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From KPI Dashboards to Auditable Decision Execution: PRGDAI-SD 360+ as a Design-Science Meta-Architecture for Evidence-Based Strategic Governance

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Abstract

Complex organisations increasingly possess abundant indicators, dashboards, risk registers, data platforms, and artificial-intelligence pilots, yet often lack an integrated architecture that converts these assets into auditable decisions and corrective action. This paper develops PRGDAI-SD 360+ as a design-science meta-architecture for evidence-based strategic governance. The artefact integrates seven decision dimensions - Performance, Risk, Governance, Data, Artificial Intelligence, Sustainability, and Decision Execution - and links them through indicator taxonomy, data-quality gates, decision protocols, accountability design, dashboard intelligence, and post-decision learning. The paper is conceptual and design-science based rather than empirical: it synthesizes established work in design science research, systems thinking, performance management, risk management, data governance, AI governance, sustainability, and the author's prior KPI-governed frameworks. A worked demonstration translates the model into an airline Chief Logistics Officer context, where AOG recovery, spare-parts availability, supplier delay risk, traceability, data quality, AI forecasting, inventory sustainability, and corrective-action completion must be governed as a single decision chain. The contribution is threefold: it reframes KPIs as decision instruments rather than reporting artefacts; it proposes an auditable seven-dimensional governance architecture; and it offers a validation pathway for future empirical, Delphi, AHP, dashboard, and longitudinal implementation studies. The model's claims are bounded to architecture development and analytical demonstration; causal performance effects require field validation.

Key words: Decision architecture, KPI governance, Design science research, AI governance, Data governance, Airline logistics.

1. Introduction

Contemporary decision-making is increasingly conducted under conditions of data abundance, institutional pressure, AI-enabled acceleration, regulatory scrutiny, sustainability expectation, and cross-functional accountability. In such environments, the basic managerial problem is no longer the absence of information. Many organisations already operate KPI libraries, dashboards, risk registers, governance committees, data warehouses, AI pilots, and strategy execution routines. The harder problem is the weak conversion of these separate instruments into auditable decisions: who must decide, on what evidence, with what risk appetite, under which data-quality threshold, with what AI boundary, with what sustainability effect, and with what corrective-action owner.

This article addresses that conversion problem. It argues that dashboards and KPI frameworks remain structurally incomplete when they report values without specifying decision rights, evidence confidence, risk escalation, AI governance, sustainability trade-offs, and execution accountability. The Balanced Scorecard tradition made a major contribution by moving performance management beyond purely financial reporting [1]. Systems thinking then clarified why performance signals must be interpreted inside feedback loops, delays, stocks, constraints, and unintended consequences [2]. Design science research provides the methodological route for building artefacts that solve such field-relevant problems while remaining theoretically communicable [3,4]. Yet a persistent integration gap remains between performance measurement, risk governance, data governance, AI governance, sustainability governance, and decision execution.

PRGDAI-SD 360+ is proposed as a meta-architecture for this integrated problem. The acronym refers to seven dimensions of decision quality: Performance, Risk, Governance, Data, Artificial Intelligence, Sustainability, and Decision Execution. The architecture does not treat these as independent departments. It treats them as a decision chain. Performance clarifies whether objectives are being achieved. Risk identifies what may fail or escalate. Governance identifies who has authority and accountability. Data establishes whether the evidence is trustworthy. Artificial Intelligence determines whether analytical automation is useful, explainable, and controlled. Sustainability assesses whether the decision remains viable over time. Decision Execution converts analysis into action, follow-up, learning, and recalibration.

The primary research question is therefore: How can performance, risk, governance, data, artificial intelligence, sustainability, and execution be integrated into a single evidence-based decision architecture that is auditable, adaptable, and suitable for complex organisational and institutional governance? Three secondary questions guide the paper. First, what design principles should govern a KPI-based architecture when the aim is decision execution rather than reporting? Second, how can the seven PRGDAI-SD dimensions be operationalized without overstating empirical validation? Third, how can the architecture be demonstrated in an airline logistics context where operational continuity, MRO support, AOG response, inventory, supplier reliability, data quality, AI forecasting, and cost control are tightly coupled?

This paper contributes by (1) reframing KPIs as governance-linked decision instruments rather than stand-alone metrics, (2) developing a seven-dimensional design-science artefact that connects evidence, risk, accountability, AI readiness, sustainability, and action, and (3) demonstrating how the artefact can be translated into a Chief Logistics Officer decision environment in airline logistics and MRO support. The article is deliberately bounded. It does not claim that the model has already produced measured performance gains in field implementation. It does not claim causality, statistical significance, or universal effectiveness.

Its contribution is architectural, methodological, and operational: it specifies a decision system that can be empirically evaluated in future research.

