

FROM DATA TO DECISIONS: A CONCEPTUAL FRAMEWORK FOR DATA-DRIVEN AIRLINE OPERATIONS AND SUSTAINMENT

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Abstract

The aviation industry is increasingly adopting data-driven technologies to enhance aircraft operations and sustainment. Advances in condition-based maintenance, prognostics and health management, fleet analytics, and digital technologies have significantly improved the ability to estimate asset health, deterioration, and operational risk. However, these capabilities remain largely focused on prediction and are often only weakly integrated into broader airline decision-making processes. As a result, predictive information frequently fails to translate into operational value. This paper introduces the concept of the Data-to-Decision Gap, describing the disconnect between predictive capabilities and operational decision-making in airline environments. To address this challenge, a technology-agnostic Data-to-Decision Transformation Framework is proposed. The framework conceptualises data-driven airline operations as a layered decision architecture comprising data sources, state representation, state impact, decision support, and governance. The framework explicitly links operational data, analytical outputs, operational consequences, and decision processes, while incorporating uncertainty management, human oversight, and organisational integration. The paper further argues that successful implementation requires not only technical capabilities but also organisational readiness to translate analytical outputs into actionable decisions. By shifting attention from prediction-centric to decision-centric approaches, the proposed framework provides a systems-level perspective for integrating data-driven methods into airline operations and sustainment. The framework is intended to support future research and industrial adoption of trustworthy decision-support systems in aviation.

Keywords: airline operations, decision support, diagnostics, prognostics and health management, operational resilience

1. Introduction

The aviation industry is undergoing a profound transformation driven by increasing system complexity, rising sustainability requirements, growing operational uncertainty, and unprecedented availability of digital data. Modern aircraft generate large volumes of operational, maintenance, and health-monitoring information, while advances in sensing technologies, connectivity, data storage, cloud computing, and artificial intelligence have significantly expanded the industry's ability to analyse and exploit these data [1-5].

Over the last two decades, substantial progress has been achieved in the fields of condition-based maintenance, prognostics and health management, fleet analytics, and digital twins. These

developments have enabled increasingly accurate estimation of component health, degradation trends, remaining useful life, and operational risk. Airlines, maintenance, repair and overhaul organisations (MROs), and original equipment manufacturers (OEMs) have invested heavily in predictive capabilities intended to improve safety, reliability, and operational efficiency.

Despite these advances, the operational impact of many data-driven technologies remains below expectations. In many cases, predictive models successfully estimate technical states of aircraft systems, yet their outputs are only weakly integrated into the planning and decision-making processes that govern airline operations. Maintenance planning, fleet assignment, network scheduling, disruption management, and resource allocation frequently continue to rely on traditional and in many cases obsolete decision frameworks that make limited use of predictive information.

This situation highlights a fundamental challenge, referred to in this paper as the "Data-to-Decision Gap". While considerable effort has been devoted to improving prediction accuracy, comparatively less attention has been paid to understanding how predictive information should be translated into operational actions and organisational decisions. As a result, airlines often possess sophisticated analytical capabilities without fully realising their potential value at the system level.

The challenge is not solely technical. Effective integration of data-driven insights requires change management, coordination across multiple organisational functions, alignment between predictive outputs and operational objectives, representation of uncertainty, establishment of governance mechanisms, and appropriate interaction between automated systems and human decision-makers. Consequently, data-driven airline operations should be viewed and understood as socio-technical systems in which analytical capabilities, organisational processes, governance mechanisms, and human decision-makers interact to influence operational outcomes [6-8].

