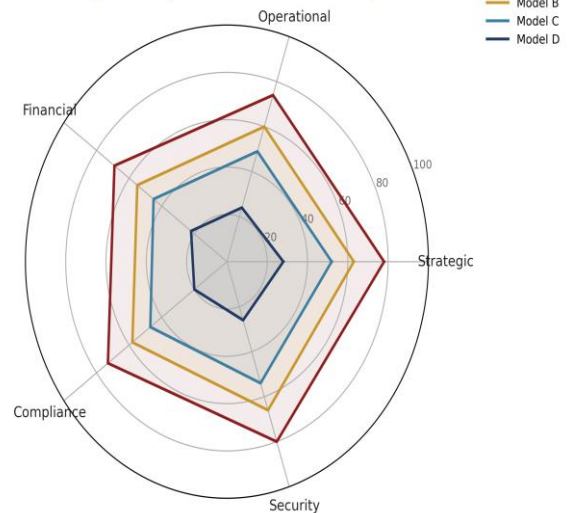


Fig. 1. Risk exposure by dimension across adoption models.

Fig. 1 shows per-dimension risk scores (Eq. 2) for each model. Model A carries elevated exposure across all five

dimensions (69–80), while Model D reduces exposure to 20–28 across the same dimensions, with the largest relative improvement observed in the compliance dimension (73 → 20), reflecting the effect of embedded policy clauses described in Section II-A.

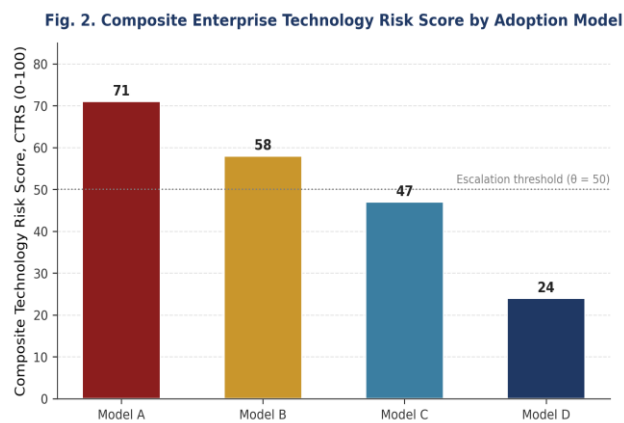


**Fig. 2. Composite Enterprise Technology Risk Score by adoption model.**

Fig. 2 reports CTRS (Eq. 1) for each model against the escalation threshold  $\theta = 50$  (Eq. 8). Models A and B exceed the threshold and would trigger governance-council escalation under the proposed framework, while Models C and D fall below it, with Model D reaching 24 — a 66% reduction relative to Model A.

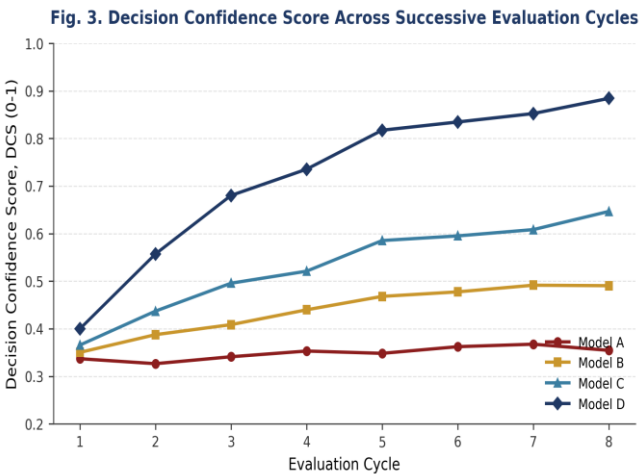


**Fig. 3. Decision Confidence Score across successive evaluation cycles.**

These are the results of DCS (Eq. 6) over 8 evaluation cycles (Fig. 3). There is a learning-curve effect of improvement as governance processes mature, but for all models, the rate and ceiling of improvement are very different: Model D gets closer to DCS = 0.88 by cycle 8, while Model A gets to 0.35, Model B to 0.49, and Model C to 0.65. DPTS (Eq. 3) by data-source category are shown in

Fig. 4. Data from internal telemetry, which scores highest (88) because its lineage and completeness are controlled directly by the organization, receives the highest score, whereas data supplied by vendors receives the lowest (58) as the organization has the least direct control of the lineage

and completeness of that data.