2. Literature Review and Theoretical Positioning

The literature review is integrative and theory-building rather than systematic. It draws on established governance, information-systems, performance-management, risk-management, data-governance, AI-governance, sustainability, and aviation-logistics sources to build a defensible conceptual architecture. No database search, screening protocol, or bibliometric review is claimed. The review therefore supports construct development, design requirements, and validation planning; it does not claim exhaustive coverage of all performance-management, aviation-logistics, AI-governance, or data-governance literature.

Performance-management literature has long recognised that organisations require a balanced set of indicators to translate strategy into operational attention. Kaplan and Norton [1] showed that financial indicators alone do not adequately capture customer, process, learning, and strategic capability dimensions. This insight remains necessary but no longer sufficient. In many contemporary settings, the issue is not whether non-financial indicators exist; it is whether indicator values are connected to ownership, thresholds, risks, decision rules, evidence provenance, and execution routines. KPI proliferation can produce reporting saturation rather than decision clarity. This article therefore treats performance measurement as an input to decision architecture, not as the final artefact.

Systems thinking provides the second theoretical lens. Meadows [2] emphasises feedback, delay, leverage points, and systemic behaviour. These concepts are important because decision systems often fail through local optimisation. A logistics unit may reduce inventory cost while increasing aircraft-on-ground exposure. A digital team may accelerate AI deployment while increasing model risk and governance opacity. A sustainability initiative may reduce waste while creating operational fragility if critical parts availability is not protected. PRGDAI-SD 360+ therefore requires each performance claim to be read together with risk, governance, data, AI, sustainability, and execution signals.

Design science research provides the methodological anchor. Hevner et al. [3] define design science in information systems as the creation and evaluation of artefacts intended to extend human and organisational capabilities. Peffers et al. [4] provide a process model that moves from problem identification to objectives, design and development, demonstration, evaluation, and communication. PRGDAI-SD 360+ is consistent with this logic. It is an artefact that aims to solve a practical and theoretical problem: fragmented governance instruments do not automatically produce evidence-based decisions. The article's demonstration is analytical and scenario-based; full evaluation remains a future field-research requirement.

Risk-management literature adds the logic of uncertainty, appetite, control, escalation, and continual monitoring. ISO 31000:2018 frames risk management as an integrated, structured, customised, inclusive, dynamic, and continually improving process [5]. For PRGDAI-SD 360+, this implies that risk indicators must not be buried in separate registers. They must be connected to decision thresholds. A red risk condition should trigger escalation, investigation, mitigation, pause, redesign, or crisis protocol activation. Otherwise risk remains documented but not governed.

Data governance provides the evidence-trust layer. DAMA International [6] positions data management as a body of practices covering governance, architecture, quality, metadata, security, integration, and lifecycle management. In a KPI-governed decision system, data quality is not a technical afterthought. It determines whether a decision is defensible. PRGDAI-SD 360+ therefore requires each indicator to specify source, owner, lineage, quality rule, refresh cadence, missing-data rule, audit trail, and confidence level. Data that is incomplete, stale, inconsistent, or untraceable should not have the same decision weight as validated evidence.

AI governance has become a separate but connected requirement. The NIST AI Risk Management Framework emphasises validity, reliability, safety, security, resilience, accountability, transparency, explainability, privacy, and fairness in AI risk management [7]. ISO/IEC 42001:2023 provides a management-system standard for organisations that develop or use AI systems [8]. The OECD AI Principles similarly stress trustworthy AI, human-centred values, transparency, robustness, security, safety, and accountability [9]. These sources converge on a central lesson: AI-generated recommendations are not governance substitutes. They require model ownership, human review, risk classification, audit logs, and boundaries on automation.

Where AI-enabled decisions interact with digital infrastructure, cybersecurity, privacy, or operational resilience, AI governance should also be linked to information-security and cybersecurity control systems, including ISO/IEC 27001 and the NIST Cybersecurity Framework 2.0.[۱۰،۱۱]

Recent enterprise AI and decision-intelligence discussions reinforce a pattern already visible in the stronger governance sources: decision architectures increasingly combine data engineering, AI-enabled analytics, explainability, secure automation, continuous monitoring, interoperability, and accountable workflow execution. This supports the article's positioning claim without requiring reliance on weakly indexed or unverified sources.

Sustainability governance widens the decision frame beyond immediate performance. The 2030 Agenda for Sustainable Development frames sustainability as an integrated agenda for people, planet, prosperity, peace, and partnership [12]. In organisational settings, sustainability includes financial durability, environmental responsibility, social legitimacy, institutional continuity, and intergenerational consequences. In airline logistics, for example, sustainability cannot be reduced to emissions or waste alone. It also includes inventory sustainability, repair-versus-replace logic, emergency shipment reduction, supplier resilience, and the avoidance of both excessive stock and operational fragility.

The author's prior frameworks provide the internal lineage of the artefact. 7S-360 supplies the indicator taxonomy that distinguishes KPIs, diagnostic indicators, impact indicators, capacity-building indicators, strategic progress indicators, crisis-warning indicators, and composite indices [13]. IKEF-360+ provides a role-based airline KPI governance foundation [14]. CAT contributes ontology-to-governance translation for normatively dense settings, while the preliminary PRGDAI-SD method note defines the seven-dimensional integration logic [15,16].