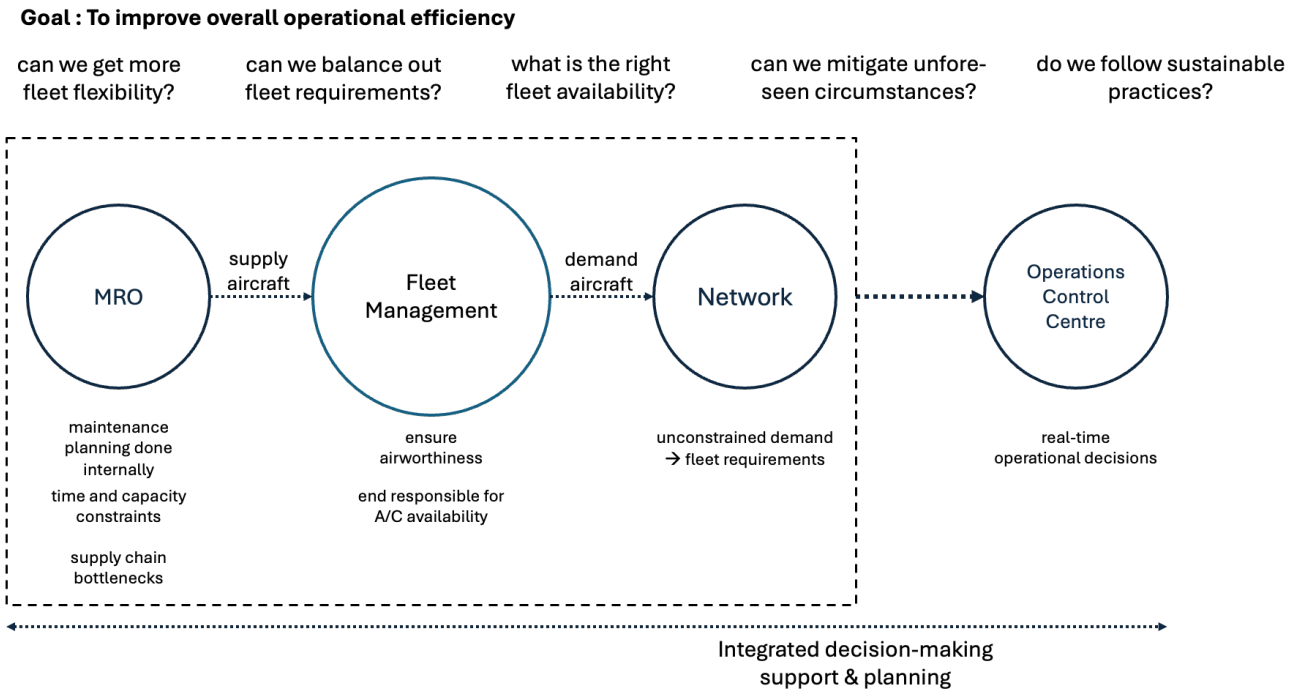


Figure 1 - Schematic layout of modern airline operations.

The contribution of this paper is threefold. First, it introduces the concept of the Data-to-Decision Gap to describe the disconnect between predictive capabilities and operational decision-making in airline environments. Second, it proposes a technology-agnostic Data-to-Decision Transformation Framework that links operational data, state estimation, impact assessment, and decision support. Third, it introduces the concept of Decision Readiness as the organisational capability required to translate analytical outputs into actionable operational decisions.

2. Evolution of Data-Driven Aviation Operations and Sustainment

Historically, airline maintenance and operational decision-making have relied primarily on reactive and preventive approaches. Corrective maintenance addressed failures after their occurrence, while preventive maintenance sought to reduce failure risk through scheduled inspections and component replacement based on predefined intervals. Although these approaches contributed significantly to aviation safety and reliability, they often resulted in inefficient resource utilisation, unnecessary maintenance actions, and limited flexibility in operational planning [9,10].

The increasing availability of aircraft operational data has progressively enabled more sophisticated maintenance and operational strategies. Modern commercial aircraft generate large volumes of information through onboard sensors, avionics systems, flight data acquisition units, aircraft condition monitoring systems, and maintenance information systems. Combined with advances in telecommunication technologies and cloud computing, these developments have created unprecedented opportunities for data-driven decision support.

One of the most significant developments has been the emergence of Condition-Based Maintenance (CBM), where maintenance actions are triggered based on observed equipment condition rather than predetermined schedules. CBM allows maintenance interventions to be better aligned with actual asset health, reducing unnecessary inspections while maintaining acceptable levels of safety and reliability. Building upon CBM principles, Prognostics and Health Management (PHM) approaches seek not only to assess current health states but also to estimate future degradation trajectories and remaining useful life of critical components [2-4].

The application of advanced analytics and artificial intelligence has further accelerated this evolution. Machine learning techniques are increasingly used to detect anomalies, identify deterioration patterns, predict component failures, and estimate operational risks. At the same time, digital twin concepts have emerged as a promising paradigm for combining physical system representations with real-time operational data and predictive models. Digital twins enable continuous monitoring, simulation, and forecasting of asset behaviour, creating new possibilities for proactive decision-making across the aircraft lifecycle [5,11,12].

These developments have delivered measurable benefits in areas such as maintenance planning, spare parts provisioning, troubleshooting, and fleet reliability management. Airlines and maintenance organisations increasingly employ predictive analytics to support workscoping activities, optimise maintenance intervals, reduce aircraft downtime, and improve resource allocation.

Despite these advances, the adoption of data-driven methods has largely focused on local optimisation problems within specific functional domains. Predictive models are typically developed to address narrowly defined objectives, such as predicting component failures, estimating maintenance demand, or detecting operational anomalies. While these applications can provide substantial value within individual processes, their outputs are often disconnected from the broader operational decision-making environment in which airlines operate [13].

Modern airline operations are characterised by complex interactions among maintenance organisations, fleet management functions, network planning departments, operational control centres, supply chain organisations, and regulatory authorities. Decisions made within one domain frequently influence performance outcomes in several others. Consequently, the value of predictive information depends not only on the quality of the underlying models but also on the ability to translate technical predictions into operationally meaningful actions.

As a result, a paradox has emerged. The aviation industry has become increasingly capable of predicting future states of technical systems, yet remains comparatively less capable of systematically incorporating those predictions into operational and strategic decision-making

processes. This observation suggests that future progress will depend not only on improvements in predictive accuracy, but also on the development of frameworks capable of linking data, predictions, operational consequences, and decisions across organisational boundaries [14-16].

