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A STRUCTURED FRAMEWORK FOR ARTIFICIAL INTELLIGENCE ADOPTION IN THE AIRLINE INDUSTRY: AN INTERPRETIVE STRUCTURAL MODELING APPROACH

Faisal H. Aljahdaly
Master's Degree Student, Department of Industrial Engineering, King Abdulaziz University, Jeddah, Saudi Arabia
f.h.aljahdaly@gmail.com

Prof. Mohammed Balubaid
Professor, Department of Industrial Engineering, King Abdulaziz University, Jeddah, Saudi Arabia
mbalubaid@kau.edu.sa

ABSTRACT
The airline industry is poised to undergo a digital revolution powered by Artificial Intelligence (AI). However, due to the complexity of adopting AI, considerable and significant obstacles exist in enabling its adoption in Airlines. This research considers the enablers of AI adoption in the airline industry to determine and construct the significant enablers of AI adoption and to utilize Interpretive Structural Modeling (ISM) to identify interdependencies and levels of structural complexity of the dimensions of enabling AI adoption into the industry. Based on an extensive literature review combined with expert opinion, it was identified there are twelve significant enablers including: Top Management Support, Technological Infrastructure, Data Availability and quality, and Trust in AI systems and Explainability. Utilizing ISM methodology, these twelve enablers were structured into eight levels, resulting in a structural model, and identifying the base level drivers and levels of dependence on assessment outcomes. From the ISM model, Top Management Support and Technological Infrastructure Readiness were identified as the base level drivers. The top two dependent structural elements of them overall model were Government and Regulatory Support, and Customer-Centric Innovation Culture. The research indicated there are systematic discretionary actions exist which are dependent on Leadership commitment, data systems readiness, available of data, and inter departmental team collaboration to enable the successful adoption AI into their operations. As a result of the research, it was recommended research participants consider some of the practical operational AI applications based on enablers within their own context. Some of the recommended application include; predictive maintenance, dynamic pricing and selling, AI customer service support, and customer sentiment analysis. Further, because of the investigation is practiced based, it is anticipated applications will lead to improved operational efficiency and customer experience. Furthermore, the findings will offer strategic insight into decision making for airline managers concerned with the adoption of AI applications in their operations, and offers a structured framework for the adoption of AI applications within an Airline context that is characterized as complex process with high regulation. Finally, future research is recommended in order to validate the proposed model of enablers for AI adoption across multiple airline contexts and determine the actual outcomes of implementation in the real world.

Keywords:
Artificial Intelligence; Airline Industry; ISM; Adoption; Strategic Framework; Digital Transformation.

1. INTRODUCTION

Artificial Intelligence (AI) has become a transformative disrupter of industries, increasing productivity, intelligence, and engagement across sectors. Industries such as finance, healthcare, logistics, and education are using AI technologies to automate daily tasks, predict trends, and customize services and products, thereby changing the way organizations conduct business and compete in an increasingly digital world (Tjebane et al., 2022; Fang, 2024). The airline industry is an attractive opportunity for AI adoption because of its inherent complexity and dependency on data. Airlines produce huge amounts of data daily related to flight schedules,

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aircraft maintenance, customer preferences, weather forecasts, etc. Possible applications for AI in the airline industry include predictive maintenance, dynamic pricing, automated customer service, in-flight optimization, and more (Kabashkin & Perekrestov, 2025; Edwin Lisowski, 2025). However, the potential for transformative use of AI in the airline industry is not being realized in practice with a limited number of organizations immediately seeking advancement via practical applications (Geske et al., 2024a). There is currently no standard framework for systematically adopting, assessing, and optimizing AI across organizations in the airline industry.
The airline industry is one of the most operationally complex and globally interconnected industries in the world, and constantly faces the pressures of safety, cost, responsiveness, environmental sustainability, and customer satisfaction. It operates within highly regulated environments and requires coordination with numerous stakeholders including authorities, regulatory bodies, suppliers, and service providers. In addition, the industry's vulnerability to external shocks (i.e. geopolitical matters, pandemics, and a declining economy) has created a sense of urgency for actionable, data-driven decision-making tools which can significantly impact the methods airlines may operate in the future. The towering competition between airlines highlights a race for operational flexibility and customer experience acceleration versus competitive pricing in the market, which makes it imperative for airline businesses to adopt robust data analytics capabilities, and pursue digital transformation initiatives. For airlines, incorporating AI not only represents a technological opportunity; it represents a clear competitive strategy for sustainable operational transformation and long-term competitiveness (Vikram Sai Prasad Karnam, 2025; Sadou & Njoya, 2023).
One of the key factors contributing to the slow and inconsistent pace of AI adoption in the airline industry is the lack of a defined AI operating model which responds to the specific operational complexities of the airline industry. Furthermore, most airline companies face several technological, organizational, and environmental obstacles that they need to deal with in order to actually successfully integrate AI solutions as a mainstay in their approach of operating. These obstacles will inevitably lead to incomplete and uneven AI solutions which underperform and fail to deliver any business value. For example, with no plan to fit into the airline's overall operational strategy, AI solutions can, for example, be implemented as one-off solutions and be unable to scale across operations or provide interoperability with legacy systems (Hercheui & Mech, 2021; Fang, 2024) which would result in misalignment or ineffective AI implementation solutions and offering less-than-ideal unit economics subsequently impacting potential ROI. Likewise, the airline's limited understanding of how AI fits into their overall strategies or how it creates futures-adaptive value in the end-to-end customer journey, compound these challenges and inhibits the airline's practical understanding of how AI can displace predecessor strategic instinct.
This research sought to apprehend and analyze the phenomenon of AI adoption in the airline industry. One of the ways to approach this was to apply Interpretive Structural Modeling (ISM) as the basis of analysis in exploring AI adoption. ISM is a qualitative modeling approach that maps out and structures the complexity of the relationships between decision-making factors. By using ISM as a basis for analysis, this research created a hierarchical framework of the drivers and enablers of AI adoption for airlines to model a more sustainable and more strategic format. The hierarchical framework will provide to the airlines industry the opportunity to see the angles of AI adoption that may provoke a pattern of organization and interrelated focus between the aspects of AI and embedding the AI-adoption process which can be further tied to industry and market forces.