In the present article, these prior works are treated as design inputs rather than empirical evidence of field impact.

The resulting research gap is therefore integrative, not merely topical. Existing frameworks explain pieces of the governance problem: strategy translation, performance measurement, systems feedback, risk management, data governance, AI governance, sustainability, or domain-specific KPI design. What remains underdeveloped is a compact architecture that connects all these elements to auditable decision execution. The gap matters because organisations can be data-rich and decision-poor, AI-enabled and accountability-weak, KPI-saturated and execution-deficient. PRGDAI-SD 360+ responds to this gap by specifying a governance architecture in which every indicator must support a decision, every decision must have an owner, every AI recommendation must be controlled, every data claim must be traceable, and every action must enter a learning loop.

A rival theoretical lens is dynamic capabilities: it would frame the model as a capability for sensing, seizing, and transforming under uncertainty [17]. That lens is useful for explaining adaptation, but it is less precise for specifying the artefact components, evidence controls, RACI logic, data-quality gates, and post-decision audit trail required here. The paper therefore uses design science as the primary methodology, systems thinking as the integration lens, and dynamic capabilities as a secondary explanatory lens for future empirical work.

3. Methodology: Design-Science Development Logic

This paper uses a conceptual design-science methodology. It develops an artefact, demonstrates its translation into a domain case, and specifies a validation pathway. The claim strength is architectural and explanatory rather than causal or predictive. The paper does not test whether PRGDAI-SD 360+ improves performance in a statistically measurable way. It proposes a structured decision architecture and shows how it can be operationalized in one complex domain. Future empirical research should test adoption, usability, decision quality, execution speed, risk reduction, and performance outcomes through field data.

The design problem is defined as follows: decision-makers possess fragmented governance instruments but lack a coherent architecture that links indicators, risks, data quality, AI outputs, sustainability concerns, decision rights, corrective action, and learning. The objective of the solution is to produce a reusable meta-architecture that can be adapted to different domains without losing its core decision logic. The artefact must satisfy six design requirements. It must be multi-dimensional, evidence-based, auditable, AI-ready, sustainability-aware, and execution-oriented.

The unit of analysis is the decision-governance system, not an individual decision-maker, a single KPI, or a single dashboard. A decision-governance system includes constructs, indicators, data sources, evidence-quality rules, decision authorities, escalation pathways, AI controls, sustainability tests, action registers, and learning mechanisms. This unit of analysis is appropriate because decision failure usually emerges from system misalignment: indicator without owner, risk without threshold, data without lineage, AI without oversight, sustainability without trade-off logic, or action without closure.

The design inputs are fivefold. First, the model draws on established literature and standards in design science, systems thinking, performance management, risk management, data management, AI governance, information security, sustainability, and governance accountability. Second, it uses the author's prior KPI-governed models as modular sources of indicator and governance logic. Third, it incorporates implementation requirements such as data-source mapping, indicator dictionary design, RACI, decision register, risk register, dashboard design, corrective-action tracking, and audit trail. Fourth, it includes the airline logistics application as a demonstration context. Fifth, it applies evidence-boundary controls: unsupported empirical claims are excluded, and validation requirements are explicitly separated from completed artefact design.

The artefact-development process followed the design-science sequence of problem identification, objective definition, architecture design, demonstration, evaluation planning, and communication. At the architecture-design stage, the seven dimensions were defined and connected to indicator families, evidence requirements, governance ownership, AI controls, sustainability logic, and execution protocols. At the demonstration stage, the model was translated into a Chief Logistics Officer context for airline logistics and MRO support. At the evaluation-planning stage, five future validation routes were specified: expert validation using Delphi, weighting validation using AHP or similar multi-criteria methods, construct validation using factor analysis where survey data exist, reliability assessment for coding and indicator dictionaries, and field evaluation using dashboard and decision-register evidence [18-20].

Data collection in the empirical sense was not conducted. No human participants were recruited, no confidential airline data were analysed, and no statistical results are claimed. The article uses a design demonstration based on a practical domain model. For future empirical implementation, the minimum data package should include indicator definitions, operational data from ERP, MRO, procurement, warehouse, finance, OCC, BI, and compliance systems, decision-register logs, action-completion records, risk-register updates, AI model logs, and expert validation records. Ethical review would be required if human participants, interviews, identifiable organisational data, or sensitive operational records are used.

Validity is treated through four controls. Construct validity is addressed by defining each dimension and linking it to operational mechanisms. Internal validity is limited because no causal test is performed. External validity is bounded by the need for domain adaptation; the model is universal at the architecture level but not at the indicator-formula level. Reliability is addressed through repeatable components: indicator dictionary, data-quality gate, scoring rule, threshold, RACI, decision protocol, action register, and recalibration routine. Trustworthiness is strengthened by clear boundary statements and by avoiding invented field results.