3. The Data-to-Decision Gap

The rapid development of predictive analytics, machine learning, and digital twin technologies has significantly enhanced the aviation industry's ability to estimate technical system states and anticipate future events. However, the availability of increasingly accurate predictions has not automatically translated into improved operational decision-making. This discrepancy constitutes what is referred to in this paper as the Data-to-Decision Gap [16,17].

The Data-to-Decision Gap describes the disconnect between the generation of predictive information and its effective utilisation within operational and strategic airline decision processes. While predictive models often produce estimates of degradation, failure probability, remaining useful life, or operational risk, these outputs rarely correspond directly to the decisions that airline stakeholders must make. Consequently, valuable information frequently remains underutilised despite significant investments in data infrastructure and analytical capabilities.

Several factors contribute to this gap.

3.1 Technical Fragmentation

Airline data ecosystems are often characterised by heterogeneous information sources, differing data standards, inconsistent data quality, and limited interoperability between operational systems. Aircraft health monitoring systems, maintenance management systems, flight operations systems, enterprise resource planning platforms, and external supplier databases are frequently developed independently and serve different organisational purposes [18,19].

As a result, predictive models may only have access to partial representations of the operational environment, limiting their ability to support broader decision-making objectives.

3.2 Semantic Misalignment Between Predictions and Decisions

A more fundamental challenge concerns the mismatch between technical predictions and operational decisions. Predictive models typically estimate variables such as remaining useful life, anomaly scores, degradation indicators, or failure probabilities. Operational decision-makers, however, are required to make decisions regarding aircraft allocation, maintenance scheduling, resource deployment, fleet availability, network robustness, and disruption management.

For example, an engine health monitoring system may estimate that a particular component has a remaining useful life of 300 flight cycles. While technically informative, this prediction alone does not indicate whether maintenance should be advanced, deferred, combined with other work packages, or incorporated into broader fleet planning activities. Additional contextual information and decision logic are required before operational action can be taken [16,17].

3.3 Organisational Fragmentation

Airline organisations are structured around specialised functional domains, each with distinct objectives, performance indicators, and decision horizons. Maintenance organisations seek to maximise technical reliability and regulatory compliance, while network planning departments focus on schedule robustness and revenue generation. Fleet management functions seek to balance aircraft availability, operational efficiency, and maintenance demand.

The absence of mechanisms for systematically integrating predictive information across these domains limits the ability of organisations to realise system-level benefits [14,15].

3.4 Uncertainty and Trust

All predictive models operate under uncertainty arising from data limitations, modelling assumptions, changing operating conditions, and incomplete system knowledge. However, uncertainty information is frequently omitted, simplified, or inadequately communicated to decision-makers.

This creates challenges for trust and adoption, particularly in safety-critical environments where incorrect recommendations may have significant operational or safety implications. Decision-makers must therefore evaluate not only the prediction itself, but also its associated uncertainty, limitations, and reliability [20,21].

3.5 Governance and Accountability

The increasing use of data-driven technologies raises important questions regarding accountability, oversight, and decision authority. As analytical systems become more influential in operational decision-making, organisations must determine how responsibilities are allocated between human operators and automated decision-support systems. These challenges are particularly relevant in aviation, where safety, regulatory compliance, and public trust remain core requirements [20-22].

Taken together, these factors demonstrate that improving predictive accuracy alone is insufficient to achieve meaningful operational transformation. Closing the Data-to-Decision Gap requires a broader systems perspective that explicitly addresses the relationships between data, predictions, operational consequences, decisions, organisational structures, and governance mechanisms.

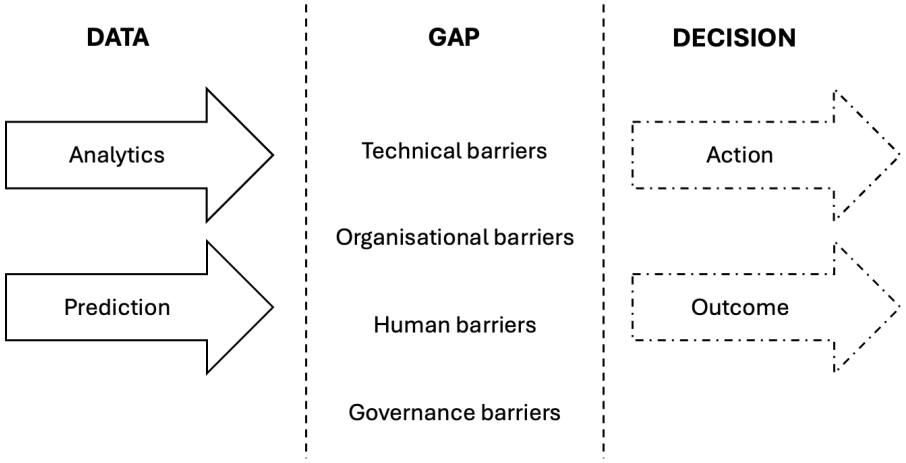


Figure 2 - Conceptual representation of the Data-to-Decision Gap.

4. A Layered Framework for Data-Driven Airline Operations and Sustainment

To address the Data-to-Decision Gap, this paper proposes a layered conceptual framework for integrating data-driven health and performance information into airline operational and sustainment decision-making [6,7]. The framework is based on the premise that predictive information does not create operational value by itself. Value is created when information about the technical state of assets is translated into operational consequences and subsequently embedded into decision processes across appropriate time horizons.

