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AISA–L: An Agentic AI Strategy Architecture for Real-Time KPI Orchestration in Sustainable, Resilient Airline Logistics

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Abstract

This study designs and validates AISA–L, a four-layer Agentic AI Strategy Architecture (Perception, Cognition, Strategy, Action) that converts a previously validated comprehensive portfolio of 110 airline logistics Key Performance Indicators (KPIs) [1] into autonomous, auditable, sustainability-aligned decisions. The novelty lies not in enumerating KPIs, but in their real-time agentic orchestration within a closed governance–optimization loop. Addressing the persistent gap between descriptive dashboards and adaptive execution, the research operationalizes KPI governance (threshold analytics, anomaly detection, bias auditing, explainability), multi-objective optimization (cost, resilience, carbon intensity, inventory balance), and disruption response (AOG rerouting, maintenance reprioritization). A mixed-methods design science approach integrates purposive expert elicitation with digital twin simulation contrasting a baseline manual governance model against the agentic configuration. Empirical results show a 22% improvement in forecast accuracy, ≈11% reduction in turnaround time, 1.6 percentage point increase in aircraft dispatch reliability, 4.8% CASK reduction, ≈9% inventory turnover uplift, 18% faster disruption recovery, 6.3% decline in CO_2/RTK, and a 7-percentage point rise in sustainable aviation fuel utilization, alongside zero material bias incidents and enhanced data timeliness. Theoretically, the study reframes KPIs from evaluative endpoints to real-time control variables within a cyber-physical logistics governance loop, extending digital maturity and ethical AI discourse. Practically, it delivers an implementable blueprint for Chief Logistics Officers and regulators to embed sustainability, resilience, and ethical compliance into continuous optimization. Recommendations include phased agent deployment, constraint-based ESG integration, lineage-centric data governance, and capability KPIs for human–AI co-leadership.

Key words: Agentic AI; Airline Logistics; KPI Governance; Digital Transformation; Sustainability Optimization; Resilience; Predictive Maintenance.

1. Background

Airline logistics is under intensifying pressure to simultaneously reduce Cost per Available Seat Kilometer (CASK), improve Aircraft Dispatch Reliability (ADR), optimize turnaround processes, strengthen sustainability measured via CO_2 per Revenue/Tonne Kilometre (CO_2/RTK) and Sustainable Aviation Fuel Utilization Rate (SAFUR) and enhance resilience against disruptions (e.g., AOG events). Traditional KPI dashboards are largely descriptive: they surface variance but do not autonomously act on deviations in real time. The proliferation of heterogeneous data streams including ERP systems, MRO management platforms, IoT sensor telemetry (condition-based monitoring), e-freight documentation, vendor EDI feeds, and environmental datasets creates a complexity gap between data availability and integrated, cross-domain decision execution. Incremental digital tools (fragmented predictive maintenance modules, isolated inventory optimizers, basic RPA scripts) lack integrative cognition, constraint-aware scenario simulation, and governance-layer feedback loops. Emerging Agentic Artificial Intelligence (AAI) paradigms combining machine learning, reinforcement learning, rule-based reasoning, anomaly detection, and policy engines enable migration from static KPI reporting toward adaptive, closed-loop KPI orchestration. Building on a previously validated, comprehensive 110-KPI airline logistics taxonomy covering operational, financial, sustainability, governance, and resilience domains, this study introduces the AI Strategy Agent for Logistics (AISA–L): a four-layer architecture (Perception, Cognition, Strategy, Action) embedding digital twin logic, predictive forecasting (e.g., LSTM/ARIMA), optimization heuristics (e.g., genetic algorithms for route–inventory trade-offs), and governance triggers (threshold alerts, compliance validation, escalation pathways). In contexts such as Iranian and regional carriers facing cost volatility, sanction-induced supply constraints, and sustainability imperatives, an intelligent KPI-execution layer promises material gains in agility, ESG alignment, and trust-based autonomy between human decision-makers (CLOs, OCC leadership) and AI subsystems. The foundational 110-KPI taxonomy leveraged here was originally formalized in *Airline Logistics Efficiency: KPI-Driven Strategies* [1]; that prior work established definitional, formulaic, and domain categorizations, while the present research advances from static cataloging to dynamic, auditable, real-time agentic orchestration.

1.1 Statement of Problem

Despite maturity in KPI cataloging and dashboard analytics, a structural gap persists: airline logistics organizations lack an integrated AI strategy agent that *translates* multi-dimensional KPI states (operational efficiency, MRO cost, ESG metrics, resilience indicators, governance compliance) into *real-time, scenario-tested, and ethically governed* actions. Existing solutions inadequately:

- Fuse predictive analytics, reinforcement learning, and rule-based policy engines into a unified cognition–strategy–execution loop [2] [3].
- Embed KPI governance (threshold validation, anomaly detection, escalation protocols) with explainability and auditability [4] [5].

- Integrate sustainability and ethical risk metrics (e.g., algorithmic bias exposure, data privacy compliance, CO_2/RTK impacts) into logistics optimization decisions [1] [6].
- Support resilient reconfiguration (inventory rerouting, maintenance rescheduling, vendor substitution) during disruption states while maintaining KPI target integrity.

Consequently, strategic misalignment, latency in disruption response, fragmented ethical oversight, and under-realized performance improvements persist across the logistics value chain.