4. PRGDAI-SD 360+ Model Architecture

The PRGDAI-SD 360+ architecture is built around seven dimensions. Performance asks whether objectives are being achieved. Risk asks what may fail, escalate, or create unacceptable exposure. Governance asks who decides, who executes, who is consulted, who is informed, and who remains accountable. Data asks whether the evidence behind the decision is complete, accurate, timely, consistent, traceable, and fit for decision use. Artificial Intelligence asks whether analytics and AI recommendations are valid, explainable, supervised, secure, fair, and within approved boundaries. Sustainability asks whether the decision remains viable in financial, operational, environmental, social, institutional, and long-term terms. Decision Execution asks whether analysis has been converted into action, closure, learning, and recalibration.

The first architectural principle is indicator-to-decision traceability. Every indicator should answer a decision question. A KPI that does not inform a decision should be downgraded, removed, or reclassified as contextual information. A red indicator should not merely appear on a dashboard; it should connect to a decision rule such as continue, correct, escalate, pause, stop, redesign, investigate, mitigate, fund, defund, train, automate, or require human review. In sensitive institutional or theological domains, parallel rules may include mediation, scholarly review, de-escalation, conditional engagement, or temporary suspension. The wording differs by domain, but the logic is the same: indicators must trigger governed choices.

The second principle is evidence confidence before decision weight. PRGDAI-SD 360+ separates the score of an indicator from the confidence of the evidence behind that score. An apparently strong performance value is weak if generated from poor data. The architecture therefore requires each indicator to specify data source, data owner, lineage, completeness, timeliness, accuracy, reconciliation rule, missing-value rule, and audit trail. A decision board should see both the score and the evidence confidence. This prevents the common problem in which dashboards create artificial certainty from weak data.

The third principle is risk-adjusted performance. Performance without risk intelligence can be misleading. A logistics team may show high procurement savings while increasing single-source dependency. A digital transformation project may report high adoption while increasing cybersecurity or AI-governance exposure. A dialogue institution may report increased events while failing to detect trust erosion or crisis signals. PRGDAI-SD 360+ therefore pairs performance indicators with key risk indicators and crisis-warning indicators. The intended output is not simply a performance score but a risk-adjusted decision posture.

The fourth principle is accountable governance. Decision quality depends on decision rights. Prior IT governance research shows the importance of decision rights and accountability in governance performance [21]. PRGDAI-SD 360+ generalises this logic. For each decision stream, the architecture requires an accountable decision authority, responsible execution owner, consulted experts, informed stakeholders, escalation path, review cadence, and audit record. This prevents decisions from becoming trapped between committees, dashboards, and operational units. Governance is not the production of documents; it is the disciplined allocation of authority, accountability, and follow-up.

The fifth principle is controlled AI augmentation. AI can improve prediction, anomaly detection, summarisation, scenario simulation, recommendation generation, and decision explanation. However, the architecture treats AI as a governed decision-support layer rather than an autonomous authority. High-risk decisions require human-in-the-loop or human-on-the-loop safeguards, model cards, validation logs, drift monitoring, bias checks, fallback procedures, and explicit automation boundaries. This position aligns with AI risk-management and AI management-system guidance [7,8].

The sixth principle is sustainability-through-execution. Sustainability must be converted from aspiration into decision logic. A decision may be financially attractive but operationally fragile; operationally urgent but environmentally wasteful; technologically efficient but socially unacceptable; or institutionally legitimate in the short run but unsustainable in the long run. PRGDAI-SD 360+ therefore requires a sustainability review at the decision level, not only at the annual reporting level. The architecture asks whether the chosen action is financially durable, operationally resilient, environmentally responsible, socially legitimate, institutionally maintainable, and consistent with long-term value creation.

The seventh principle is learning-loop closure. A decision architecture is incomplete until it asks whether the decision worked. The model therefore requires post-decision review: what was decided, what action was taken, what changed, what did not change, what evidence improved, what risk materialized, what assumption failed, what corrective action remains open, and which thresholds or weights should be recalibrated. This loop is essential for avoiding static governance. It transforms the architecture from a reporting model into a learning system.

The architecture uses a layered operating sequence. It begins with domain diagnosis: the organisation defines the decision problem, scope, stakeholders, constraints, and governance setting. It then designs indicators using a taxonomy such as KPI, diagnostic indicator, impact indicator, capacity-building indicator, strategic progress indicator, crisis-warning indicator, and composite index. Next, it maps data sources and evidence quality. It then scores and weights dimensions using explicit rules. It applies risk and sustainability thresholds, reviews AI recommendations under governance controls, assigns decision authority, records the decision, tracks the corrective action, and completes a post-decision learning cycle.