The proposed framework consists of three transformation layers: state representation, state impact, and decision-making. These layers are supported by data sources and embedded within cross-cutting governance, trust, and human oversight mechanisms. These layers are not intended to describe a specific software architecture or implementation roadmap. Rather, they provide a systems-level abstraction for understanding how data, models, operational context, and human decisions interact within airline operations.

4.1 Layer 1: State Representation

The first layer concerns the transformation of operational data into representations of the technical and operational state of the airline system. Relevant data sources include aircraft sensor data, aircraft condition monitoring messages, flight data, maintenance records, defect reports, troubleshooting histories, utilisation patterns, environmental conditions, and operational events.

At this layer, data-driven models are used to estimate quantities such as component health, deterioration rates, anomaly likelihood, remaining useful life, failure probability, and confidence in the estimated state. These estimates may be generated using statistical models, physics-based models, machine learning methods, hybrid approaches, or digital twin representations.

A key requirement of the state representation layer is that uncertainty should be treated as a first-class output rather than as an afterthought. In safety-critical operational environments, a prediction without an associated indication of confidence, validity, or applicability is of limited value. For example, two aircraft may have the same predicted remaining useful life for a given component, but the operational implications may differ significantly if one estimate is based on high-quality recent data and the other on sparse, incomplete, or noisy observations.

The state representation layer therefore needs to capture not only the predicted state of the system, but also the conditions under which the prediction is valid. This includes information about data quality, model confidence, operating regime, known limitations, and potential sources of bias or degradation in model performance.

4.2 Layer 2: State Impact

The second layer translates technical states into operational consequences. This is a critical interface that is frequently underdeveloped in current data-driven aviation applications. Predictive models often produce technically meaningful outputs, but these outputs do not automatically correspond to operational decisions.

For example, a predicted component degradation trend may be meaningful to an engineer, but its operational significance depends on its effect on dispatch reliability, maintenance demand, aircraft availability, fuel consumption, schedule robustness, customer experience, and regulatory compliance [23-24]. Similarly, an increase in failure probability may have different implications depending on whether the aircraft is assigned to a short-haul rotation, a long-haul mission, an isolated station, or a route with limited recovery options.

The state impact layer therefore converts technical predictions into decision-relevant consequences. This translation requires explicit modelling of the relationships between asset health, operational constraints, and airline performance objectives. Such relationships may include:

- the impact of component deterioration on dispatch reliability;
- the effect of aircraft condition on maintenance demand and capacity utilisation;
- the implications of technical restrictions on aircraft routing and network robustness;
- the relationship between deterioration and fuel burn or environmental performance;
- the effect of deferred maintenance actions on future maintenance workload;
- the consequences of technical uncertainty for operational resilience.

This layer is essential because airline operations involve multiple interacting objectives. An action that improves maintenance efficiency may reduce network flexibility. A decision that maximises short-term aircraft availability may increase future maintenance demand. Conversely, advancing a maintenance action may reduce technical risk but create short-term capacity pressure. These trade-offs cannot be resolved by predictive models; they require a representation of operational impact.

4.3 Layer 3: Decision-Making

The third layer embeds state-impact information into decision processes. Airline decisions occur across multiple time horizons, each with different objectives, constraints, and levels of uncertainty.

At the strategic level, decisions concern fleet planning, long-term capacity, investment in maintenance capability, digital infrastructure, and sustainability strategy. At the tactical level, decisions include maintenance planning, resource allocation, spare parts positioning, and fleet availability management. At the operational level, decisions include aircraft assignment, routing, short-term maintenance scheduling, and disruption recovery. At the real-time level, decisions are made by operational control centres in response to technical events, irregular operations, weather, crew constraints, and network disruptions [14,15].

The proposed framework emphasises that the same technical prediction may have different meanings at different decision horizons. A degradation trend identified months in advance may support maintenance capacity planning or spare parts positioning. The same trend identified days before operation may influence aircraft routing or maintenance packaging. If identified during the day of operation, it may become an operational control decision involving disruption management and risk assessment.

Therefore, data-driven airline operations require decision architectures that preserve the relationship between prediction, consequence, and action across time horizons. The objective is not to automate all decisions, but to ensure that human decision-makers receive information in a form that is aligned with their responsibilities, constraints, and operational context.

4.4 Information Flow and Feedback

The framework should not be interpreted as a simple linear pipeline from data to decision. In practice, decision-making generates feedback that influences future data, model performance, operational learning, and organisational behaviour [6,7].

For example, if a maintenance action is advanced based on a predictive recommendation, the outcome of that action should be used to evaluate the validity of the original prediction. If an operational control decision is made under uncertainty, the resulting operational consequences should be captured and used to improve future decision support. Similarly, if a model repeatedly produces recommendations that are not adopted by human users, this may indicate a problem not only with model performance, but also with explainability, usability, trust, or organisational alignment.

Feedback mechanisms are therefore necessary at multiple levels. Technical feedback supports model monitoring and improvement. Operational feedback supports evaluation of decision outcomes. Organisational feedback supports learning about adoption, accountability, and decision authority.