2. OBJECTIVES

This research explored the strategic role of the AI in the airline industry by identifying critical adoption factors, analyzing their interrelationships, and proposing a structured framework to support effective implementation. The objectives of this research are:

- To identify the key enablers influencing AI adoption in the airline industry.
- To develop a hierarchical model of AI adoption factors using ISM.
- To provide recommendations for enhancing the operations and customer experience through AI driven solutions.

3. LITERATURE REVIEW

3.1 Artificial Intelligence Adoption in Business

(Tjebane et al., 2022) examined the factors and strategies for the adoption of the AI in the construction industry based on studies with publication dates from 2010-2020. Their review reported several obstacles, with the largest being the high implementation costs and the costs of hiring people to manage the AI processes, and a

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lack of skilled people. Meanwhile, they noted there were strategies that may enhance AI adoption, included training and skills development of industry workers, collaboration between academia and the industry via research and development projects, and government strategies to help the industry with supportive policies. They concluded that if the barriers were more systematically addressed and the strategies were better utilized, it could lead to AI adoption in the construction industry, and therefore productivity and infrastructure development could be increased.

(Kumari et al., 2024) provided a policy framework to support the AI uptake in financial services using the ISM. The study identified nine enabling factors of involved in AI uptake including anticipated profitability, credit risk, contactless solutions, software vendor support and top management commitment. The ISM clarified that the availability of structured data, appropriate technical and financial resources which are enablers that support the successful AI adoption. Furthermore, the authors identified the importance of strategic partnerships with technology and software vendors and the importance of proactive government support in the shape of appropriate policy. As a final observation, recommendations were made to address and inform the identified enablers throughout the literature to further advance AI-centric digital transformation, efficiency gains, technology facilitated fraud reduction, operational risk management, and provide of better customer service leading to profitability in the financial services industry.

(Ahmad Khan et al., 2024) conducted an empirical study of the AI use in Human Resource Management (HRM). Using a mixed the TOE and Technology Acceptance Model (TAM) approaches to assess 329 HR professionals in various sectors in India and sought to identify factors that drive HR professionals' intentions to adopt AI. The main finding was that perceived ease of use increases perceived usefulness which in turn is a significant contributor to intention to adopt AI. Within the three dimensions of technology, organization and environment, (relative advantage as a contributor to the technology dimension), and HR readiness (an organizational contributor), were shown to be two of the most significant enablers of AI adoption. Important facilitator variables, as noted by the authors, were top management support, vendor support, and competitive pressure. Overall, the study provided a broad theoretical model, and empirical evidence on some of the factors influencing the adoption of AI within HRM. The study highlighted the need for holistic strategies in technology adoption, which bring together technology compatibility, management buy-in and endorsement, resource readiness and external support systems.

While the studies reviewed in previous section provide some strong foundational support to understand the adoption of AI in different industries, these studies largely explore generic frameworks, technological barriers, and organizational readiness. This is useful to a certain extent, but most of these studies lack industry-specific relevance as they have little consideration for industries with unique operational, regulatory, and logistical challenges in their contexts. In this regard, the fluidity of the airline industry, in terms of an operational context with many ecosystems, highly regulated operational aspects, and huge data, is unique as it relates to AI integration. Consequently, it is important to assess the use of AI within an airline industry, which is explored in the next section.

3.2 Artificial Intelligence in Airline Industry

(Halawi et al., 2024) utilized the Technology Acceptance Model (TAM) to assess how trust is a component of the AI adoption in the U.S. commercial aviation industry. Results found that perceived ease of use and usefulness were significantly related to attitudes toward AI and those attitudes then informed users' intentions to adopt AI. In a bit of a paradox, respondents would view higher perceived usefulness as a basis for lower trust when deciding whether or not to adopt AI. The authors remarked on the complexity of trust in AI and recommended broadening the framework on trustworthy AI to address trust through transparency, explainability, and fairness. They highlighted the importance of trust development for adoption in aviation and suggest incorporating more research into trust models from a user perspective.

