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Driving AI Integration in Air Cargo: Exploring Cause-Effect Dynamics of Key Enablers

Arnab Chakraborty
PhD Student, Operations
Vinod Gupta School of Management, Indian Institute of Technology
Kharagpur
ch.arnab@yahoo.com

M Vimala Rani
Assistant Professor, Production & Operations Management
Vinod Gupta School of Management
Indian Institute of Technology
Kharagpur)
vimala@vgsom.iitkgp.ac.in

Abstract

The rapid advancements in artificial intelligence (AI) have revolutionized industries worldwide, with the air cargo sector poised to benefit significantly. However, the adoption of AI in this sector is hindered by complex interdependencies among various enablers. This study systematically identifies and analyzes the critical enablers influencing AI adoption in the air cargo industry using the Fuzzy Decision-Making Trial and Evaluation Laboratory (FDEMATEL) approach. An expert-driven evaluation shortlisted sixteen enablers, categorized into two groups: drivers (cause enablers) and outcomes (effect enablers). The findings indicate that Real-Time Analytics, Access to Real-Time Information, Automation, Transparency and Visibility, and Quick Adaptation to Changing Market Demand serve as the primary drivers facilitating AI integration. These enablers emphasize data-driven decision-making, predictive capabilities, and operational adaptability as critical success factors.

On the other hand, the study reveals that Cost Savings, Knowledge Sharing, Competitive Advantage, and Sustainability Initiatives emerge as key outcomes influenced by AI adoption. Strengthening these effect enablers ensures long-term collaborative and competitive benefits, including enhanced customer satisfaction, resource optimization, and regulatory compliance. The research highlights the need for strategic investments in AI infrastructure, leadership commitment, and cultural transformation to enable a seamless integration into the Industry 4.0 framework.

Keywords
Artificial Intelligence, Air cargo, Enablers, FDEMATEL and Industry 4.0.

1. Introduction
Artificial Intelligence (AI) aims to emulate and understand human intelligence through advanced computational algorithms, enabling the generation of actionable insights for problem-solving. With the growing need to remain competitive and sustainable in a rapidly transforming technological landscape, organizations are increasingly restructuring their logistics networks (Min, 2021). Global logistics firms are leveraging AI to address the surging demands of the e-commerce sector. Despite its transformative potential, research exploring the full spectrum of AI's

applications in supply chains remains underdeveloped (Winkelhaus & Grosse, 2020). Supply chains, characterized by high volumes, slim profit margins, constrained asset allocation, and stringent time pressures, present ample opportunities for AI to optimize operations and streamline coordination among channel partners (Dubey et al., 2020). These businesses face constant disruptions from economic, technological, and environmental shifts, underscoring the urgency to adopt innovative and adaptive strategies. Emerging technologies like AI not only provide a competitive edge but are also expected to redefine industry standards, with organizations increasingly integrating AI to maintain market relevance (Toorajipour et al., 2021).

The logistics sector is embracing Industry 4.0 technologies, which employ innovative solutions to modernize traditional systems and optimize cargo handling processes (Gurjar et al., 2024). Cyber-physical systems enable seamless goods movement, automate storage and transportation, and enhance control over logistics software. They facilitate real-time material tracking and improve handling unit management (Facchini et al., 2019) . In the air cargo industry, Industry 4.0 solutions are pivotal for ensuring fast identification, real-time monitoring, and accurate data management. These technologies address key requirements such as safety protocols, time-sensitive operations, and error-free labeling, thereby minimizing human error and enhancing service efficiency (Tubis et al., 2023).

1.1 Research Questions

Given the transformative potential of AI, there is a critical need to evaluate its integration into the air cargo sector, focusing on the enablers that facilitate its adoption. Despite the evident benefits, AI implementation in this domain encounters distinct challenges. Existing studies provide limited insights, and to the best of our knowledge, this research is among the first to contribute to academia and industry by systematically investigating the enablers of AI adoption in the air cargo industry. The study addresses the following Research Questions (RQs):

i. (RQ1) What are the critical enablers facilitating the adoption of AI in the air cargo industry?
ii. (RQ2) How can the relationships among these enablers be quantified?
iii. (RQ3) What insights can be gained from analyzing the enablers and their interrelationships in the context of AI adoption?

2. Literature Review

The adoption of AI in supply chains is significantly driven by the need to optimize operations and improve overall efficiency. Access to real-time information (E1) and real-time analytics (E2) are critical enablers that enhance decision-making capabilities, enabling better demand forecasting, inventory management, and risk mitigation. These enablers ensure improved operational efficiency and environmental sustainability within supply chains (Hao & Demir, 2024). The availability of high-quality data and robust IT infrastructure supports the seamless functioning of real-time systems, fostering a data-driven culture (Cannas et al., 2024).

Enhanced customer loyalty and satisfaction (E3) is facilitated through personalized services, fast delivery, and improved product quality, which are critical for maintaining a competitive edge in supply chains. These outcomes are further reinforced by transparency and visibility (E7), which improve customer trust and confidence (Kar & Kushwaha, 2023). Similarly, environmental sustainability improvement (E4) and greenhouse gas reduction (E14) are vital components of AI adoption that align operational goals with global sustainability objectives. These initiatives are supported by predictive maintenance (E6), which minimizes waste and ensures resource optimization (El Bhilat et al., 2024).