4.5 Role of Human Decision-Makers

The proposed framework assumes that airline operations will remain human-centred, particularly in safety-critical and operationally complex contexts. Data-driven systems should therefore be designed to support, rather than replace, accountable human decision-making.

Human decision-makers contribute contextual understanding, operational judgement, ethical reasoning, and responsibility for trade-offs that may not be fully captured in formal models. At the same time, data-driven systems can improve the timeliness, consistency, and analytical depth of decision support. The challenge is to define appropriate interfaces between human expertise and automated analysis.

This requires clarity regarding decision authority. Some decisions may be suitable for automation,

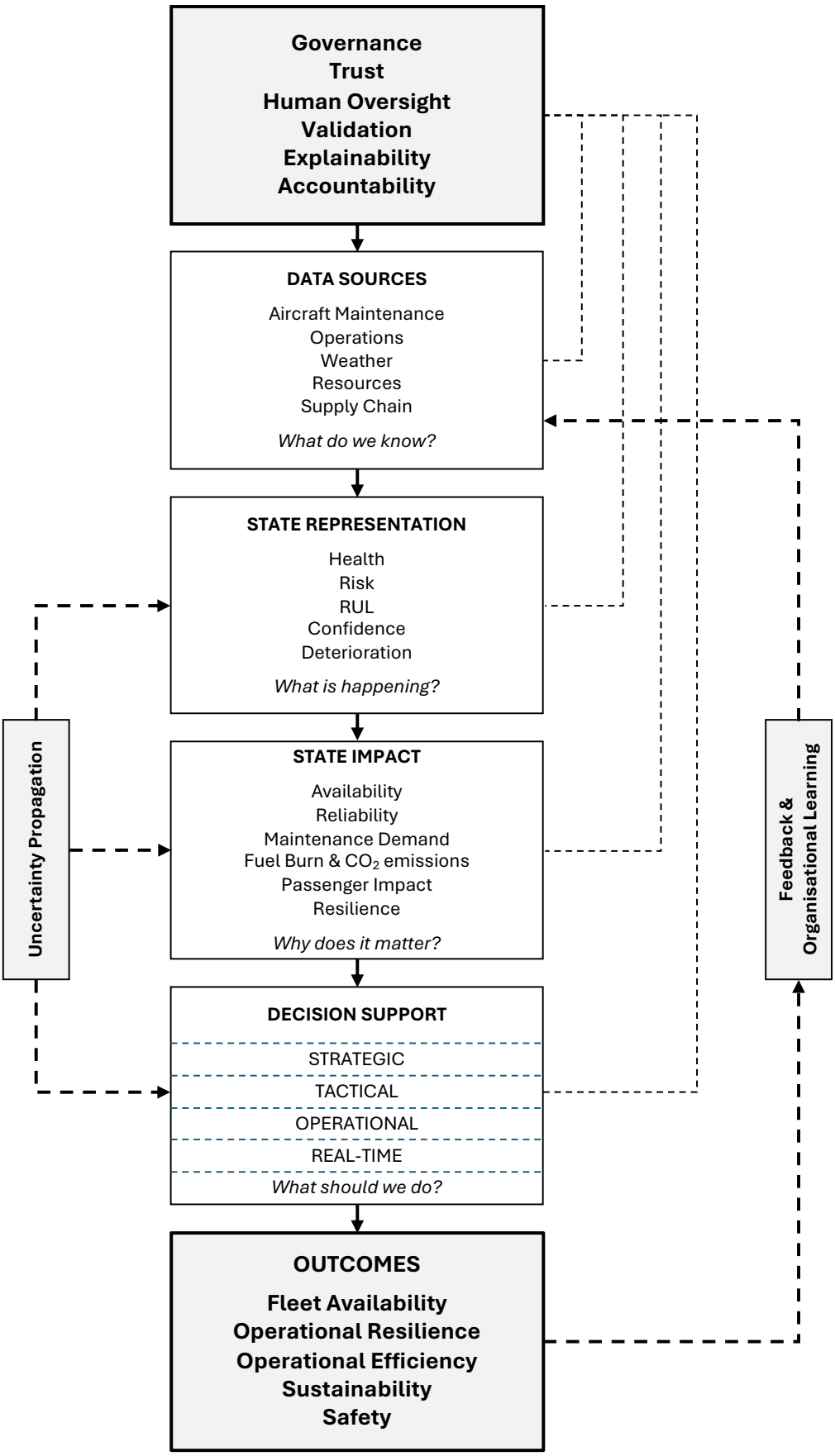


Figure 3: Technology-agnostic Data-to-Decision Transformation Framework for airline operations and sustainment.

particularly when they are repetitive, low-risk, and governed by well-defined rules. Other decisions require human approval or active supervision, especially when uncertainty is high, consequences are significant, or operational objectives conflict.

4.6 Framework Implications

The layered framework has several implications for the design of future data-driven airline systems.

First, predictive models should be developed with explicit consideration of the decisions they are intended to support. Prediction accuracy remains important, but it is not sufficient. Models should produce outputs that are interpretable, uncertainty-aware, and operationally meaningful.