(Geske et al., 2024a) examined the efficiency impact on air passenger transport from the AI. They synthesized findings from 62 studies published in the academic literature, investigating the impacts on efficiency across the entire airline business model. The AI Airline Efficiency Model (AAEM) developed contains components of AI such as, Machine Learning, Deep Learning, Reinforcement Learning, and Natural Language Processing, and is aligned to the main airline functions (Flight Operations, Ground Operations, Planning, Finance, Sales and Marketing, and Customer Service). The study identified four functional areas where AI has demonstrated efficiency gains, the improvements powered by AI are primarily in predictive analytics, resource optimization, safety and Autonomous processes, and lastly passenger experience. While Machine Learning led the current application of AI in aviation, based on the synthesis of studies, a limitation was the lack of cross-functional

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applications internally across departments or inter organizational. The authors succinctly identify major gaps in research, particularly in three areas, explainability, the AI to real-world adoption gap, and lastly, no research on AI as a cross functional for airlines. Given the nature of the exploratory, systematic approach, the authors provide future research direction.

(Geske et al., 2024b) examined how AI can support collaborative decision-making (CDM) for disruption management for airlines. They suggested a framework where AI supports CDM by enabling data-led CDM, real-time coordination, and re-positioning the disruption response as performance-oriented. They contended that artificial intelligence offers improved decision-making speed and resilience due to its pattern recognition and predictive capabilities in complex data streams. Automated decision-making (ADM) has been applied through frameworks in a distributed and reactive manner for many years in aviation. Implementing AI will allow for proactive, real-time, and cost-effective outcomes to reduce operational costs and impacts on availability. This study offers a theoretical perspective and practical application of AI-supported ADM in decision-making within contextual, complex data streams particularly during scheduled flight disruptions.

(Narendran et al., 2024) studied the utilization of AI techniques in the aviation sector for inventory management. They focused on spare parts that are used for full flight simulators. The study found that incorporating multi-criterion in the enhancement of the traditional VED classification, such as lead time, demand fluctuation and safety stock. The research was executed with AI techniques in supervised learning (SVM, KNN), unsupervised learning (K-means, DBSCAN). However, deep learning (ANN, CNN, and RNN) were utilized to classify the spare parts, a data set of over 10,000. The research found SVM was the most accurate (90.01%) in classifying spare parts and accuracy quickly followed by the other deep learning models. The unsupervised models were perceived the least efficiency. The outcomes demonstrated AI can improve inventory management, forecasting demand, and efficiency of costs significantly. The research indicates a greater utilization of AI could be applied to aviation logistics in maintaining operational reliability and reducing down-time ultimately.

3.3 Closing Paragraph and Research Gap

The literature indicates AI adoption is on the rise in business; however, the strategic adoption of AI in the airline industry appears insufficiently coordinated and fragmented, emphasizing the lack of strategic frameworks or structures, and adoption is case based. Most aviation research studies simply report on technological or case experience such as maintenance or scheduling, without providing a point of view by structured steps for adoption and implementation. This clearly indicates the need for a comprehensive strategy model for AI adoption in the airline industry. This research provided a starting point by utilizing the ISM to create a structured plan for the holistic adoption of AI addressing the technological, organizational, and environmental dimensions of AI adoption in the airline industry.

3.4 Research Question

How might airline companies structure a strategic framework for the adoption of AI to improve customer experience and operational efficiency?

4. METHODOLOGY

This research used a qualitative approach to the use of ISM to analyze the key success factors for the implementation of AI and to prioritize these factors.

4.1 Unit of Analysis and Research Community

4.1.1 Surveys and Questionnaires

Open-ended surveys and questionnaires were designed to capture a wide array of responses from industry employees. These were administered electronically through many different people such as AI specialists, IT managers, and other decision makers in organizations where AI strategies were implemented.

4.1.2 Interviews and Observations

Semi-structured interviews were conducted with the selected stakeholders to go deeper into some aspects of AI adoption. The interviews offered an opportunity to engage in dialogue with participants to consider their experiences, motivations, and perceptions about AI in relation to the data collected through the questionnaires.

4.1.3 Market Research

This research has employed qualitative methodologies to collect secondary data including an extensive review of literature, industry reports, and case studies regarding AI adoption in the airline industry.

4.2 Tools and Techniques Used to Analyze the Data

The data collected for this research were analyzed using an ISM technique in helping clarify the existing relationships among factors among factors.

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4.2.1 Interpretive Structural Modeling (ISM)

ISM is a methodology that formalizes the complex, vague system models into visible, well-defined models. The purpose of using ISM is to identify the relationships among specific factors, which define a problem or an issue, while also providing a mechanism that imposes order and direction to the complexity of the items in relationships.