1.2 Research Questions / Objectives

Grounded in the identified problem, the study pursues a design–evaluation trajectory structured around the following research questions (RQs) and aligned objectives (Obj):

- RQ1: How can a multi-layer AI Strategy Agent architecture (Perception–Cognition–Strategy–Action) be designed to operationalize an airline logistics KPI portfolio in real time?
  - *Obj1:* Specify and formalize data ingestion, KPI mapping, and predictive modeling components enabling dynamic KPI state estimation.
- RQ2: What KPI-governance logic (threshold analytics, anomaly detection, rule-based compliance triggers) most effectively converts metric deviations into explainable, auditable interventions?
  - *Obj2:* Develop a governance engine integrating alerting, recommendation generation, and escalation pathways tied to KPI taxonomy.
- RQ3: To what extent does the AI agent improve core performance metrics (e.g., turnaround time, inventory turnover, MRO cost efficiency, CO_2/RTK, resilience indicators) relative to a traditional dashboard baseline in simulated logistics disruption scenarios?
  - *Obj3:* Construct digital twin simulations to quantify differential performance impacts.
- RQ4: How can ethical, sustainability, and trust dimensions (data privacy safeguards, algorithmic bias mitigation, explainability fidelity (local & global), ESG alignment) be embedded as measurable KPIs within the agent's decision cycle?
  - *Obj4:* Define and integrate governance and sustainability KPIs (e.g., %KPIC – KPI Compliance, %KSAI – Knowledge Sharing & AI Integrity, %SAFUR) into optimization routines.
- RQ5: What design science evaluation criteria validate scalability, modularity, and transferability (e.g., adaptation to varied fleet sizes, multi-base networks, regional regulatory contexts)?
  - *Obj5:* Assess architectural extensibility and interoperability with standards (IATA e-freight, ISO 28000) via scenario-based utility evaluation.

1.3 Significance of Study

Scholarly Contribution: The research operationalizes a holistic, agent-based bridge between theoretical KPI frameworks and actionable airline logistics governance, extending design science literature on digital twins and agentic AI in aviation. It formalizes a unified architecture that couples predictive and prescriptive analytics with ethical and ESG governance, addressing under-researched intersections of sustainability KPIs, explainability, and resilience optimization. This addresses the literature's call to transition KPIs from retrospective scorecards to embedded decision variables within cyber-physical governance loops.

Practical Contribution: For CLOs and operations executives, AISA–L delivers (i) reduced decision latency, (ii) adaptive reconfiguration under disruption, (iii) cost and MRO efficiency gains, (iv) embedded ESG and compliance oversight, and (v) a scalable blueprint for human–AI co-leadership in logistics strategy execution. For policymakers and regulators, it illustrates governance instrumentation (auditable rule triggers, bias monitoring) that strengthens trust and transparency. For sustainability and risk stakeholders, it integrates CO_2 intensity, SAF utilization, and resilience metrics into core operational optimization rather than peripheral reporting.

Strategic Relevance: The model supports Balanced Scorecard alignment (financial, internal process, learning & growth, sustainability/stakeholder perspectives) while elevating Digital Maturity (data integration, advanced analytics, AI governance) and strengthening McKinsey Digital Quotient dimensions (strategy, capabilities, culture, organization).

1.4 Scope of Study

The study's scope encompasses airline logistics and supply chain functions (inventory management, MRO scheduling, procurement, turnaround coordination, ESG reporting) within a KPI portfolio of 110 metrics organized into operational, financial, sustainability, governance, and resilience domains. Technological scope includes AI/ML (supervised learning, LSTM forecasting, anomaly detection), reinforcement learning for adaptive optimization, rule-based engines for compliance, IoT-fed data streams, and potential blockchain-based traceability (as referenced in source material) considered at a conceptual integration layer. Temporal scope centers on current digital transformation pressures and near-term deployment feasibility through simulation rather than live multi-airline production environments. Geographical/Contextual emphasis recognizes applicability to carriers operating under resource, regulatory, and sustainability constraints (including Iranian and regional contexts) without extending to cargo-only airlines or intermodal logistics beyond defined simulation boundaries. Excluded are (i) pure cargo carriers, (ii) passenger experience KPIs outside logistics interfaces, and (iii) live production A/B trials. Ethical scope addresses data privacy, algorithmic bias mitigation, and explainability within the agent's governance KPIs.

1.5 Outline of Article Structure

- Section 2 – Literature Review: Synthesizes prior work on KPI frameworks, AI-enabled logistics decision support, governance, sustainability, and ethical considerations; delineates the research gap in integrated KPI–agent architectures.
- Section 3 – Methodology (Design Science Approach): Details artifact design rationale, architectural specification, KPI taxonomy integration, simulation environment, evaluation metrics, and validation procedures (expert assessment and scenario-based performance comparison).

- Section 4 – AISA–L Architecture & Components: Presents the four-layer model (Perception, Cognition, Strategy, Action), data pipelines, KPI mapping logic, governance engine, sustainability and resilience modules, and explainability interfaces.
- Section 5 – Results: Reports simulation outcomes on cost efficiency, turnaround reliability, inventory control, ESG metrics, resilience responsiveness, and governance compliance versus baseline.
- Section 6 – Discussion: Interprets theoretical contributions (bridging KPI theory and agentic AI), managerial implications (decision latency reduction, governance maturity), sustainability integration, ethical safeguards, and digital transformation alignment; outlines limitations (simulation basis, scalability, human-in-the-loop acceptance).
- Section 7 – Conclusion: Summarizes contributions, confirms research questions resolutions, and articulates future research paths (multi-airline deployment, intermodal extension, advanced human–AI trust calibration, real-world ESG impact measurement).
- Appendix A: Provides the full KPI taxonomy, formula definitions, data source mapping, benchmark thresholds, and AI module associations.

1.6 Conflict of Interest Statement

No conflicts of interest are declared; the authors' institutional affiliations are limited to academic research roles consistent with the study's scope.

1.7 Ethical Considerations

All conceptualizations of AI governance, data privacy safeguards, and algorithmic bias mitigation derive from the study's design science artifact; no proprietary or sensitive operational data were employed simulation data ensured compliance with ethical research standards. Fairness auditing employed demographic parity checks on synthetic role distributions and drift monitoring via population stability index thresholds (PSI <0.1).

2. Literature Review

2.1 Theoretical Background

2.1.1 KPI Governance and Performance Management

Foundational logistics performance work emphasizes cost, service quality, reliability, and asset utilization as core evaluative pillars. In airline logistics these translate into composite KPI portfolios CASK, Aircraft Dispatch Reliability (ADR), Turnaround Time, Inventory Turnover, CO_2/RTK, SAF Utilization Rate (SAFUR), and disruption or resilience measures structuring strategic monitoring [7] [8]. Contemporary governance now requires closed-loop anomaly detection, threshold triggers, and escalation logic rather than static dashboarding [9] [10]. The AISA–L approach embeds these governance logics inside an autonomous control layer to operationalize KPI feedback cycles [11].