Table 1. PRGDAI-SD 360+ design controls

Dimension	Decision question	Minimum governance control
Performance	Are objectives and value targets being achieved?	KPI/SPI owner, target, threshold, trend, corrective-action trigger.
Risk	What may fail, escalate, or exceed appetite?	KRI/CWI threshold, escalation rule, mitigation owner, risk register linkage.
Governance	Who decides, executes, approves, and learns?	RACI, decision authority, consulted roles, audit trail, review cadence.
Data	Is the evidence trusted enough for decision use?	Data source, lineage, DQI rule, missing-data policy, evidence-confidence score.
Artificial Intelligence	Is AI useful, explainable, supervised, and bounded?	Model owner, validation log, drift alert, explainability note, human oversight.
Sustainability	Is the decision viable over financial, operational, environmental, and institutional horizons?	Trade-off assessment, sustainability metric, long-term risk, value impact check.
Decision Execution	Did insight become accountable action and learning?	Action owner, deadline, closure status, post-decision review, recalibration rule.

The dashboard layer of PRGDAI-SD 360+ must be decision-oriented. A conventional dashboard reports status. A decision-intelligence dashboard should report status, trend, risk, evidence confidence, AI confidence, sustainability effect, owner, deadline, decision option, recommended action, escalation rule, and action-closure status. Visual design matters, but governance design matters more. A visually attractive dashboard that does not specify who must act, by when, under what authority, and with what evidence is not a decision system. The model therefore defines dashboard readiness as a combination of data readiness, indicator readiness, governance readiness, AI readiness, and execution readiness.

5. Demonstration: Airline Logistics and the Chief Logistics Officer Context

Airline logistics is an appropriate demonstration context because it combines operational urgency, financial pressure, regulatory sensitivity, supply-chain uncertainty, data complexity, and cross-functional dependency. A shortage of one critical component can ground an aircraft, disrupt schedules, increase passenger dissatisfaction, trigger emergency logistics cost, pressure maintenance planning, and create reputational damage. Conversely, excessive inventory can tie up capital, increase obsolescence, create warehouse inefficiency, and hide poor forecasting. The CLO context therefore shows why performance, risk, governance, data, AI, sustainability, and execution cannot be governed separately.

In the CLO adaptation, the core decision question becomes: Is the airline's supply chain, parts inventory, procurement, warehouse, repairable-parts management, AOG response, and MRO support operating in a way that prevents avoidable aircraft grounding, controls cost, reduces risk, maintains data trust, governs AI assistance, and preserves long-term resilience? This question immediately exceeds a simple KPI dashboard. It requires a decision system that can identify critical stockout exposure, supplier delay risk, data-quality weakness, certificate traceability gaps, AI forecast reliability, emergency shipment trade-offs, repair-versus-replace decisions, and corrective-action closure.

The Performance dimension in the CLO context includes AOG Recovery Time, Spare Parts Availability Rate, Order Fulfilment Cycle Time, Warehouse Picking Accuracy, Parts Dispatch On-Time Rate, Stock Accuracy Rate, and Material Request Fulfilment Rate. These metrics are useful only if they are linked to decisions. For example, if AOG Recovery Time crosses a threshold, the decision protocol may require escalation to a logistics control tower, expedited procurement, controlled pooling, exchange, repair acceleration, or executive authorisation. If Spare Parts Availability falls below the service-level target for critical parts, the decision protocol may require reorder policy review, supplier escalation, or safety-stock recalibration.

The Risk dimension includes Critical Stockout Risk, Supplier Delay Risk, AOG Escalation Alert, Lead-Time Variability Risk, Customs Clearance Delay Risk, and Single-Source Supplier Risk. These are not merely monitoring indicators. They are early-warning instruments. A rising supplier delay risk should trigger a mitigation pathway before it becomes an AOG event. A customs delay risk should trigger documentation review, broker escalation, or alternative routing where lawful and feasible. A repeated AOG escalation alert should trigger root-cause analysis across planning, procurement, warehouse, repair management, finance approval, and supplier performance.

The Governance dimension translates cross-functional ambiguity into accountability. Airline logistics decisions often sit between logistics, MRO, CAMO, procurement, finance, quality, compliance, OCC, and executive operations. PRGDAI-SD 360+ requires a RACI-style decision map for AOG management, critical procurement, inventory planning, supplier evaluation, repairable-parts management, parts data governance, traceability control, and emergency cannibalisation. In this configuration, the CLO may be accountable for logistics execution, while COO-level authority may be required for high-risk operational trade-offs. Finance and compliance are consulted, but their consultation must not create indefinite decision delay. This application builds on prior airline logistics AI performance and stock-control work that emphasized safety, sustainability, efficiency, inventory optimisation, and innovation in aviation logistics [22,23].

The Data dimension is especially important in aviation logistics because wrong part numbers, serial numbers, certificates, shelf-life records, interchangeability data, inventory balances, supplier records, or repair status can produce unsafe, costly, or non-compliant decisions. The CLO dashboard must therefore include Inventory Data Accuracy, Part Number Accuracy Rate, Certificate Traceability Score, Shelf-Life Data Completeness, Vendor Master Data Quality, and Repair Status Accuracy. The decision architecture should prevent a high-risk procurement or installation decision from proceeding when data confidence is below the approved threshold.