Fig. 4. Data Provenance Trust Score by Source Category

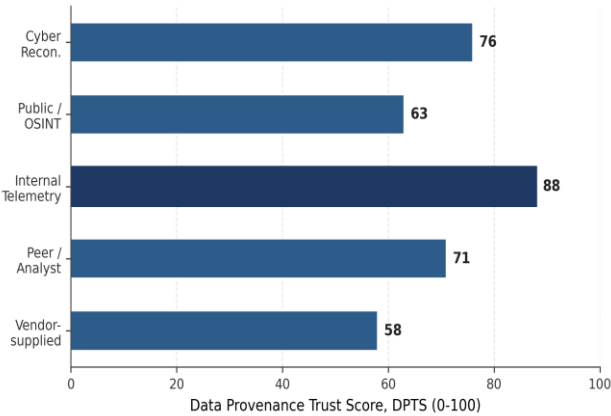


Fig. 4. Data Provenance Trust Score by source category.

Fig. 5. Relationship Between Governance Maturity and Decision Confidence

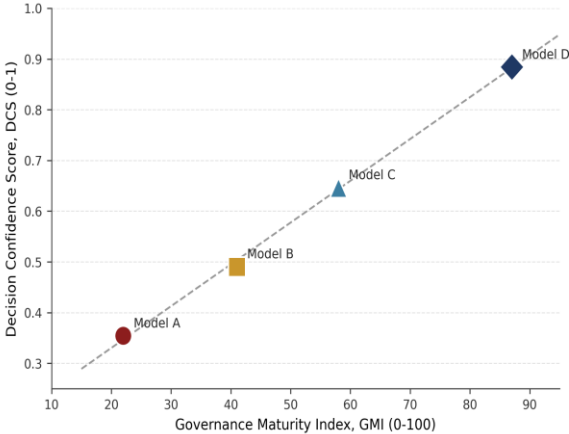


Fig. 5. Relationship between governance maturity and decision confidence.

Fig. 5 plots final-cycle DCS against GMI (Eq. 4) for each model, together with a linear trend. The near-monotonic relationship supports the logistic construction of Eq. (6): governance maturity is a strong predictor of the confidence attached to technology-adoption decisions across the sampled models.

Fig. 6. Evaluation Cycle Time Breakdown by Governance Phase

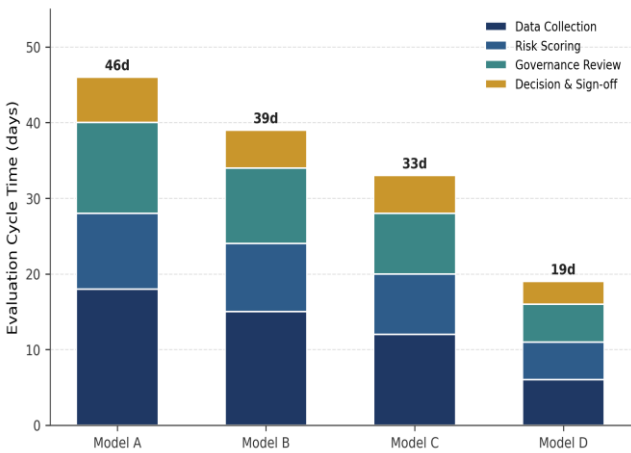


Fig. 6. Evaluation cycle time breakdown by governance phase.

Fig. 6 decomposes total evaluation-cycle time into four governance phases. Model D compresses total cycle time to 19 days versus 46 for Model A (a 59% reduction), with the largest absolute gains in data collection, reflecting the effect of the provenance-aware data architecture of Section II-B on reducing manual sourcing effort.