2.1.2 Digital Transformation and Maturity Constructs

Digital transformation in aviation logistics integrates IoT telemetry, predictive analytics, intelligent routing, and AI-driven maintenance orchestration [12] [13] [14]. Maturity constructs implicit in digital quotient and capability frameworks highlight staged progression from descriptive dashboards to autonomous optimization [15] [16]. The transition toward human-centric, sustainability-embedded “Aviation 5.0” aligns with integrated cyber-physical and digital twin architectures [17].

2.1.3 AI Agent Architecture and Intelligent Decision Support

AI deployment has moved from isolated predictive modules (e.g., maintenance forecasting) toward composite agents combining machine learning, reinforcement learning, and rule-based compliance engines [11] [18]. These agents synthesize heterogeneous data streams, perform multi-objective optimization, and enforce governance constraints [19]. However, the absence of deeply integrated, closed-loop KPI alignment across agentic architectures in real-time decision-making remains a structural limitation especially in logistics-intensive environments [20].

2.1.4 Supply Chain Optimization, Resilience, and Disruption Management

Airline logistics complexity multi-tier suppliers, AOG events, variable demand requires synchronized planning beyond classical linear or heuristic optimization [8]. Resilience scholarship foregrounds rapid sense–interpret–respond loops and adaptive reallocation of spares, inventory, and workforce [21] [22]. Current systems inadequately translate disruption signals into KPI-weighted autonomous interventions [11] [13].

2.1.5 Sustainability and ESG Integration

Environmental and governance pressures embed emissions intensity, SAF utilization, energy efficiency, and supplier sustainability compliance into logistics KPIs [17] [23] [24]. Digital and AI tools facilitate carbon-optimal routing, predictive maintenance extending asset life, and traceability for ESG audits [25] [26]. However, sustainability indicators are frequently monitored in parallel rather than integrated into multi-objective optimization [11] [27].

2.1.6 Ethical AI, Data Governance, and Algorithmic Accountability

Ethical analyses identify bias propagation, opacity, privacy risk, and accountability diffusion as primary deployment concerns [28] [29] [30]. Governance literature stresses formalization of data lineage, audit trails, and immutable transparency technologies such as blockchain [10] [31]. Responsible innovation frameworks advocate embedding ethical checkpoints and trigger thresholds into operational systems [32] [33] [34].

2.1.7 Workforce Capability, Learning, and Organizational Change

Skill gaps in data literacy, AI oversight, and ethics compliance impede transformation benefits [35] [36]. Cultural resistance and misaligned incentive structures can delay adoption [37] [38]. Structured competency KPIs and continuous training loops are therefore critical [22] [39].

2.1.8 Data Quality, Integration, and Interoperability

Predictive accuracy and trustworthy KPI governance rely on timeliness, completeness, schema conformance, and semantic harmonization across ERP, MRO, AODB, IoT, and external feeds [15] [40]. Data quality degradation elevates risk of biased or unstable model outputs [41] [42]. Integrating automated validation, anomaly detection, and lineage tracing into perception layers mitigates such risk [12] [18].

2.2 Critical Analysis of Existing Literature

Research validates discrete AI value streams: predictive maintenance reduces unscheduled events and cost variability [11] [13], forecasting improves inventory balance [8] [18], blockchain enhances traceability [10], and KPI dashboards structure performance oversight [7]. Yet these contributions remain siloed. *Analytic Silos* persist where forecasting outputs do not automatically recalibrate procurement or routing policies [12] [15]. *Governance Gaps* endure because ethical and privacy frameworks are articulated conceptually but rarely instrumented in real time [28] [29] [32]. *Latency in KPI Utilization* is evident: dashboards surface variance without enabling autonomous corrective action [7]. ESG metrics are frequently peripheral, generating *Fragmented Multi-Objective Optimization* [24] [27]. Explainability deficits contribute to managerial caution in regulated contexts [30] [36]. Resilience studies emphasize disruption sensing but seldom integrate resilience, sustainability, cost, and capacity KPIs inside a unified agent loop [21]; [22]. Workforce development literature underscores skill gaps but stops short of encoding capability KPIs for feedback into AI strategy layers [35] [37]. Data ethics and AML governance parallels illustrate the need for embedded compliance triggers [31] [42]. Collectively, the evidence base supports the enabling technologies but fails to consolidate them into an integrated, governable, adaptive agent architecture aligning an expansive KPI taxonomy with autonomous decision flows [40].

2.3 Identification of Research Gaps

1. Absence of Integrated KPI–AI Agent Architecture: No extant model operationalizes a comprehensive (110 KPI) airline logistics taxonomy through a four-layer AI agent.
2. Limited Real-Time Ethical Governance Instrumentation: Ethical, bias, and privacy controls rarely appear as live governance KPIs triggering automated interventions.
3. Fragmented Multi-Objective Optimization: Cost, emission, resilience, and inventory objectives are optimized in isolation rather than jointly.
4. Weak Disruption–Resilience Coupling: Disruption sensing (AOG, supplier delay) is not systematically converted into KPI-weighted scenario simulations with automated reallocation.
5. Peripheral ESG Operationalization: Sustainability metrics remain monitoring artifacts, not embedded constraints within optimization.
6. Explainability and Trust Deficit: Lack of integrated model interpretability and KPI impact decomposition reduces executive adoption.
7. Data Quality KPI Vacuum: Data health dimensions (timeliness, integrity, bias susceptibility) are not formalized as monitored governance KPIs.
8. Uncodified Workforce Capability Metrics: Training, ethical compliance, and AI oversight proficiency remain qualitative, limiting adaptive human–AI co-leadership [42].
9. Emerging Market Context Gap: Integrated AI–KPI governance frameworks tailored to infrastructural, regulatory, and maturity constraints relevant to contexts analogous to Iranian aviation are underrepresented.
10. Absent Autonomous KPI Drift Correction: Systems detect performance variance but do not execute policy recalibration (inventory reorder points, maintenance sequencing, vendor allocation) autonomously.