Second, airlines should invest in the state impact layer as a distinct capability. This requires combining engineering knowledge, operational research, fleet management expertise, maintenance planning knowledge, and business understanding.

Third, governance mechanisms should be embedded throughout the framework. Data quality, model validity, decision authority, accountability, and human oversight should be treated as architectural requirements rather than late-stage implementation concerns.

Finally, the framework suggests that the future of data-driven aviation lies not merely in better prediction, but in better integration between prediction and decision-making. The central challenge is to move from isolated analytical tools toward coherent socio-technical decision systems.

5. Trustworthy Decision Support for Airline Operations

The increasing availability of predictive analytics, machine learning, and advanced modelling techniques has significantly improved the ability of aviation organisations to estimate future system states. However, the practical value of these capabilities depends not only on predictive accuracy but also on the degree to which decision-makers trust, understand, and appropriately utilise the resulting information.

Within the context of airline operations, decision support systems influence decisions that affect fleet availability, operational resilience, resource allocation, maintenance planning, environmental performance, and customer experience. Consequently, the effectiveness of a data-driven decision architecture cannot be evaluated solely on the basis of analytical performance. It must also be evaluated on its ability to support trustworthy operational decision-making.

5.1 From Predictive Accuracy to Decision Trustworthiness

Many data-driven aviation initiatives focus primarily on improving predictive performance. Metrics such as classification accuracy, prediction error, anomaly detection rate, or remaining useful life estimation error are frequently used to assess model quality. While such measures are important, they do not necessarily indicate whether a model contributes to improved operational decisions [17].

A technically accurate prediction may fail to generate value if it is not actionable, if it arrives too late to influence planning processes, or if decision-makers lack confidence in its validity. Conversely, a prediction with moderate uncertainty may still support effective decision-making if its limitations are properly understood and incorporated into operational planning.

The focus of data-driven airline operations should therefore extend beyond predictive performance towards what may be described as decision trustworthiness. Decision trustworthiness refers to the extent to which analytical outputs are sufficiently transparent, contextualised, reliable and actionable.

Within the proposed framework, decision trustworthiness emerges from the interaction of five complementary dimensions: uncertainty representation, explainability, human oversight, accountability, and continuous validation.

5.2 Uncertainty Representation

All predictions are subject to uncertainty. In operational environments characterised by high complexity and changing conditions, uncertainty is unavoidable and should be explicitly represented rather than concealed.

Two broad categories of uncertainty are particularly relevant within airline operations. Epistemic uncertainty arises from incomplete knowledge, limited data availability, model limitations, or previously unseen operating conditions. Aleatory uncertainty arises from inherent variability within the system and its operating environment, including weather conditions, operational disruptions, utilisation patterns, and stochastic failure behaviour.

The operational significance of uncertainty can be illustrated through a fleet assignment example. Consider an aircraft for which a predictive model estimates an elevated probability of an engine-related maintenance event within the next one hundred flight cycles. If the associated uncertainty is low, fleet planners may confidently adjust aircraft utilisation or maintenance scheduling. If uncertainty is high, the same prediction may require additional monitoring, engineering assessment, or operational contingency planning. In both cases, uncertainty directly influences the appropriate operational response [25].

The proposed framework therefore treats uncertainty as an integral component of state representation and impact assessment rather than as a secondary attribute of the prediction itself [20,21].

5.3 Explainability, Human Oversight and Governance

Trustworthy decision support requires more than accurate predictions. Recommendations must be understandable, actionable, and aligned with organisational responsibilities. Airline decisions frequently involve coordination between engineering, maintenance planning, fleet management, network planning, and operational control functions. Consequently, decision-makers require sufficient information to understand why a recommendation has been generated and how it relates to operational objectives.

Human oversight remains essential, particularly when decisions involve uncertainty, conflicting objectives, or potentially significant operational consequences. Data-driven systems should therefore augment rather than replace accountable human decision-making [26-28].

Governance provides the organisational foundation for trustworthy adoption. Clear responsibilities must be established for model development, validation, operational use, and performance monitoring. As operational conditions evolve, continuous monitoring is required to ensure that analytical outputs remain valid and relevant [20,21].

Ultimately, the objective of data-driven methods is not prediction itself, but the support of trustworthy operational decisions capable of balancing fleet availability, resilience, efficiency, sustainability, and safety.

6. Organisational Integration and Decision Readiness

The successful implementation of data-driven airline operations depends not only on technical capabilities, but also on the ability of organisations to effectively incorporate analytical outputs into operational decision-making processes. While significant attention has been devoted to predictive modelling, comparatively less attention has been paid to the organisational conditions required for those predictions to generate operational value [6,7].

The proposed framework therefore introduces the concept of Decision Readiness.

Decision Readiness describes the extent to which analytical outputs are sufficiently contextualised,

trusted, governed, and integrated into organisational processes to support operational decision-making. A technically valid prediction does not automatically become decision-relevant information. Additional organisational capabilities are required to translate analytical outputs into actions that improve operational outcomes.