Fig. 7. Escalation Noise-Reduction Rate Following Governance Adoption

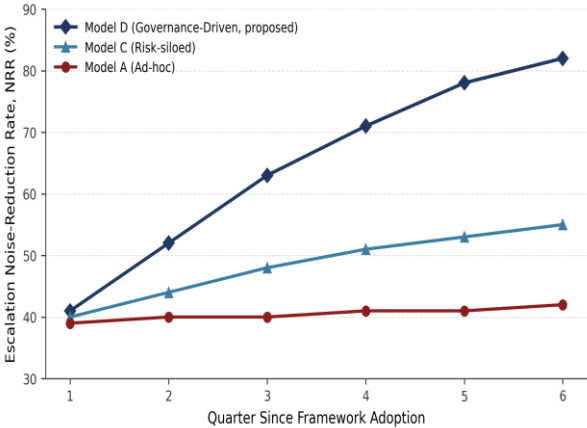


Fig. 7. Escalation noise-reduction rate following governance adoption.

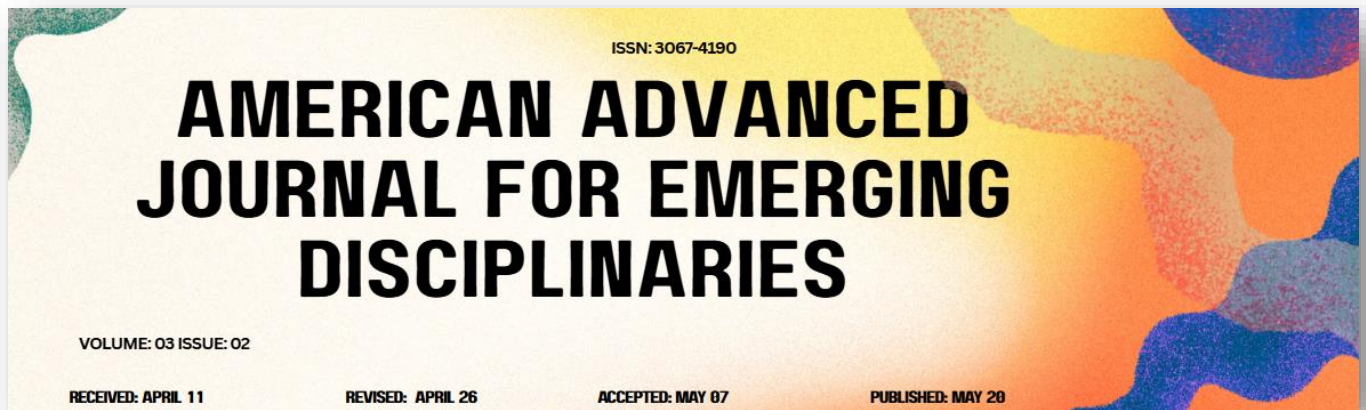


Fig. 7 tracks NRR (Eq. 11) over six quarters following framework adoption. Model D shows continued improvement, reaching 82% noise reduction by quarter six, while Model A remains near its initial rate of 40–42%, indicating that noise reduction accrues primarily from the integrated escalation and review process rather than from experience alone.

#### IV. DATA ARCHITECTURE FOR PRODUCT INTELLIGENCE

Data systems can have a significant impact on decisions, and data problems are frequently overlooked or unknown. Employing the governance model presented earlier, a data architecture for product intelligence is established to ensure decision-relevant product data about all technology solutions—used, considered, or monitored—is available when required and with necessary reliability. No single product, or a handful of vendors, can be expected to meet an enterprise's need for product intelligence. There is a huge amount of data generated and consumed from different internal and external systems like cloud SaaS applications, security applications, on-premise servers, other enterprise applications and that's just going to keep increasing day by day. The internal sources are operations, the cybersecurity team, corporate communications, IT support, risk management, and continuous assurance teams, and the external sources are product market research reports, cybersecurity reconnaissance portals, technology risk maps, and news websites. Such a big data universe is often unused. The information stored in these vast technical networks, both structured and unstructured, offers great potential to safeguard an organisation against wrong or risky choices. Product intelligence requires technical measures for management and effective methods for interpreting data, filtering out the noise without eliminating relevant signals, and yielding the necessary information.