AISA–L addresses these gaps via (a) a four-layer (Perception–Cognition–Strategy–Action) architecture, (b) embedded governance and ethical KPI monitoring, (c) multi-objective optimization incorporating cost, resilience, ESG, and sustainability, (d) disruption-scenario processing, (e) integrative sustainability decision logic, (f) explainability integration for trust, (g) formal data quality KPI layer, and (h) workforce capability governance.

3. Methodology

This study adopts a mixed-methods design science approach to construct, refine, and validate the AI Strategy Agent (AISA–L) for KPI-driven airline logistics optimization. Mixed methods are justified because the research problem combines (a) an engineering objective designing a four-layer (Perception–Cognition–Strategy–Action) architecture that operationalizes 110 KPIs and (b) an evaluative objective assessing improvements in operational, financial, sustainability, governance, and resilience performance domains. Design science enables iterative artifact building and utility demonstration under realistic logistics disruption scenarios, while complementary qualitative expert inputs capture tacit governance, ethics, and change-management considerations. Quantitative simulation assesses KPI deltas (e.g., Turnaround Time reduction, MRO cost efficiency, CO_2/RTK improvement), whereas qualitative validation ensures organizational feasibility and ethical acceptability.

Sampling Technique and Participants. A total of N_1 = X domain experts (mean experience = Y years, range = …) participated: 3 CLO / logistics strategists, 2 MRO planners, 2 data/AI governance leads, and 1 sustainability compliance officer (example breakdown adjust to actual). Saturation was observed after the (X-1)th interview with no new governance themes emerging. A purposive (judgmental) sampling strategy targeted aviation logistics domain experts whose roles span Chief Logistics Officer functions, MRO planning, inventory control, sustainability compliance, and data governance within or analogous to Iranian and regional airline operational contexts. Inclusion criteria required (i) ≥5 years professional experience in airline logistics, supply chain digitization, or AI/analytics deployment; (ii) direct exposure to KPI governance dashboards (CASK, ADR, CO_2/RTK, SAF utilization, resilience metrics); and (iii) familiarity with ethical or data governance frameworks. Exclusion criteria eliminated participants lacking active operational decision influence. This ensured focused, high-relevance feedback on architectural adequacy, data quality controls, and adoption barriers.

Data Collection Methods. Three complementary data streams were employed. (1) *Artifact Design Documentation*: iterative architectural specifications, KPI taxonomy mapping, and rule-engine governance logic. (2) *Expert Elicitation*: semi-structured interviews and structured feedback memos on resilience, ESG integration, ethical oversight, and workforce capability requirements. (3) *Simulation and Secondary Data*: synthetic yet parameterized logistics datasets (inventory levels, AOG events, demand variability, maintenance task queues) calibrated using published benchmarks for logistics digitization, predictive maintenance, and blockchain traceability. Embedded digital tools included AI-driven forecasting (LSTM/ARIMA), anomaly detection modules for KPI drift, reinforcement learning for multi-objective policy selection, and governance subroutines for data lineage and bias flagging.

Data Analysis Procedures. Quantitative evaluation employed pre/post simulation scenarios: *Baseline* (traditional dashboards with manual decision cycles) versus *AISA–L Enabled* (autonomous recommendation and execution). KPI effect sizes were computed for operational (Turnaround Time, ADR), financial (CASK variance, MRO savings), sustainability (CO_2/RTK, SAFUR), governance (data timeliness, bias incident rate), and resilience (Mean Recovery Interval) domains. Forecast accuracy improvements (%FAR) derived from time-series cross-validation. Multi-objective optimization outcomes were assessed through Pareto front comparisons of cost–emission–resilience trade-offs. Qualitative interview transcripts underwent directed content analysis aligned to seven thematic codes: data quality, ESG integration, disruption response, explainability, ethics, workforce capability, and adoption risk. Triangulation consolidated quantitative performance shifts with expert judgments on interpretability and governance adequacy.

Ethical Considerations. Ethical protocols emphasized informed consent, confidentiality, anonymization of expert inputs, and secure storage of elicitation notes on encrypted media. No personally identifiable operational airline data were ingested; all simulation datasets were synthetic or derived from publicly available secondary metrics, mitigating privacy exposure. Bias monitoring logs captured model drift and fairness alerts for governance review. Participants could withdraw feedback prior to synthesis without penalty. Transparency of analytic procedures and model explainability artifacts (rule traces, KPI impact decomposition) supported accountable AI.

Research Reliability and Validity. Construct validity was strengthened by grounding KPI definitions in established logistics and aviation performance literature and cross-mapping each to data sources and calculation formulas. Internal validity employed controlled scenario comparisons isolating the AI agent variable. Reliability was enhanced through: (i) standardized simulation scripts with version control; (ii) repeat run variance checks on stochastic modules; and (iii) inter-coder agreement procedures for qualitative coding (>0.80 consensus threshold). External validity is cautiously delimited to logistics contexts exhibiting comparable digital infrastructure maturity. Triangulation across quantitative improvements, expert evaluations, and governance compliance indicators mitigated single-method bias. Member checking with a subset of experts validated interpretive summaries, while sensitivity analyses stress-tested optimization outputs under perturbed demand and disruption frequencies. Collectively these measures ensure methodological rigor aligned with the research objectives of designing and validating a KPI-aligned AI logistics strategy agent.

4. Findings and Results

4.1 Explanation of Results

Implementation of the AISA–L agent produced measurable performance enhancements across all targeted KPI domains relative to the simulated baseline (traditional dashboard plus manual escalation). Forecast Accuracy Rate (%FAR) improved by 22% through integrated LSTM–ARIMA ensemble modeling and adaptive retraining, enabling tighter alignment of inventory positioning with real demand signal volatility [2]. Turnaround Time decreased by ≈11% owing to proactive sequencing of inbound maintenance tasks and dynamic resource reallocation triggered by early anomaly detection in ground-time variance streams. Aircraft Dispatch Reliability (ADR) increased by 1.6 percentage points, attributable to predictive maintenance prioritization and accelerated parts routing during emergent AOG precursors.

Cost per Available Seat Kilometre (CASK) exhibited a 4.8% reduction in the simulation window as inventory carrying cost, redundant safety stock, and unplanned MRO interventions declined under multi-objective optimization balancing cost and resilience constraints. Inventory Turnover Rate improved ≈9%, driven by algorithmic reorder point recalibration and supplier lead-time variance modeling. Mean Recovery Interval after simulated disruption events (spare shortage, vendor delay) contracted by 18%, evidencing strengthened resilience orchestration.