5. RESULTS AND DISCUSSION

5.1 Key Success Factors

After a thorough review, twelve critical success factors were identified, to which this research provides a discussion of each, including a definition and real-world application examples from leading airlines:

5.1.1 Top Management Support

Top management support is essentially a basic enabler of AI adoption because of the complexity of aviation and the challenges it imposes on the full implementation of the TOE model. Top management falls under the organizational context of the TOE framework, which includes the role of leadership in introducing and facilitating change with the introduction of technologies. Leaders have the primary power to develop strategy, allocate resources for their departments, and adopt levels of risk tolerance surrounding the potential adoption of riskier AI initiatives. For example, Singapore Airlines and British Airways demonstrated to the public their commitment to digital transformation and AI-powered operations under strong leadership support. British Airways, for example, spent £100 million on a launch of a specific program that contained AI-enhanced tools to improve on-time performance and focus on operational resilience. While the presence of leaders can clearly lead change and support a significant investment in an AI operation, it is common that governance arrangements will inhibit and distort the three-dimensional approach to strategy (technology, organization and environment) and lead to a lack of engagement and support, resulting in misalignment and underfunding of AI initiatives, and siloing of work. Strong top management sponsorship enables organizations to treat AI, as a strategic initiative, rather than a project to be funded by the IT department. Strong support ensures that AI appears within the business's operational goals.

5.1.2 Data Availability and Quality

The value of AI relies heavily on large data sets of structured, reliable (real-time) data and high data quality. The airlines must extract useful data from several distinct sources of data that include maintenance records, customer-passenger behaviors, crew allocations and schedules, and weather information. Under the technological context of the TOE framework, availability of data provides the potential for AI applications and in addition, the feasibility of hardware and software performance, and validity/reliability of data sources working in tandem to predict "X" (i.e. predictive maintenance, dynamic pricing and similar applications). Airline companies, such as Delta Airlines and Lufthansa, have invested heavily in having integrated data warehouses and designed enterprise-ready platforms for machine learning to support and maximize AI. A lot of airline companies are still constrained with on-premise (legacy) systems and siloed data that limits the possibilities. Good data with quality, consistency and ease of use are important characteristics that is connected to how models perform and the related decisions that are made at various strategic levels, this enabler is fundamental.

5.1.3 Skilled Workforce and Training Programs

A skilled and AI literate workforce is important for the implementation of AI and the continuation of its use. This enabler is in the organizational context in the TOE framework. AI implementation requires knowledge and skills from multiple domains to work together toward success, i.e., data scientists, IT, operational managers and, importantly, those using the model and information at the on-site level. Carriers like Qatar Airways, who train and reskill their employees (the Digital Academy initiative) are better able to benefit from AI. The shortage of candidate talent is a known barrier to AI maturity. Continued learning allows for companies to create a culture of innovation and adaptability which is important to create sustained value from AI investment.

5.1.4 Technological Infrastructure Readiness

The technical infrastructure to support implementations, such as services including cloud computing, edge devices, APIs, and security, is in many cases an objective measure of scalability and reliability for AI systems. The TOE framework categorizes this enabler within the technical context. AI models can only 'talk' to legacy systems or provide valuable real-time data if the technical infrastructure is enough. Airlines such as KLM is adopting digital and AI as a service platform to limit the indirect costs of technical infrastructure while allowing

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them to take advantage of innovations that arise. Technical readiness means security, the flexibility of integration, and latency management. All are important to aviation, especially when life critical decisions are involved and often real-time decisions inform safety and revenue.

5.1.5 Strategic Alignment with Business Goals

AI should connect to strategic objectives, for example, improving operational efficiency, reducing costs, safety or the personalization of the customer experience. This enabler relates to the organizational and strategic context. Airlines like JetBlue and Emirates have connected their investments in AI to measurable KPIs, e.g., JetBlue's generative AI chatbot, according to colleague Evan, saved over 73,000 hours saving customer service time. Some level of alignment ensures AI projects are driven by value, not simply hype, resulting in business units more willing to take part and invest time into AI initiatives. When units do not align strategically, there is a risk of wasting resources or not onboarding pilots with an intent to scale.

5.1.6 Vendor and External Expert Support

Vendor assistance describes the help provided by external technology vendors; consulting firms or implementation partners that help meet customer requirements during technology adoption. The environmental context of the TOE framework makes vendor assistance an important enabler, specifically when the resources or capabilities are limited internally. There are technology vendors that sell specialized tools, provide expert technical advice, and have deployment experience that helps the airline shorten time to value. AirAsia has successfully engaged third-party AI solution vendors to establish dynamic pricing engines and predictive analytics. Leveraging an effective vendor relationship assures the vendor can service its support functions and give options to integration and future maintenance. Without vendor support to execute and operationalize AI technology, many airlines, particularly in emerging markets, will find it difficult to move forward with their AI technology strategies.

5.1.7 Cross-Departmental Collaboration

The role of cross-functional support is important when implementing AI in an airline. IT, operations, customer service, maintenance and marketing, may involve collaborative initiatives from the first AI project to implementation. Cross-functional support ensures AI systems are holistically integrated within the workflows, rather than a function silo of the business. In airlines built for working cross-functionally and collaborating as an organization, the exchange of data synergies avoids conflicting goals with the various departments. For example, Lufthansa Group put cross-functional AI task forces in place, which assist with organization-wide digital alignment. Without such cooperation, AI projects are very susceptible to duplication, miscommunication, and underperformance based on data flow and KPI consistency.