The AI dimension can support demand forecasting, predictive inventory planning, anomaly detection, AOG risk prediction, supplier delay prediction, recommended reorder points, and repair-versus-replace analysis. However, PRGDAI-SD 360+ requires AI governance controls before these outputs can affect sensitive decisions. Suggested controls include Parts Demand Forecast Error, AI Recommendation Explainability Score, Human Approval Rate for AI Purchase Suggestions, Model Drift Alert, Feature Quality Score, and AI Override Documentation Rate. The aim is not to slow innovation. The aim is to make AI useful without allowing opaque recommendations to bypass accountable aviation decision-making.

The Sustainability dimension includes Inventory Carrying Cost Ratio, Obsolete Inventory Value, Emergency Shipment Dependency, Repairable Reuse Rate, Supplier On-Time Delivery Rate, Waste and Scrap Reduction, and Net Financial Index. Sustainability here is multi-dimensional. A decision to hold more critical parts may increase inventory cost but reduce AOG exposure. A decision to reduce emergency shipments may support environmental and cost objectives but requires better planning accuracy. A repairable-parts strategy may reduce replacement cost and waste but requires reliable repair turnaround, quality control, and lifecycle economics. The architecture makes such trade-offs explicit.

The Decision Execution dimension is the closure mechanism. Corrective Logistics Action Completion Rate, Decision Cycle Time, AOG Decision Closure Rate, Escalation Response Time, Implementation Delay, and Post-Decision Review Completion Rate show whether the organisation actually acts on its analysis. This is where PRGDAI-SD 360+ differs from a dashboard. It asks not only what the indicator shows but whether the decision was made, whether the owner accepted responsibility, whether the action was funded, whether the action was completed, whether the result changed the risk, and whether the model's assumptions require recalibration.

A minimal CLO implementation would therefore require ten practical outputs: a PRGDAI-SD dashboard, a critical-parts risk register, an AOG decision protocol, a logistics RACI matrix, a supplier scorecard, a logistics data-quality register, an inventory optimisation plan, an AI forecast pilot, a corrective-action log, and a monthly logistics governance report. Together, these outputs create a chain from data to indicator, from indicator to warning, from warning to decision, from decision to owner, from owner to action, from action to review, and from review to learning. A mature implementation could expand toward 100-160 indicators, but the executive dashboard should display only the critical subset required for decision quality.

Table 2. Airline CLO implementation traceability matrix

Layer	CLO indicators	Primary source systems	Decision output
Performance	AOG recovery time; spare-parts availability; repairable TAT; supplier OTD.	ERP, MRO, WMS, procurement, OCC.	Expedite, replenish, reallocate, repair, or supplier escalation.
Risk	Critical stockout risk; supplier delay risk; customs delay risk; AOG warning.	Risk register, procurement, logistics events, customs data.	Mitigate before AOG, activate crisis protocol, change sourcing plan.
Governance	Decision-owner assignment; approved-vendor compliance; approval SLA.	RACI, procurement policy, finance approval, compliance logs.	Assign authority, remove bottlenecks, trigger board escalation.
Data	Inventory accuracy; part-number accuracy; certificate traceability; vendor master quality.	ERP, MRO, warehouse, quality and compliance records.	Clean master data, stop weak-evidence decisions, improve lineage.
AI	Forecast error; AI recommendation acceptance; model drift; explainability score.	AI model logs, demand history, failure/removal rates, flight hours/cycles.	Approve, override, recalibrate, or suspend AI recommendation use.
Sustainability	Inventory value; obsolete stock; repair-vs-replace saving; emergency shipment dependency.	Finance, inventory, repair management, logistics cost records.	Balance resilience, cost, waste reduction, and operating continuity.
Execution	Decision-cycle time; action-closure rate; escalation response; post-action review.	Decision register, action log, governance meeting records.	Close actions, learn from deviations, recalibrate thresholds and weights.

This demonstration does not prove that PRGDAI-SD 360+ improves airline performance. It shows that the architecture can be translated into a domain where decision coupling is high. The next research step is field evaluation: implement the model in one airline logistics environment, collect baseline and post-implementation data, evaluate decision-cycle time, action-closure rate, data-quality improvement, AOG-related logistics exposure, inventory value, supplier reliability, AI forecast error, and governance meeting effectiveness, and compare outcomes against a matched or historical control where possible.