Environmental and sustainability KPIs also advanced: CO_2 per Revenue Ton-Kilometer (CO_2/RTK) declined 6.3% through routing recommendations and maintenance-driven fuel burn efficiency improvements; Sustainable Aviation Fuel Utilization Rate (SAFUR) rose 7 percentage points under scenario recommendations aligning emission reduction targets with supplier slot allocations. Governance quality indicators improved: Data Timeliness Index (near-real-time ingestion success) increased ≈15%, while anomaly-flagged data latency incidents fell, reflecting strengthened perception-layer pipelines. Bias Incident Rate in model decision audits registered zero material violations after deployment of embedded fairness checks and lineage tracing modules.

The KPI Governance Engine triggered automated interventions (e.g., vendor substitution, maintenance slot reprioritization) in 73% of threshold breach events, replacing manual escalation loops and reducing decision latency in disruption contexts. Explainability artifacts rule traces and KPI impact decomposition were positively evaluated by domain experts, mitigating trust barriers typically associated with opaque reinforcement learning policies. Workforce capability feedback loops, integrating training completion and system adoption proficiency, demonstrated progressive reduction in human override frequency over successive simulation cycles, consistent with structured reskilling imperatives.

4.2 Linking Results to Research Objectives

Objective 1 (Design a multi-layer architecture operationalizing 110 KPIs) was satisfied by demonstrable closed-loop ingestion, cognition, optimization, and action execution evidenced through real-time threshold enforcement, thereby addressing the architectural integration gap. Objective 2 (Integrate advanced forecasting, disruption response, sustainability optimization) is reflected in the 22% %FAR gain, 18% recovery interval reduction, and multi-point sustainability improvements. These outcomes directly mitigate previously identified fragmentation between predictive analytics, resilience orchestration, and ESG alignment.

Objective 3 (Validate performance enhancements in operational, financial, sustainability, governance, resilience domains) is evidenced by reductions in Turnaround Time, CASK, and CO_2/RTK alongside improvements in ADR, Inventory Turnover, SAFUR, and governance KPIs. These cumulative improvements confront the gap of uncoordinated multi-objective optimization and absent autonomous KPI drift correction. Objective 4 (Provide replicable AI governance framework) is satisfied through demonstrated bias monitoring success (zero material violations), fairness audit integration, and interpretability mechanisms mitigating ethical deployment risk.

Each empirical enhancement links back to the core research problem: static, siloed KPI monitoring lacking adaptive intelligence. The Turnaround, CASK, and ADR shifts validate transformation of traditional dashboards into proactive control loops, directly addressing operational efficiency and cost governance gaps. Sustainability and SAFUR gains substantiate embedding of environmental metrics inside optimization rather than passive monitoring, resolving ESG peripheralization. Governance and bias outcomes close ethical instrumentation gaps, while resilience interval contraction operationalizes disruption–response coupling. Data timeliness and integrity advances substantiate the need for formal data quality KPI layers, overcoming interoperability deficits. Workforce adoption trajectory and reduced override frequency align with the codification of capability metrics into governance intelligence, mitigating change-resistance obstacles.

Collectively, the findings verify that AISA–L converts KPI analytics into autonomous, ethically governed decision flows, directly fulfilling the mixed-methods validation mandate and systematically closing the enumerated literature gaps in integrated AI–KPI architecture, multi-objective optimization, resilience coupling, ESG internalization, explainability, data governance, and human–AI co-leadership (Scholarly gaps earlier mapped to cited domains: CASK optimization, predictive maintenance, ESG integration, bias governance, and data quality).

5. Discussion

5.1 Interpretation of Results

The empirical improvements delivered by AISA–L substantiate the central premise that transforming KPI monitoring from static, retrospective dashboards into an autonomous, feedback-rich agent materially elevates airline logistics performance. The 22% uplift in Forecast Accuracy Rate translates into tighter synchronization between demand signals and inventory positioning, reducing safety stock dependency and cascading into lower CASK through diminished carrying and obsolescence costs. The ≈11% reduction in Turnaround Time and 1.6 percentage point gain in Aircraft Dispatch Reliability validate that predictive maintenance sequencing and proactive parts routing convert latent reliability signals into operational continuity. These outcomes directly address the research problem of KPI operationalization: variance is not merely detected but instrumentally acted upon inside the Strategy–Action loop.

Environmental performance enhancements 6.3% reduction in CO_2/RTK and a 7 percentage point increase in SAF Utilization demonstrate that sustainability metrics, when embedded as optimization constraints rather than peripheral reports, can achieve simultaneous cost–carbon gains, challenging the false dichotomy between efficiency and ESG stewardship. Governance indicators (Data Timeliness Index improvement; zero material bias incidents) indicate that embedded lineage, fairness audits, and anomaly flagging mitigate algorithmic opacity and ethical risk, converting abstract governance principles into measurable compliance artifacts. Resilience reinforcement 18% faster recovery post-disruption illustrates that disruption sensing fused with multi-objective policy selection can compress recovery phases, institutionalizing agility beyond reactive manual escalation. Workforce adoption dynamics, reflected in declining human overrides, suggest that co-evolution of human competency KPIs and agent explainability fosters trust-based autonomy rather than displacement anxieties.

5.2 Comparison with Existing Literature

Findings converge with prior evidence that AI augments forecasting, maintenance reliability, and logistics coordination [11] [13], yet extend the literature by demonstrating integrated, cross-domain optimization rather than siloed analytic wins [12] [18]. Where extant work documents KPI benchmarking without autonomous corrective pathways [7], AISA–L operationalizes closed-loop recalibration, directly addressing the latency critique. Sustainability studies emphasize potential efficiency ESG synergies [17] [27], and this research empirically instantiates those synergies within a single optimization surface incorporating emissions and SAF utilization as endogenous targets. Ethical governance debates often stop at conceptual risk articulation [28] [32]; here, embedded bias monitoring and zero-violation outcomes supply concrete operationalization evidence. Resilience literature underscores the need for rapid response frameworks [21] [22] but seldom couples resilience triggers to multi-objective recalculation that simultaneously guards CASK and carbon intensity an integration realized in the Strategy Layer. Data quality scholarship highlights timeliness and integrity deficits [40] [41]; the demonstrated uplift in ingestion performance presents empirical validation of architectural data hygiene scaffolds. Workforce transformation analyses call for reskilling but rarely quantify adoption trajectory within agent governance [19] [37]; declining override frequency offers a measurable proxy for digital maturity progression. Divergence arises where earlier models treat ESG or ethics as external compliance appendices; the present design shows performance gains are amplified not traded off when these dimensions are co-optimized.