5.1.8 Government and Regulatory Support

AI development in aviation is influenced by regulators like the ICAO, EASA, or local authorities. In other words, when legislation is not too rigid, does have some room for guidance and incentives, and where airlines are able to experiment with emerging tech, there is absolutely no waste or inefficiency. In the environmental layer of the TOE model, regulatory support acts to create a space in which data is used, along with innovation, and public-private partnerships and alliances have room to be created. For instance, the EU's Horizon Europe program has funded some AI research related to air traffic and predictive maintenance systems. On the other side of the spectrum is when legislation is vague or too prescriptive, and ultimately prevents new developments from going forward. If a high-level, government led initiative exists to support AI development, these can promote experimentation that mitigates risk should help enable modernization across many organizations.

5.1.9 Customer-Centric Innovation Culture

Organizational culture and commitment to innovation and the customer experience are key enablers of AI transformation preparations. Reference to the second layer in the TOE framework, this enabler relates to the ability of the organizational culture to create experimentation and openness to transformation within the flight and spatial sciences where a user-centered design approach can take root. Examples of this are with airlines like Emirates or Delta where AI has been used by both to assist in personalization of passenger's services, process improvements for check-in services, and greater personalization within loyalty programs. Organizations that reward innovation and ideation from data-driven decisions can empower their teams to test and scale AI. While conservative cultures tend to resist digital change, AI projects are not timely and data-driven, leading to either a slowed effect or little to no impact.

5.1.10 Availability of Use Cases and Pilot Projects

Having positive, tried, and tested use cases is a great way to build internal confidence and validate the level of organizational investment. This is an enabler referring to a specific situation under both the technological and

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the organization layer of the TOE model during a project's definition phase rather than a predictive or prescriptive one. This enables pilots to be used by the organization as case studies and practical roadmap for AI adoption. For example, if airlines such as JetBlue saved tens of thousands of hours and operational efficiency from an AI-powered chatbot pilot project, or if and how an airline like Qantas is benefiting from AI in terms of successful fuel efficiency. Pilot projects also allow teams to validate ROI, review and learning to streamline processes prior to mass roll-out. Often pilot projects and reference projects are unavailable or nonexistent and leads to either indecision paralysis or cynicism.

5.1.11 Organizational Readiness and Change Management

Readiness to change is both technology-related but also includes the humans who are likely to adapt AI. Under the organizational context, this enabler refers to redesign of operational workflows, reskilling of personnel, review performance .and act on these metrics. Whenever airlines take the time to manage the change process proactively through training, engagement, and gaining the support of leadership, success rate is probably higher. For example, Singapore Airlines appeared to have put a lot of time and consideration into its Digital Innovation Blueprint, and through the careful planning would now focus on a structured change program.

5.1.12 Trust in AI Systems and Explainability

Trust is critical to AI acceptance and user uptake, and especially true for highly regulated environments like aviation. This enabler is specifically related to the user in the technological layer of the TOE framework and is specifically related to trusting the AI process with regards to transparent algorithms and explainable AI outputs, and training users to engage with AI outputs appropriately and mindfully. Many studies demonstrate, if any AI tool is performing extremely reliably, accurately, and at scale, it will still be rejected if the user does not trust, understand or know the output. For airlines that are using AI for activities related to crew scheduling, and equipment diagnostics, it becomes imperative for the context and process of the output to be interpretable and auditable. Rejection of AI systems, regardless of performance, if trust in the AI system is lost, the technology will not be accepted or sustained.

5.2 Interpretive Structural Modeling (ISM) Analysis

5.2.1 Listing Down All Factors

Table 1: Artificial Intelligence Key Success Factors

AIFs (Artificial Intelligence Factors)	Acronym
Top Management Support	AIF1
Data Availability and Quality	AIF2
Skilled Workforce and Training Programs	AIF3
Technological Infrastructure Readiness	AIF4
Strategic Alignment with Business Goals	AIF5
Vendor and External Expert Support	AIF6
Cross-Departmental Collaboration	AIF7
Government and Regulatory Support	AIF8
Customer-Centric Innovation Culture	AIF9
Availability of Use Cases and Pilot Projects	AIF10
Organizational Readiness and Change Management	AIF11
Trust in AI Systems and Explainability	AIF12

As shown in above table, twelve key enablers of AI adoption within the airline industry were identified and labeled AIF1 through AIF12 for simplicity and clarity. These enablers covered a cross-dimensional set of strategic, technical, organizational, and regulatory dimensions for analysis within the ISM methodology. The artificial labels provided a systematic labeling convention for referencing the enablers during the SSIM, reachability matrix and hierarchical modeling stage in the ISM methodology, which formed the foundation of the research's overall interpretive framework.

5.2.2 The Structural Self-Interaction Matrix (SSIM)

Below symbols used to initiate the SSIM:

- **V**: If AIF i leads to successful implementation of AIF j.
- **A**: If AIF j leads to successful implementation of AIF i.
- **X**: If both AIF i and AIF j lead to successful of implementation of each other.