6. Findings as Design Outputs

Because the paper is design-science and conceptual, its findings are not statistical findings. They are design outputs, analytical mechanisms, and propositions for future evaluation. The first design output is the seven-dimensional decision stack. It defines the minimum dimensions required for auditable strategic governance: Performance, Risk, Governance, Data, Artificial Intelligence, Sustainability, and Decision Execution. Omitting any dimension creates a predictable weakness. Without performance, objectives are unclear. Without risk, success may be fragile. Without governance, accountability is weak. Without data confidence, evidence is unreliable. Without AI governance, automation may become unsafe or opaque. Without sustainability, decisions may optimise the short term. Without execution, analysis does not become action.

The second design output is the indicator-to-decision protocol. The protocol requires each indicator to have a decision question, owner, data source, threshold, evidence-confidence score, risk interpretation, possible decision option, corrective action, review cadence, and audit record. This output addresses the central failure of many KPI systems: indicators are measured but not governed. In PRGDAI-SD 360+, an indicator is not complete until its decision implication is specified.

The third design output is the evidence-confidence overlay. Instead of treating all dashboard values as equally reliable, the model requires a separate data-quality and evidence-confidence assessment. This overlay is particularly important in organisations with multiple systems, manual workarounds, inconsistent master data, incomplete records, and delayed reconciliations. It also matters in theological, civilizational, and dialogue settings, where textual authority, translation, institutional source quality, and interpretive boundaries must be handled carefully. The design output is transferable because every domain must distinguish signal from evidence quality.

The fourth design output is the controlled-AI decision layer. The model integrates AI without allowing AI to become a hidden decision authority. It requires model ownership, validation, explainability, drift monitoring, bias review, human oversight, and audit logging. This output responds to the current risk that organisations may adopt AI-generated recommendations faster than they build governance capacity. In the architecture, AI is valuable when it improves decision intelligence; it is dangerous when it obscures accountability.

The fifth design output is the closed execution-learning loop. Many governance models stop at reporting or decision approval. PRGDAI-SD 360+ continues to action closure and post-decision learning. The model therefore treats decision execution as a measured dimension. This is especially important for executive governance because unresolved corrective actions, delayed approvals, unclear owners, and repeated unresolved issues often create more operational risk than the original indicator deviation.

7. Discussion

The article's central argument is that decision architecture must become the next maturity stage of KPI governance. Traditional performance management answers the question, "What is happening?" Decision architecture adds the questions, "How reliable is the evidence, what risk does it imply, who must decide, what role can AI safely play, what sustainability trade-off exists, what action must be completed, and what must be learned after execution?" This shift is not semantic. It changes the unit of governance from indicator reporting to decision accountability.

The model extends the Balanced Scorecard logic by adding risk, data trust, AI governance, sustainability trade-off analysis, and decision execution as mandatory architectural layers. It extends systems thinking by operationalizing feedback into action registers and recalibration protocols. It extends design-science methodology by converting a broad governance problem into an artefact with domain demonstration and validation pathway. It extends data governance by placing data quality directly inside the decision process rather than in a separate technical function. It extends AI governance by connecting model risk to human authority and execution accountability.

The airline logistics demonstration shows why integration matters. AOG exposure cannot be governed by a single KPI. It is produced by interactions among demand forecasting, supplier reliability, customs lead time, repair turnaround, stock policy, finance approval, warehouse accuracy, certificate traceability, MRO planning, and executive escalation. A dashboard that reports only AOG count or stock availability may identify pain but not govern causality or action. PRGDAI-SD 360+ provides the structure for converting that pain into decision pathways.

Alternative explanations must be considered. One rival explanation is that organisations do not need a new architecture; they need better discipline in existing tools such as ERP, BI, risk registers, and project management platforms. This objection is partly valid. PRGDAI-SD 360+ does not replace those tools. It specifies how they should be connected. Another rival explanation is that integrated frameworks become too complex and may produce governance burden. This risk is real. The model therefore recommends executive dashboards with a limited critical subset of indicators and deeper diagnostic layers for analysts. A third rival explanation is that decision quality depends more on leadership culture than on architecture. This is also valid. The model cannot replace leadership judgment, but it can make weak accountability, poor evidence, and open actions more visible.

Theoretical implications are threefold. First, the model suggests that KPI theory should distinguish reporting indicators from decision instruments. Second, it proposes evidence confidence as a necessary companion construct to performance score. Third, it positions AI governance as part of decision architecture, not as an isolated technology policy. These implications can be developed into testable propositions: organisations with stronger indicator-to-decision traceability should have faster corrective-action closure; dashboards that include evidence-confidence scoring should reduce decision rework; and AI recommendations with explicit human oversight and audit logs should be more acceptable in high-risk operational domains.

Practical implications are also direct. Executives should review not only KPI values but also decision ownership, evidence quality, and action closure. Data leaders should prioritise lineage, master-data quality, and decision-critical data domains rather than treating all data equally. AI leaders should implement model registries, model cards, drift monitoring, and approval thresholds before AI recommendations influence sensitive decisions. Risk and compliance leaders should connect risk registers to escalation rules and action owners. Sustainability leaders should embed sustainability trade-offs into investment, procurement, logistics, and operational decisions rather than leaving them in annual reports.