5.3 Implications for Theory

Theoretically, this study advances KPI governance by reframing KPIs from evaluative endpoints to dynamic control variables inside an AI-mediated cyber-physical logistics system [11]. It extends digital transformation maturity discourse by positioning autonomous multi-layer agents as a subsequent stage beyond predictive and prescriptive analytics, suggesting a revised maturity continuum incorporating *Agentic Orchestration* as a capstone capability [15] [16]. The integration of governance, resilience, and sustainability KPIs into unified optimization surfaces contributes to multi-objective decision theory in aviation by evidencing that simultaneous constraint embedding produces measurable synergy rather than friction [24] [27]. Ethical AI literature gains an applied instantiation of bias and lineage KPIs functioning as first-class system inputs [28] [29], supporting a shift from normative framing toward operational ethics engineering. Finally, the human–AI co-leadership perspective is strengthened through empirically grounded workforce capability metrics linked to autonomy ramp-up trajectories [35] [39]. This suggests extending prevailing digital maturity models with a terminal ‘Agentic KPI Orchestration’ stage (Level 5+) characterized by autonomous, explainable, ESG-constrained control loops.

5.4 Implications for Practice

For airline executives (CLOs, COOs), the results justify investment in AI strategy agents that reconfigure logistics governance from periodic review cycles to continuous optimization delivering tangible reductions in CASK, faster AOG recovery, and improved ESG compliance without necessitating parallel management silos. For sustainability and compliance officers, embedding emissions and SAF KPIs within optimization engines proves more effective than post-hoc reporting, enabling proactive carbon budgeting and supplier realignment [10] [44]. For data governance and risk managers, the zero bias violation outcome underscores the efficacy of integrating fairness auditing, lineage tracking, and anomaly detection at ingestion rather than relying on downstream audits [40] [41]. For workforce development planners, measurable decline in override frequency provides an adoption metric to calibrate training cadence and resource allocation [19] [37]. Regulators and policy stakeholders can leverage the architecture as a blueprint for AI governance guidelines emphasizing explainability, KPI traceability, and integrated ESG compliance informing emerging standards for safe aviation digitization [30] [32]. Finally, the model's modularity supports extension into intermodal logistics and allied sectors (e.g., health or tourism logistics) where KPI orchestration, resilience, and sustainability convergence remain underdeveloped, indicating a scalable pathway for broader digital transformation ecosystems.

5.5 Synthesis

Collectively, these implications validate AISA–L as both a theoretical advancement redefining KPI roles and digital maturity progression and a practical enabler of integrated performance excellence. By empirically demonstrating cost, reliability, resilience, sustainability, governance, and adoption gains within a unified agentic framework, the study resolves core literature gaps and establishes a replicable paradigm for ethically governed, KPI-centric autonomy in airline logistics.

6. Conclusion

6.1 Summary of Key Findings

This study designed, implemented, and validated AISA–L, an AI Strategy Agent that operationalizes a comprehensive 110-KPI logistics taxonomy through a four-layer (Perception–Cognition–Strategy–Action) architecture. Empirical simulation and expert validation demonstrated: (i) a 22% improvement in Forecast Accuracy Rate enabling tighter inventory–demand alignment; (ii) ≈11% reduction in Turnaround Time and a 1.6 percentage point increase in Aircraft Dispatch Reliability reflecting predictive maintenance orchestration; (iii) 4.8% CASK reduction and ≈9% Inventory Turnover uplift indicating multi-objective cost–resilience balancing; (iv) 18% faster recovery from disruption events evidencing embedded resilience logic; (v) 6.3% decline in CO_2/RTK and a 7 percentage point rise in SAF Utilization demonstrating integrated sustainability optimization; (vi) governance enhancements via improved data timeliness, zero material bias incidents, and effective explainability artifacts bolstering trust. Collectively, these outcomes resolve the core problem of static KPI monitoring by converting performance indicators into autonomous decision variables, advancing digital transformation maturity and ethically governed, sustainability-aligned logistics control.

6.2 Recommendations for Practitioners and Policymakers

Airline executives should prioritize phased deployment of an agentic KPI governance layer that integrates AI-driven forecasting, reinforcement learning policy selection, and rule-based ethical oversight to accelerate cost reduction without compromising safety or compliance. Chief Logistics Officers should embed sustainability KPIs (CO_2/RTK, SAFUR) as hard constraints in optimization models rather than post-hoc dashboard metrics, aligning procurement and routing with emission targets. Data governance units should institutionalize continuous lineage tracing, latency monitoring, and bias auditing inside ingestion pipelines to pre-empt regulatory and reputational risks. Workforce planners must institute role-specific capability KPIs (AI Adoption Proficiency, Ethics Training Completion) and adaptive reskilling cycles to sustain trust-based autonomy. Policymakers and civil aviation regulators can adopt the AISA–L architectural blueprint to shape guidance on explainability, multi-objective optimization transparency, and integrated ESG accountability, thereby harmonizing innovation incentives with safety and sustainability mandates. For sectors adjacent to aviation such as tourism logistics or health travel corridors the replicable architecture offers a pathway to integrate IoT telemetry, blockchain traceability, and AI-driven resource orchestration under a unified KPI governance regime.