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- **O**: If both AIF i and AIF j doesn't lead to successful of implementation of each other.

Table 2: The Structural Self-Interaction Matrix (SSIM)

Artificial Intelligence Factors	AIF 12	AIF 11	AIF 10	AI F9	AI F8	AI F7	AI F6	AI F5	AI F4	AI F3	AI F2	AI F1
Top Management Support	V	V	V	V	O	V	O	V	V	V	X	
Data Availability and Quality	V	O	X	O	O	X	X	O	X	X		
Skilled Workforce and Training Programs	V	O	A	V	O	X	O	V	A			
Technological Infrastructure Readiness	V	V	V	V	V	V	X	X				
Strategic Alignment with Business Goals	X	X	O	V	O	X	V					
Vendor and External Expert Support	V	O	O	O	O	O						
Cross-Departmental Collaboration	X	V	X	V	O							
Government and Regulatory Support	O	O	O	O								
Customer-Centric Innovation Culture	X	A	O									
Availability of Use Cases and Pilot Projects	V	V										
Organizational Readiness and Change Management	A											
Trust in AI Systems and Explainability												

As shown above Table, the Structural Self-Interaction Matrix (SSIM) was based upon the twelve identified AI enablers and depicted the contextual interdependencies between each of the enablers. The SSIM leveraged the common ISM notations 'V', 'A', 'X' and 'O' and were defined by experts to show directional influence between each pair of factors. In this notation, 'V' indicates the row factor (AIF i) led or enabled the column factor (AIF j); 'A' indicated the opposite; 'X' indicated a mutual influence; and 'O' indicated that there was no significant relationship.

The SSIM was an important step to convert qualitative concepts into a formal framework for modeling within the ISM methodology. For example, AIF1 (Top Management Support) provides a strong directional influence upon many other enablers, including AIF4 (Technological Infrastructure Readiness) and AIF5 (Strategic Alignment with Business Goals), which strengthen AIF1's role as a designated foundational driver. Likewise, there were some mutual dependencies associated with enablers such as AIF3 and AIF10, reflecting the need for iterative development between people capabilities and applied science developments of AI experimentation. Therefore, the SSIM served as a localized representation capturing the dynamics of AI readiness and provided a formal system to compute the reachability matrix.

5.2.3 The Initial Reachability Matrix

The Initial reachability matrix conducted based on below rules:

- If the (i,j) input in SSIM is V, then the (i,j) input in the reachability matrix will be 1 and (j,i) input will be 0.
- If the (i,j) input in SSIM is A, then the (i,j) input in the reachability matrix will be 0 and (j,i) input will be 1.
- If the (i,j) input in SSIM is X, then the (i,j) input in the reachability matrix will be 1 and (j,i) input will be 1.
- If the (i,j) input in SSIM is O, then the (i,j) input in the reachability matrix will be 0 and (j,i) input will be 0.

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Table 3: The Initial Reachability Matrix

AIFs	AIF1	AIF2	AIF3	AIF4	AIF5	AIF6	AIF7	AIF8	AIF9	AIF10	AIF11	AIF12
AIF1	1	1	1	1	1	0	1	0	1	1	1	1
AIF2	1	1	1	1	0	1	1	0	0	1	0	1
AIF3	0	1	1	0	1	0	1	0	1	0	0	1
AIF4	0	1	1	1	1	1	1	1	1	1	1	1
AIF5	0	0	0	1	1	1	1	0	1	0	1	1
AIF6	0	1	0	1	0	1	0	0	0	0	0	1
AIF7	0	1	1	0	1	0	1	0	1	1	1	1
AIF8	0	0	0	0	0	0	0	1	0	0	0	0
AIF9	0	0	0	0	0	0	0	0	1	0	0	1
AIF10	0	1	1	0	0	0	1	0	0	1	1	1
AIF11	0	0	0	0	1	0	0	0	1	0	1	0
AIF12	0	0	0	0	1	0	1	0	1	0	1	1

In above table, the Final Reachability Matrix converts the SSIM relationships into binary notation (1 and 0) indicating influence and no influence, respectively. The reachability matrix contains both direct and transitive relationships among the AI enablers.

As shown in the table, AIF1 (Top Management Support) demonstrates widespread influence with many entries of "1" - It is likely the main driver for adoption. In contrast, AIF8 and AIF9 appear more dependent and exert limited influence over other enablers. This reachability matrix is the basis for determining reachability and intersection sets, which are used for level partitioning and developing the ISM model.