Within this context, Decision Readiness may be viewed as a socio-technical capability emerging from the interaction between technology, processes, governance, and human actors.

Table 1 - From prediction-centric analytics to decision-ready operational support in airline operations and sustainment.

Dimension	Prediction-Centric Approach	Decision-Ready Approach
Objective	Estimate future state	Support operational decisions
Primary Output	RUL, probability, anomaly score	Actionable recommendation
Primary User	Analyst / Data Scientist	Decision-maker / Operations
Validation	Prediction accuracy	Decision effectiveness & outcomes
Context	Technical	Operational
Uncertainty	Often implicit	Explicitly represented
Governance	Model-focused	System-focused
Success Metric	Prediction quality	Operational value

6.1 Beyond Technical Readiness

Many data-driven initiatives focus primarily on technical readiness. Common objectives include improving prediction accuracy, increasing data quality, expanding analytical coverage, and deploying new computational capabilities.

While these objectives are important, they represent only part of the overall challenge. A predictive model may achieve excellent technical performance while having little influence on operational decisions. This can occur when decision-makers do not trust the outputs, when organisational responsibilities are unclear, when recommendations arrive outside relevant planning cycles, or when the information provided does not align with operational needs.

Consequently, technical readiness should be regarded as a necessary but insufficient condition for successful data-driven operations.

6.2 Dimensions of Decision Readiness

The proposed framework identifies five dimensions that contribute to Decision Readiness.

Analytical Readiness

Analytical readiness concerns the validity, reliability, and robustness of the underlying analytical capabilities. Models must demonstrate acceptable levels of performance, stability, and applicability within the operational environment in which they are deployed.

Operational Readiness

Operational readiness concerns the extent to which analytical outputs are aligned with decision processes. Information must be delivered at the appropriate planning horizon, presented in a usable form, and linked to operational objectives and constraints.

Organisational Readiness

Organisational readiness concerns ownership, responsibilities, governance structures, and cross-functional collaboration. Decision support systems frequently operate across organisational boundaries involving engineering, maintenance, operations, network planning, and management functions. Effective coordination between these groups is therefore essential.

Human Readiness

Human readiness concerns user understanding, trust, skills, and willingness to adopt analytical recommendations. The effectiveness of a decision-support system ultimately depends on the individuals responsible for interpreting and acting upon the information provided.

Governance Readiness

Governance readiness concerns accountability, monitoring, validation procedures, regulatory compliance, and mechanisms for managing risk. Governance structures provide the institutional foundation necessary for sustained adoption of data-driven decision-making.

6.3 Cross-Functional Integration

Airline operations involve multiple interconnected decision domains operating across different time horizons [14,15]. Engineering organisations focus on asset health and technical risk. Maintenance planning organisations focus on workscoping, resource allocation, and maintenance capacity. Fleet management organisations focus on aircraft availability and utilisation. Operational control centres focus on real-time operational continuity and disruption management.

The value of predictive information frequently emerges only when these domains are considered together.

For example, a deterioration trend identified through aircraft health monitoring may initially appear as a technical issue. However, its broader implications may include future maintenance demand, fleet availability constraints, spare parts requirements, operational disruption risk, and customer service impacts. Effective decision-making therefore requires integration across multiple organisational functions rather than optimisation within individual silos.

The proposed framework consequently views organisational integration as a fundamental architectural requirement rather than a secondary implementation consideration.

Information / Prediction	Strategic (Years)	Tactical (Months)	Operational (Days/Week	Real-Time (Hours)
Health State	Fleet planning Asset Strategy	Maintenance planning	Aircraft assignment	Dispatch support
Failure Risk	Investment decisions	Workscoping	Routing decisions	Recovery actions
Maintenance Demand	Capability planning	Resource allocation	Schedule adjustments	Immediate support
Availability Impact	Capacity strategy	Fleet allocation	Operational robustness	OCC intervention
Resilience Impact	Network design	Contingency planning	Recovery preparation	Disruption management
The same predictive information support ndamentally fferent decisions, depending on the time horizon and operational context.				

Figure 4 – Decision horizons and information requirements in airline operations.

6.4 Decision Horizons and Information Requirements

Different organisational functions operate on different decision horizons and require different forms of information. Strategic decision-makers focus on long-term investment, fleet planning, and capability development. Tactical decision-makers focus on maintenance planning, resource allocation, and schedule robustness. Operational decision-makers focus on aircraft assignment, maintenance execution, and short-term disruption management. Real-time decision-makers focus on immediate operational continuity.

A key challenge for data-driven airline operations is ensuring that analytical outputs are translated into forms appropriate for each decision horizon.

The same underlying prediction may therefore support different decisions depending on when it is generated and who receives it. A degradation trend identified six months in advance may influence maintenance capacity planning. The same information identified several days before operation may influence aircraft routing decisions. During active operations it may influence disruption recovery strategies.

Decision Readiness therefore requires alignment between analytical outputs and decision horizons [1,14].

6.5 Organisational Learning and Decision Readiness

Decision Readiness should not be viewed as a static organisational capability. Operational environments evolve continuously due to changes in fleet composition, operating practices, regulations, and business priorities. Consequently, organisations require mechanisms that support continuous learning from both analytical outputs and operational outcomes.