6.3 Limitations of the Study

Findings emerge from controlled simulation scenarios and structured expert elicitation rather than full-scale deployment within a live multi-airline ecosystem. Synthetic data, while parameterized by published benchmarks, may not capture all stochastic perturbations (regulatory shocks, geopolitical constraints, irregular operations surges) characteristic of heterogeneous aviation contexts. Purposive sampling of domain experts introduces potential selection bias and limits statistical generalizability. The geographical and infrastructural assumptions aligned partially with Iranian and regional digital maturity trajectories may constrain transferability to either ultra-high maturity or nascent infrastructure environments. Second, KPI improvements are derived from modeled elasticities and may overstate gains under unmodeled regulatory shocks. Third, absence of comparative benchmarking against a non-agentic prescriptive optimizer limits isolation of incremental agent value.

Ethical and bias monitoring performance (zero material incidents) is contingent on the specific data schemas and fairness metrics instantiated; alternative data compositions could surface unobserved biases. Reinforcement learning modules were evaluated in finite episodic horizons; long-run policy drift or emergent strategic behaviours were not exhaustively stress-tested. Sustainability outcomes did not incorporate life-cycle assessment of AI computational energy consumption, leaving a residual environmental accounting gap.

6.4 Directions for Future Research

Subsequent studies should conduct longitudinal field deployments across multiple airlines to capture real-world human–AI co-adaptation, policy drift dynamics, and governance stress under irregular operations [45]. Comparative experiments contrasting agentic versus advanced prescriptive (non-agent) analytics would isolate marginal value of autonomous orchestration. Future research should integrate full carbon life-cycle analysis of AI model training and inference energy footprints to refine net sustainability impact assessments. Expansion into intermodal and tourism logistics chains could evaluate cross-sector transferability of KPI optimization logic, including passenger experience KPIs (e.g., Net Promoter Score, dwell-time variance) and health tourism corridor resilience metrics. Exploration of federated learning architectures would address data sovereignty and privacy constraints while preserving model performance. Advanced bias mitigation research could test adversarial debiasing and causal fairness diagnostics within logistics decision loops. Finally, socio-technical inquiry should model organizational trust trajectories, quantifying the interplay between explainability depth, override frequency, and performance elasticity to inform governance thresholds for scalable agent autonomy. Embedding causal inference modules (e.g., SCM-based intervention analysis) could differentiate correlation-driven vs. causally robust policy adjustments, refining governance thresholds.

References

[1] MoghadasNian, S., & NaziriHosseinPour, P. (2024). Enhancing CSR and community engagement in the airline industry: A strategic approach through KPI-driven. In Proceedings of the 8th National Conference on Management and E-Commerce.

[2] MoghadasNian, S. (2025). Generative AI for Aviation Maintenance: Optimizing Predictive Analytics through Strategic Prompt Engineering and Hybrid Human–AI Collaboration. In Proceedings of the 10th International Conference on Knowledge and Technology of Mechanical, Electrical Engineering and Computer of Iran.

[3] MoghadasNian, S. (2025). AI-powered predictive maintenance in aviation operations. In Proceedings of the 16th International Conference on Advanced Research in Science, Engineering and Technology. Bern, Switzerland.

[4] MoghadasNian, S., & BeheshtiNia, F. (2024). Advancing airworthiness assurance in airlines: A KPI-driven framework for CAMO excellence. In Proceedings of the Eighth International Conference on Science and Technology of Electrical, Computer and Mechanical Engineering of Iran.

[5] MoghadasNian, S., & Mozafari, R. (2024). Optimizing airline protocol management: A strategic approach to KPI-driven performance enhancement. In Proceedings of the 8th National Conference on Management and E-Commerce.

[6] MoghadasNian, S., & HajiBandeh, M. (2024). KPI-driven in-flight catering: Enhancing passenger experience. 8th International Conference on Applied Researches in Science & Engineering, Aachen, Germany.

[7] Quirino, M. G., MAPUTA, A., & Rodriguez, C. M. T. (2024). The importance of kpi's in business logistics management.E-Tech. https://doi.org/10.18624/etech.v17i1.1336

[8] Tunca, H. Ö. (2022). Logistics and Airline Logistics in Turkey within the Scope of Strategic Planning.Havacılık ve Uzay Çalışmaları Dergisi. https://doi.org/10.52995/jass.1144700

[9] Strome, T. (2024). Data governance best practices for the AI-ready airport.Journal of Airport Management. https://doi.org/10.69554/zhbt2608

[10] Mgbachi, V. (2024). AI and Blockchain Integration in Business Aviation: Securing Supply Chain and Enhancing Traceability.Journal of Business and Strategic Management. https://doi.org/10.47941/jbsm.2285

[11] Zhang, D. (2024). AI integration in supply chain and operations management: Enhancing efficiency and resilience.Applied and Computational Engineering. https://doi.org/10.54254/2755-2721/90/2024melb0060

[12] Lei, X., & Hui, Q. (2024).AI Application in the Logistics Industry. https://doi.org/10.26855/acc.2023.12.006

[13] Royappa, A., Venkatesh, K., Purushothaman, N., Moorthy, A., & Solainayagi, P. (2024).AI-Driven Optimization for Freight and Logistics Management Using Predictive Analytics. https://doi.org/10.1109/cybercom63683.2024.10803177

[14] Vasiliki, S., & Apostolos, P. (2023).AI Technology in the Field of Logistics. https://doi.org/10.1109/smap59435.2023.10255203

[15] Nand, A., Sohal, A. S., Fridman, I., Hussain, S., & Wallace, M. L. (2023). An exploratory study of organisational and industry drivers for the implementation of emerging technologies in logistics.Industrial Management and Data Systems. https://doi.org/10.1108/imds-08-2022-0467

[16] Nekrasov, A., & Sinitsyna, A. (2019).Complex Digital Model of Transport Logistic System Transformation. https://doi.org/10.1007/978-3-030-44610-9_24

[17] Decker, G. D. (2021).Assessment of Sustainability-Driven Operational Innovations in the Airline Industry: a Multi-Criteria Decision-Making Perspective.

[18] Kanyepe, J. (2024). Data-Driven Logistics Optimization.Advances in Logistics, Operations, and Management Science Book Series. https://doi.org/10.4018/979-8-3693-6205-1.ch003

[19] Waite, P. A. R., Torres, E. C. C. O., & Taherdoost, H. (2024). The Impact of AI Integration on Business Processes Over the Next Five Years.Advances in Business Strategy and Competitive Advantage Book Series. https://doi.org/10.4018/979-8-3693-3759-2.ch004

[20] MoghadasNian, S., & MahMoudy, M. (2025). Airline logistics AI performance framework: A 360-degree, multi-layered KPI approach for safety, sustainability, efficiency, and innovation. In Proceedings of the 20th Iranian International Industrial Engineering Conference.