##### A. Data Sources and Provenance

A comprehensive catalogue of data sources guides product intelligence across different enterprise domains. Reliable product intelligence requires not only diverse internal and external sources, but also information provenance enabling parentage tracing, quality assessment, and policy compliance verification. Provenance trails help ascertain whether product intelligence is based on trustworthy data, thereby fulfilling one of the model's key attributes: transparency. Data sources stem from product and service suppliers, peer and analyst community interactions,

technical indicators and qualitative attributes, collaborative resources across the broader information systems ecosystem, and the enterprise ecosystem. Provenance information indicates data lineage, associated metadata, quality indicators, and possible data sovereignty considerations. Data sourced from provenance-deficient locations may attract additional scrutiny to ascertain data accuracy, completeness, and relevance.

Analytical conclusions are only as credible as the data that underpin them. The use of public cloud vendors also introduces data sovereignty considerations. Data valued as sensitive or confidential should remain within the hosting country's jurisdiction. Specific issues might include data quality and provenance integrity for public information and data categorization for third-party data clouds. Consideration must also be given to the identification of these provenance trails. Data integrity and confidentiality need to be supported by the common controls assurance framework and specific data quality policy clauses during the design and operational phases.

#### V. RISK-AWARE EVALUATION OF TECHNOLOGIES

Governing Product Intelligence for Risk-Aware Technology Adoption offers a product-intelligence-based examination of technologies and their potential acquisition through the lenses of governance, risk, and decision-making under uncertainty. Adopting a model to ensure such a view is supported by all involved not only guides the requisite data, analytics, and knowledge but also determines the conditions under which the technology evaluation is performed. The first stage of this undertaking is the definition of a risk taxonomy that maps risk beyond security to include the broader dimensions of strategy, operations, vendors, finance, and compliance. Once defined, the risk categories can be assessed through suitable measures that, once calculated, could form part of any technology evaluation.

Once the modelling of the risks associated with technology is defined, the remaining intricacies consist of how those models can be brought together to support the evaluation of a candidate technology use cases or a technology requirement. Such an assessment should preferably be done through scenarios defined by a selected set of product teams that can evaluate judged technologies through a common set of criteria. The overall assessment should be done in a transparent manner, allowing different parties to take the underpinning decision-support components and combine them in their own manner, thereby assuring adoption of product intelligence while at the same time

providing warning of risks ignored or not sufficiently considered by others

TABLE I

Risk Taxonomy and Measurement Framework

| Dimension   | Representative Metrics                | Weight (w <sub>i</sub> ) | Primary Data Source                                  |
|-------------|---------------------------------------|--------------------------|------------------------------------------------------|
| Strategic   | Business-alignment index, roadmap fit | 0.25                     | Portfolio strategy documents, executive review notes |
| Operational | Uptime impact, failure-mode severity  | 0.20                     | Operations telemetry, incident logs                  |
| Financial   | TCO variance, hidden-cost ratio       | 0.20                     | Procurement and finance systems                      |
| Compliance  | Regulatory-gap count, audit findings  | 0.20                     | Compliance registers, audit reports                  |
| Security    | CVE exposure, control-coverage gap    | 0.15                     | Security tooling, reconnaissance portals             |

TABLE II

Comparative Performance Across Adoption Models

| Metric                        | Model A | Model B | Model C | Model D |
|-------------------------------|---------|---------|---------|---------|
| GMI (0–100)                   | 22      | 41      | 58      | 87      |
| CTRS (0–100, lower is better) | 71      | 58      | 47      | 24      |
| DCS (0–1)                     | 0.35    | 0.49    | 0.65    | 0.88    |
| PIQI (0–100)                  | 31      | 48      | 62      | 90      |
| Evaluation cycle time (days)  | 46      | 39      | 33      | 19      |
| Cost savings vs. Model A (%)  | 0       | 9       | 18      | 34      |
| NRR at quarter 6 (%)          | 42      | 55      | 55*     | 82      |

\*Model C NRR shown for a risk-siloed configuration; escalation review remains organizationally separate from procurement decision rights.