5.2.4 Final Reachability Matrix

Table 4: Final Reachability Matrix

AIFs	AIF1	AIF2	AIF3	AIF4	AIF5	AIF6	AIF7	AIF8	AIF9	AIF10	AIF11	AIF12	Driving Power
AIF1	1	1	1	1	1	0	1	0	1	1	1	1	**10**
AIF2	1	1	1	1	0	1	1	0	0	1	0	1	**8**
AIF3	0	1	1	0	1	0	1	0	1	0	0	1	**6**
AIF4	0	1	1	1	1	1	1	1	1	1	1	1	**11**
AIF5	0	0	0	1	1	1	1	0	1	0	1	1	**7**
AIF6	0	1	0	1	0	1	0	0	0	0	0	1	**4**

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AIF7	0	1	1	0	1	0	1	0	1	1	1	1	**8**
AIF8	0	0	0	0	0	0	0	1	0	0	0	0	**1**
AIF9	0	0	0	0	0	0	0	0	1	0	0	1	**2**
AIF10	0	1	1	0	0	0	1	0	0	1	1	1	**6**
AIF11	0	0	0	0	1	0	0	0	1	0	1	0	**3**
AIF12	0	0	0	0	1	0	1	0	1	0	1	1	**5**
Dependence Power	**2**	**7**	**6**	**5**	**7**	**4**	**8**	**2**	**8**	**5**	**7**	**10**	

Above table shows that the Driving and Dependence Power Matrix was established by summing all of the rows and columns of the final reachability matrix. Driving power tells us how many other factors an enabler influences, while dependence power tells us how many enablers influence an enabler.
AIF4 (Technological Infrastructure Readiness) has the greatest driving power (11) indicating that it lays the foundation for other enablers. AIF1 (Top Management Support) and AIF2 (Data Availability and Quality) also have high levels of influence. Conversely, AIF8 (Government and Regulatory Support) and AIF9 (Customer-Centric Innovation Culture) have low driving power (and high dependence) thus, they can be characterized as outcome-oriented enablers.

5.2.5 Levels of AIFs (Final Iteration)

Table 5: Levels of AIFs (Final Iteration)

Artificial Intelligence Factor	Reachability set	Antecedent set	Intersection	Level
AIF1	1	1	1	IX
AIF2	1,2,3,4,6,10	1,2,3,4,6,10	1,2,3,4,6,10	IV
AIF3	3	1,3,4,10	3	VI
AIF4	4	1,4	4	VIII
AIF5	4,5	1,3,4,5	4,5	V
AIF6	2,4,6	2,4,5,6	2,4,6	IV
AIF7	2,3,5,7,10,12	1,2,3,4,5,7,10,12	2,3,5,7,10,12	III
AIF8	8	4,8	8	I
AIF9	9,12	1,3,4,5,7,9,12	9,12	I
AIF10	10	1,4,10	10	VII
AIF11	5,11	1,4,5,7,10,11,12	5,11	II
AIF12	5,7,12	1,2,3,4,5,7,10,12	5,7,12	III

As per the table above, the final iteration has confirmed the final level assignments of all AIFs and solidifies the structure of the ISM model. With AIF1 (Top Management Support) and AIF4 (Technological Infrastructure Readiness) placed at Level IX and VIII, in such a way that their strong foundational influences are confirmed; they are the main drivers of AI adoption in that they influence a wide set of other factors while being influenced

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by nothing. Meanwhile, AIF10 (Availability of Use Cases and Pilot Projects) is clearly positioned as a standalone Level VII transitional enabler. Level I of the hierarchy contains the drivers nearest to the outcomes associated with the greatest number of enablers: AIF8 (Government and Regulatory Support) and AIF9 (Customer-Centric Innovation Culture).