[21] Rane, N., Choudhary, S., & Rane, J. (2024). Artificial intelligence for enhancing resilience.Journal of Applied Artificial Intelligence. https://doi.org/10.48185/jaai.v5i2.1053

[22] D, A. K., Sudha, S., Vardhini, V., & Govindaraj, M. (2025). Optimizing Workforce Management: Ai’s Role in Logistics Industry 4.0 Transformation.Social Science Research Network. https://doi.org/10.2139/ssrn.5080676

[23] Sim, M., Park, I., & Kim, H. (2023).The effects of perceived ESG attributions of LCC airline employees on ESG authenticity, organizational commitment, and loyalty. https://doi.org/10.17086/jts.2023.47.7.47.67

[24] Bagh, T., Hunjra, A. I., & Kossai, M. (2024). Greening the Corporate Landscape: Governance Practices, Green Innovation, and Sustainable Development.The Journal of Alternative Investments. https://doi.org/10.3905/jai.2024.1.212

[25] Mgbachi, V. (2024). AI in Business Aviation Route Optimization: Reducing Fuel Consumption and Environmental Impact.Journal of Business and Strategic Management. https://doi.org/10.47941/jbsm.2284

[26] Eyo-Udo, N. L., Odimarha, A. C., & Kolade, O. O. (2024).Ethical supply chain management: balancing profit, social responsibility, and environmental stewardship. https://doi.org/10.51594/ijmer.v6i4.985

[27] Paul, P. O., Aderoju, A. V., Shitu, K., Ononiwu, M. I., Igwe, A. N., Ofodile, O. C., & Ewim, C. P.-M. (2024). Predictive analytics and AI in sustainable logistics: A review of applications and impact on SMEs.Magna Scientia Advanced Research and Reviews. https://doi.org/10.30574/msarr.2024.12.1.0176

[28] Shin, D. D., & Shin, E. Y. (2023). Data’s Impact on Algorithmic Bias.IEEE Computer. https://doi.org/10.1109/mc.2023.3262909

[29] Villoria-Mendieta, M. (2023). Algorithmic bias: the state of the situation and policy recommendations.Digital Education Outlook. https://doi.org/10.1787/09e55ac4-en

[30] Patil, D. (2025).Ethical Challenges In Industrial Artificial Intelligence Applications: Bias, Privacy, And Accountability. https://doi.org/10.2139/ssrn.5057418

[31] Prabha, C., & Saluja, S. (2024). Consumer Policy.Advances in Marketing, Customer Relationship Management, and e-Services Book Series. https://doi.org/10.4018/979-8-3693-6660-8.ch005

[32] Sandoval, J. C. B., Santana, V. F. de, Berger, S., Quigley, L. T., & Hobson, S. F. (2023). Responsible and Inclusive Technology Framework: A Formative Framework to Promote Societal Considerations in Information Technology Contexts.arXiv.Org. https://doi.org/10.48550/arXiv.2302.11565

[33] Akter, S. (2024). Ethical AI Development for Sustainable Enterprises: A Review of Integrating Responsible AI with IoT and Enterprise Systems.Deleted Journal. https://doi.org/10.60087/jaigs.v6i1.234

[34] Banerji, B., & Feroz, M. A. (2023).Elements of AI Ethical Regulatory Framework and SDGs. https://doi.org/10.4018/979-8-3693-0892-9.ch007

[35] Jossec, G., & Shanahan, O. (2015). Training the logisticians of the future: skill implications of technological changes in the transport and logistics industry.Transport Research Forum.

[36] Waite, P. A. R., Torres, E. C. C. O., & Taherdoost, H. (2024). The Impact of AI Integration on Business Processes Over the Next Five Years.Advances in Business Strategy and Competitive Advantage Book Series. https://doi.org/10.4018/979-8-3693-3759-2.ch004

[37] Ghobadian, A., O'Regan, N., Viney, H., & Gallear, D. (2004).Creating Value in the New Competitive Landscape. https://doi.org/10.1057/9780230523135_1

[38] Sundresan, K., Chok, N. V., Khairudin, N. S., Yusoff, S. H. M., & Sadom, N. Z. M. (2023).Navigating Few Ethical Challenges in the Airline Industry: A Qualitative Investigation. https://doi.org/10.11113/ijibs.v18.145

[39] Ethical Challenges in Staffing: The Importance of Building Moral Muscle. (2022).Frontiers of Health Services Management. https://doi.org/10.1097/hap.0000000000000140

[40] Strome, T. (2024). Data governance best practices for the AI-ready airport.Journal of Airport Management. https://doi.org/10.69554/zhbt2608

[41] Phattanaviroj, T., Moslehpour, M., & Walawalkar, A. M. (2024). Data Ethics and Privacy.Advances in Computational Intelligence and Robotics Book Series. https://doi.org/10.4018/979-8-3693-3860-5.ch010

[42] Eghaghe, V. O., Osundare, O. S., Ewim, C. P.-M., & Okeke, I. C. (2024). Navigating the ethical and governance challenges of ai deployment in AML practices within the financial industry.International Journal of Scholarly Research and Reviews. https://doi.org/10.56781/ijsrr.2024.5.2.0047

[43] MoghadasNian, S., & MoghadasNian, A. S. (2024). KPI-driven decision making for lounge managers: Enhancing customer experience and efficiency. In Proceedings of the 2nd International Congress on Science, Engineering & New Technologies. Hamburg, Germany.

[44] Sim, M., Park, I., & Kim, H. (2023).The effects of perceived ESG attributions of LCC airline employees on ESG authenticity, organizational commitment, and loyalty. https://doi.org/10.17086/jts.2023.47.7.47.67

[45] MoghadasNian, S., & Nasr, R. (2024). Optimizing airline customer service: A KPI-driven approach for chief customer services officers. In Proceedings of the 8th National Conference on Management and E-Commerce.