For airline logistics, the immediate governance implication is to build a logistics decision control tower that links ERP, MRO, warehouse, procurement, finance, quality, compliance, and BI data. The control tower should not become a passive screen wall. It should operate through a weekly governance cadence, daily exception management for critical parts, AOG decision protocols, supplier scorecards, data-quality gates, and corrective-action closure review. The most important executive KPI may not be a single performance value but the percentage of critical exceptions with verified owner, decision, action, deadline, and post-action review.

Boundary conditions are important. PRGDAI-SD 360+ is most suitable where decisions are multi-dimensional, evidence-dependent, risk-sensitive, and cross-functional. It may be unnecessary for simple, low-risk, repetitive decisions. It also requires data maturity, governance discipline, and leadership willingness to expose accountability gaps. In religious, theological, or civilizational applications, the architecture must be used carefully: indicators can support governance and learning, but they must not reduce sacred meanings, doctrinal integrity, or human dignity to numerical scores. The model's ethical rule is that measurement serves understanding and responsible action; it does not replace judgment.

The main limitation is the absence of field validation. A Q1 empirical outlet may require stronger evaluation before accepting the model as more than a conceptual framework. The second limitation is domain adaptation: the architecture is universal at the decision-governance level, but indicators, thresholds, weights, data sources and escalation rules must be adapted to each sector. The third limitation is domain breadth. A universal architecture risks overextension if adaptation is superficial. The fourth limitation is implementation cost. Indicator design, data governance, AI controls and action registers require resources. The fifth limitation is behavioural: managers may resist transparent accountability even when the architecture is technically sound.

8. Conclusion

This paper developed PRGDAI-SD 360+ as a design-science meta-architecture for evidence-based strategic governance. The model responds to the gap between fragmented governance instruments and executable decision accountability. It integrates Performance, Risk, Governance, Data, Artificial Intelligence, Sustainability, and Decision Execution into one auditable architecture. Its central proposition is that KPIs become strategically useful only when they are connected to evidence quality, decision rights, risk thresholds, AI controls, sustainability trade-offs, corrective actions, and learning loops.

The article contributes to scholarship by reframing KPI systems as decision systems, by specifying evidence confidence as a companion to performance scoring, and by integrating AI governance into the wider decision-governance chain. It contributes methodologically by using design-science logic to define an artefact that is demonstrable, adaptable, and open to future validation. It contributes practically by showing how the architecture can be translated into airline logistics and the CLO function, where AOG response, spare-parts availability, supplier risk, traceability, inventory sustainability, AI forecasting, and action closure must be governed together.

Practitioners should implement the model in staged form. The first stage is to create an indicator dictionary and classify indicators into performance, diagnostic, impact, capacity, strategic progress, crisis-warning, and composite families. The second stage is to assign data owners, decision owners, risk owners, AI model owners, and corrective-action owners. The third stage is to establish data-quality gates and evidence-confidence scoring for decision-critical indicators. The fourth stage is to define decision protocols for green, yellow, red, and crisis conditions. The fifth stage is to build a dashboard that displays not only score and trend but also risk, evidence confidence, owner, action, deadline, and closure status. The sixth stage is to review decisions after implementation and recalibrate thresholds, weights, and assumptions.

Future research should evaluate PRGDAI-SD 360+ through Delphi expert panels, AHP weighting studies, survey-based construct validation, dashboard usability testing, longitudinal field implementation, and comparative case studies across sectors. In airline logistics, future studies should measure whether the architecture improves AOG recovery time, critical parts availability, supplier delay risk, inventory carrying cost, data accuracy, AI forecast error, decision-cycle time, and corrective-action closure. In theological or civilizational applications, future work should focus on governance learning, dialogue quality, trust indicators, interpretive safeguards, and institutional accountability rather than simplistic numerical reduction.

Operationally, the first-year deployment pathway should remain deliberately modest. A governance sponsor should select one decision domain, such as AOG logistics or critical-parts availability, and build a minimum viable PRGDAI-SD package around it: ten to fifteen executive indicators, clear thresholds, one data-quality register, one decision register, one action log, one RACI map, and a monthly review cadence. Only after this controlled pilot should the organisation expand toward a larger indicator architecture. This staged approach reduces the risk of KPI overload, protects managerial attention, and allows the model to mature through actual decision use rather than through documentation volume.

The study's limitations are clear. It is a conceptual and design-science article, not a completed empirical evaluation. It does not claim causal impact. It does not provide statistical validation. It does not replace domain-specific regulation, professional judgment, ethical deliberation, or theological interpretation. Its value lies in architecture: a structured way to connect evidence, indicators, risks, AI, sustainability, governance, decisions, and learning.

This paper changes KPI-governance literature from a measurement-centred conversation into a decision-execution conversation and enables executives, policymakers, researchers, and institutional boards to convert complex evidence into accountable, auditable, and learning-oriented strategic governance.

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