The proposed framework suggests that Decision Readiness emerges from the combined effectiveness of analytical capabilities, organisational integration, governance structures, and human expertise. Improvements in predictive accuracy alone are unlikely to realise the full value of data-driven operations unless accompanied by corresponding improvements in decision processes and organisational alignment.

From this perspective, Decision Readiness complements the concept of the Data-to-Decision Gap. While the Data-to-Decision Gap describes the disconnect between predictive capabilities and operational decisions, Decision Readiness describes the organisational capability required to bridge that disconnect [6,7].

7. Research Challenges and Future Directions

The framework proposed in this paper is intended as a conceptual foundation for future research into data-driven airline operations and sustainment. While significant progress has been achieved in predictive analytics, prognostics, digital technologies, and operational optimisation, substantial challenges remain before the full potential of data-driven decision-making can be realised [29].

The following research directions are considered particularly important.

7.1 From Prediction-Centric to Decision-Centric Systems

Much of the existing literature focuses on improving predictive performance. Research efforts frequently target improvements in anomaly detection, remaining useful life estimation, fault diagnosis, or forecasting accuracy. While these developments remain important, future research should increasingly focus on how predictive information contributes to decision quality [17].

This shift requires the development of methodologies capable of evaluating the operational value of analytical outputs rather than solely their statistical performance. Future studies should investigate how predictive information influences operational outcomes such as fleet availability, schedule robustness, maintenance efficiency, sustainability performance, and resilience to disruption.

7.2 Integrated Operational Decision Architectures

Current airline decision-support systems are often developed within individual organisational domains. Maintenance planning, fleet management, network planning, operations control, and resource allocation frequently rely on separate analytical environments and optimisation processes.

Future research should explore integrated decision architectures capable of supporting system-level

optimisation across organisational boundaries [14,15]. Such approaches would enable predictive information to be evaluated in the context of broader operational objectives and competing constraints. Particular attention should be given to mechanisms for balancing local and global optimisation objectives within complex airline systems.

7.3 Uncertainty-Aware Decision Support

Although uncertainty is widely recognised within predictive modelling, it remains insufficiently integrated into operational decision-making processes.

Future research should investigate methods for propagating uncertainty across the entire Data-to-Decision Transformation process. This includes uncertainty associated with data quality, model validity, operational assumptions, environmental conditions, and organisational factors.

The objective should not be the elimination of uncertainty, but rather the development of decision-support mechanisms capable of operating effectively under uncertain conditions [20,21].

7.4 Human-AI Collaboration in Airline Operations

As analytical systems become increasingly sophisticated, the relationship between human decision-makers and automated decision-support systems will become progressively more important.

Future research should examine how responsibilities are allocated between human operators and analytical systems across different decision horizons. Questions concerning trust, explainability, cognitive workload, authority management, and decision accountability remain only partially understood within airline operational environments.

Particular attention should be given to understanding how human expertise and analytical capabilities can be combined to achieve superior operational outcomes compared with either approach in isolation [26-28].

8. Conclusions

The aviation industry is undergoing a significant transformation driven by increasing data availability, advances in analytical capabilities, and growing operational complexity. Considerable progress has been achieved in fields such as condition-based maintenance, prognostics and health management, fleet analytics, and digital technologies. However, the operational value generated by these capabilities remains constrained by the limited integration of predictive information into broader airline decision-making processes.

This paper introduced the concept of the Data-to-Decision Gap to describe the disconnect between predictive capabilities and operational decision-making within airline operations and sustainment. The paper argued that improvements in predictive accuracy alone are insufficient to realise the full potential of data-driven aviation. Instead, attention must increasingly focus on the mechanisms through which predictive information is transformed into decision-relevant knowledge.

To address this challenge, a technology-agnostic Data-to-Decision Transformation Framework was proposed. The framework conceptualises data-driven airline operations as a layered decision architecture comprising data sources, state representation, state impact, decision support, and governance. By explicitly defining the interfaces between these domains, the framework seeks to support more effective integration between analytical capabilities and operational decision processes.

The paper further introduced the concept of Decision Readiness, describing the organisational capability required to translate analytical outputs into actionable decisions. Decision Readiness emphasises the importance of organisational integration, governance, human factors, and operational alignment in addition to technical performance.

A central theme throughout the paper is that airline operations should be viewed as a multi-objective socio-technical system in which decisions simultaneously affect fleet availability, operational resilience, operational efficiency, sustainability performance, and safety in different time horizons. Consequently, future data-driven decision systems should be evaluated not only according to predictive performance, but also according to their contribution to operational outcomes.

The proposed framework does not advocate any specific analytical methodology, artificial intelligence technique, or digital technology. Rather, it provides a conceptual foundation for understanding how operational data can be transformed into trustworthy decision support within complex airline environments. Nevertheless, future work will evaluate the framework through (airline) case studies and decision-support applications

Future research should increasingly focus on decision-centric approaches that integrate predictive analytics, uncertainty management, organisational learning, governance, and human oversight. Such efforts will be essential for enabling the next generation of data-driven airline operations and sustainment systems.

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