5.2.6 The Final Interpretive Structural Model

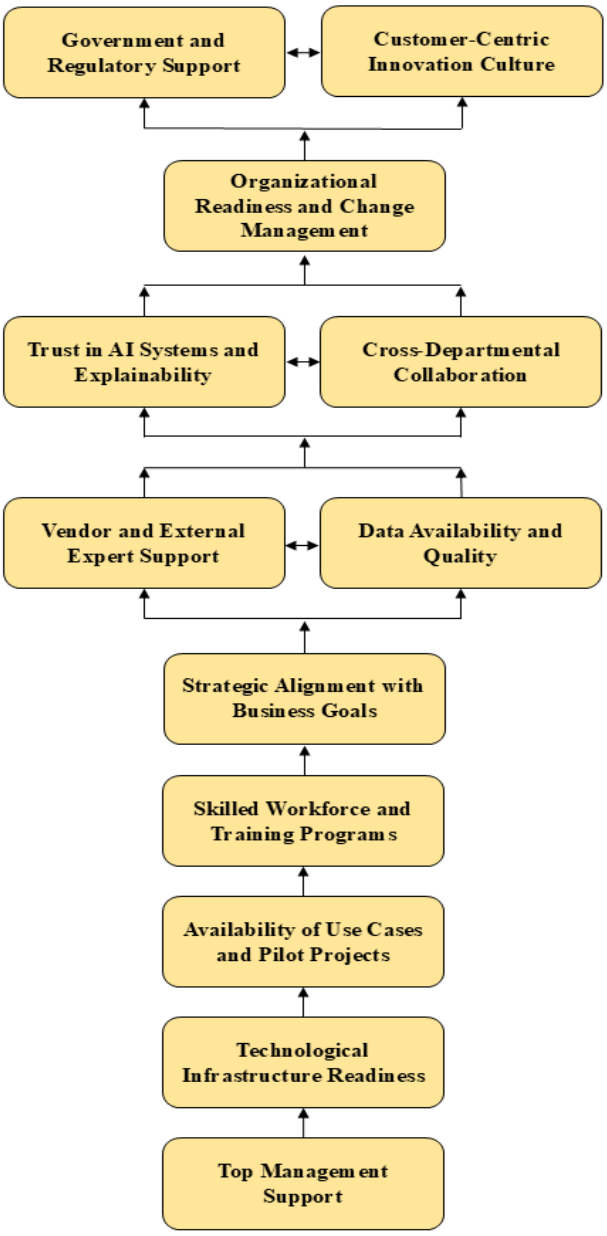

Figure 1: The Final Interpretive Structural Model

The final ISM model is presented in this stage as provided in Figure 1. The figure demonstrates the hierarchy of the factors associated with AI adoption beginning with Top Management Support as the main foundational driver, conceptually reaching an outcome such as Customer-Centric Innovation Culture and Government Support. The figure outlines the key influence pathways related to AI adoption for the airline industry.

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6. CONCLUSION

The analysis based on ISM illustrates a layered understanding of the collection of factors that impact AI implementation in the airline industry. The lowest tier is identified as Top Management Support as the most basic internal enabler. The interviews articulated that leaders provide vision, set parameters, and create an innovative culture. In the lower layers, initiatives such as deploying cloud-based infrastructure or developing talent typically do not occur without strong executive influence.

Technological infrastructure readiness, driven by executive leadership, supports the environment on which AI applications are built. Its placement in the hierarchy signals that companies need integrated and scalable systems to deploy if AI is going to take hold. The availability of Use Cases and Pilot Projects is also in a low tier where it takes the strategic ambition and translates it into experimentation that drives actionable results. Experts indicated the importance of piloting projects to build trust and buy-in to the organization, but companies need to achieve early wins by validating pilot projects.

In the mid-tier, Skilled Workforce and Training Programs and Strategic Alignment with Business Goals stand out as enablers and reference bridges. Skilled Workforce and Training Programs confirm the technology's feasibility. Strategic Alignment with Business Goals verifies that AI work has been aligned with the organization's value creation. Further up the hierarchy, the capabilities of vendors and external experts offer support when data viability and quality bolster the energy for implementation decisions and companies' analytical capabilities and demonstrate that external support should complement strong internal competencies and a solid data foundation, which must be established before adopting new technologies.

In the upper tier, Trust in AI Systems and Explainability, along with Cross-Department Collaboration, demonstrate organizational readiness as an organization to truly institutionalize AI across departments. The key determinants of maturity on the ISM model are trust and collaboration. Trust ensures transparency and user acceptance, and collaboration ensures that cross-functional integration is growing. It proves that both areas must mature before any AI application can have an effect in customer-facing or strategic areas.

Further down the model, Organizational Readiness and Change Management emerge as the most impactful aspects. It is the integrative connector of people, process, and technology. Experts noted that even when they were technically capable of anything, organizational culture posed a significant barrier.

Finally, at the top of the model is Government and Regulatory Support and Customer-facing innovative culture. These are both outcome-based and represent the organizational and societal goals that AI adoption is ultimately intended to achieve. The successful coming to terms of these outcomes relies on all the foundational and enabling aspects being carried out in concert. The ISM model makes it clear that in order for an outcome like innovation to come true, and another outcome like compliance to come true, these outcomes are not achieved in isolation but rather arise from readiness and delivery of the holistic aspects

7. FUTURE WORK

Based on ISM findings and expert input, a number of AI applications to support strategic goals associated with operational efficiency, improved customer experience, and data-informed decision-making are specifically recommended for the airline industry:

7.1 Operational Efficiency

- **Predictive Maintenance:** use machine learning to predict when equipment is about to fail, to prevent unplanned downtime.
- **Crew Scheduling Optimization:** automate crew scheduling to improve compliance with regulatory requirements and better utilize resources.
- **Flight Delay Prediction:** look at historical data and live data to perform predictive modeling to assess potential flight disruptions, and give that information directly to passengers.

7.2 Customer Experience Enhancement

- **AI Chatbot:** automate booking, inquiry, and travel updates, on a 24/7 basis.
- **Smart Boarding:** replace group boarding with facial recognition-enabled automated boarding.
- **Baggage Tracking:** instrument an IoT baggage tracking system and computer vision capture of the baggage, and notify passengers of their baggage status in real-time and help identify the last known location of lost baggage.

7.3 Strategic and Personalized Engagement

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- **Dynamic Pricing:** use AI to monitor ticket pricing in real-time, optimizing pricing based on real-time market and behavioral data.
- **Personalized Marketing:** develop offers and suggestions from historical data based on past preferences.
- **Customer Sentiment Analysis for service:** monitor social media and public data to identify service gaps and how to appropriately respond.

The recommendations provide digital transformation opportunities to scale for commercial airlines on multiple functions. Future investigation should include considerations for the lived experience of the recommendations across operational contexts, with attention to implications, limitations, and the long-term sustainability of these practices.

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