### A. Risk Taxonomy and Measurement

Technology-risk management has become an increasingly important discipline within enterprise technology procurement and adoption. The evaluation of prospective technologies, products, and services should account for the business and technology-related risks posed by that technology. A taxonomy is incorporated into the model to identify, categorize, and measure the risks and potential sources of risk associated with technologies in general, and enterprise technology in particular.

Five dimensions of risk are defined: strategic, operational, financial, compliance, and security. The strategic dimension represents the business risks of adopting technologies that are not aligned with the business's strategy. Operational risk scores provide a measure of the potential impact a technology failure or vulnerability might have on daily operations. Financial risks include all costs that are not readily identifiable as operational costs. Compliance risks reflect the risk of failing to comply with laws and regulations. Security risks evaluate all risks related to the security of information technology systems, environments, and data. For each dimension, suitable measurable metrics are derived, and scoring procedures specified to enable quantitative assessments.

## VI. CONCLUSION

An evidence-based, objective analysis supports the Governance-Driven Product Intelligence Model for risk-aware enterprise technology adoption. Specifically, product intelligence encompasses decision-useful information about commercial technologies underpinning critical business processes. Seven themes—product-intelligence data, analytics, supportive governance, risk taxonomy, risk-aware evaluation methodology, measurement framework, and decision-support outputs—provide a holistic picture. Together, they clarify stakeholder roles and responsibilities; establish accountability and decision-making rights; guide policy creation, monitoring, and enforcement; supply comprehensive product-intelligence data and integration; and enable risk-aware assessments of enterprise technology adoption, thereby embedding data governance and assurance.

Three avenues warrant further attention. The proposed model should be empirically tested at scale, reshaped as necessary, and refined and generalised into an overarching product-intelligence framework that encompasses broader analytics and effectiveness assessments of product-intelligence data. Furthermore, a drone model should be

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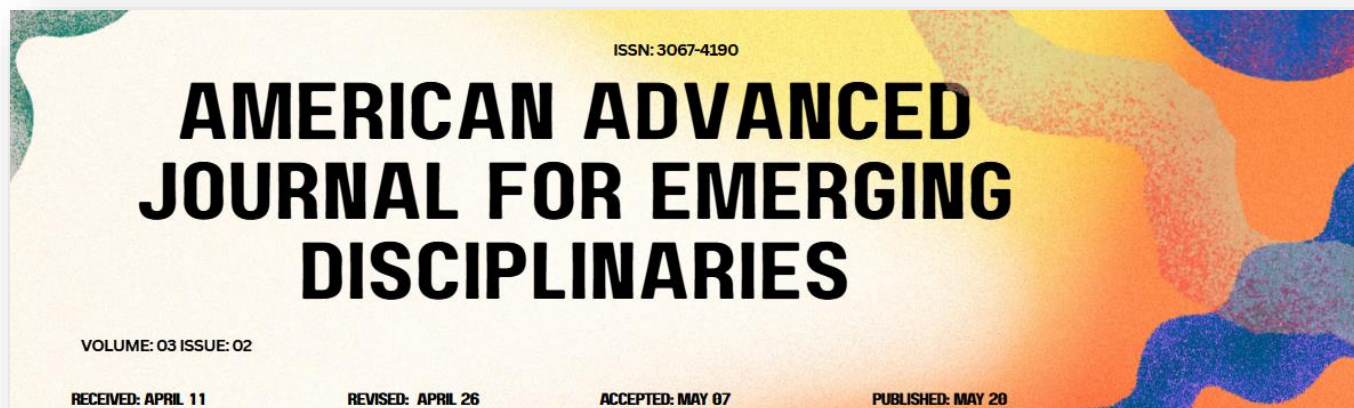
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developed for building the data-architecture component. The matrix of data-sources and -provenance themes should be productised, offering templates for data teams collecting or sourcing from varied internal and external product-intelligence sources. Finally, individual products marked as in-need or red should automatically feed planning and budgeting discussions, and alert associated stakeholders for timely action ahead of the technology's planned renewals, albeit impeachment might require escalation.

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