Cost savings, waste reduction, and resource optimization (E5) are direct benefits of AI-driven automation (E11). Automation enhances operational accuracy, reduces manual errors, and improves efficiency (Hangl et al., 2022). Knowledge sharing (E10) is pivotal in ensuring cross-functional collaboration and aligning AI adoption strategies with organizational goals. Strong top management leadership and support (E15) play a vital role in driving AI initiatives by allocating resources, fostering a culture of innovation, and overcoming resistance to change (Pozzi et al., 2023).

The ability to adapt quickly to changing market demands (E9) and achieve synergy between supply and demand (E13) reflects the dynamic flexibility AI introduces into supply chain networks. Competitive advantage (E12) emerges as an overarching enabler, driven by enhanced operational efficiency, customer satisfaction, and environmental responsibility (Nam et al., 2021). Organizational culture (E16) further complements these efforts by fostering an environment conducive to innovation, collaboration, and change management, which is critical for sustained AI integration (Radhakrishnan & Chattopadhyay, 2020).

In conclusion, the identified enablers collectively highlight the multidimensional benefits of AI adoption, addressing operational, strategic, and environmental aspects. These enablers are interconnected and form the foundation for a successful AI-driven transformation in supply chains and related industries. A summary of the enablers are given in Table 2.

3. Methods

The research process was carried out in two distinct phases, as illustrated in Figure 1. The first phase involved conducting a comprehensive literature review, which resulted in the identification of 47 potential enablers. Due to the limited availability of literature specifically addressing enablers in the air cargo sector, these findings were validated within the Indian context. To achieve this, 12 experienced industry professionals from various segments of the air cargo ecosystem—such as freight forwarders, cargo terminal operators, customs agents, general sales and service agents, and cargo airport operators—were consulted through detailed pre-study interviews. The majority of these experts had over 20 years of professional experience (refer to Table 1). Based on their insights, 16 key enablers were subsequently refined to derive the final list for further analysis in the second phase of the study (see Table 2).

The criteria for expert selection ensured the inclusion of participants with diverse and relevant expertise. The requirements were:
i. A minimum of fifteen years of experience in the air cargo or related sectors.
ii. Availability and willingness to engage actively in the research process.
iii. Freedom from conflicts of interest or prior involvement in related research efforts.
iv. Proficiency in the language used for the study to ensure effective communication.
v. Representation from a wide range of organizations across the Indian air cargo industry.

Table 1. Experts information

Sl no.	Type of Organization	Role in Organization	Sector in Air Cargo Industry	Work Experience
1	Private	Managing Director	Freight forwarder	>20 years
2	Private	Managing Director	Freight forwarder	>20 years
3	Public	General Manager	Cargo airport	>20 years
4	Private	CEO	Cargo terminal operator	>20 years
5	Private	Head Sales	Customs broker	>15 years
6	Public	General Manager	Cargo airport	>15 years
7	Private	CEO	General sale and service agent (GSSA)	>20 years
8	Private	COO	Ecommerce operator	>15 years
9	Private	Managing Director	Freight forwarder	>20 years
10	Private	Head Sales	Customs broker	>20 years
11	Public	General Manager	Cargo airport	>20 years
12	Private	Head IT	Freight forwarder	>15 years

In the second phase of the research, the Fuzzy Decision-Making Trial and Evaluation Laboratory (FDEMATEL) method was used to explore the interactions among the selected 32 enablers. This phase involved administering a structured questionnaire to the same group of experts. The FDEMATEL method was utilized to evaluate the interconnections among the enablers, determining their relative importance and causal relationships.

The DEMATEL technique, originally developed by the Geneva Research Centre of the Battelle Memorial Institute, is a well-established approach for mapping complex causal structures through the use of matrices and digraphs (Gabus & Fontela, 1972). The FDEMATEL approach, an enhancement of the conventional DEMATEL method, incorporates fuzzy set theory to manage uncertainties and imprecisions often present in expert assessments. By employing Triangular Fuzzy Numbers (TFN) to express linguistic variables, FDEMATEL provides a more nuanced analysis of subjective human judgments, thereby strengthening decision-making processes (Singh et al., 2023).

Table 2. Top 16 enablers coded

Sl no.	Code	Enablers	Reference
1	E1	Access to real time information	(El Bhilat et al., 2024) (Siddiqui et al., 2024) (Hao & Demir, 2024) ; (Hangl et al., 2022)
2	E2	Real time analytics	(Hao & Demir, 2024) (Hangl et al., 2022)
3	E3	Enhanced customer loyalty and satisfaction	(Kar & Kushwaha, 2023) (Hangl et al., 2022) (Hangl et al., 2023) (Nam et al., 2021)
4	E4	Environmental sustainability improvement	(Cannas et al., 2024) (El Bhilat et al., 2024)
5	E5	Saves cost, waste and resources	(Cannas et al., 2024) (El Bhilat et al., 2024) (Hangl et al., 2022)
6	E6	Improved predictive maintenance	Industry expert
7	E7	Transparency and visibility	(Booyse & Scheepers, 2024) (Kar & Kushwaha, 2023) (Siddiqui et al., 2024)
8	E8	Enhanced privacy and security	(Merhi & Harfouche, 2024) (Booyse & Scheepers, 2024)
9	E9	Quick adaptation to changing market demand	(Nam et al., 2021) (Hangl et al., 2022) (Hangl et al., 2023)
10	E10	Knowledge sharing	(Pozzi et al., 2023)
11	E11	Automation	(Hangl et al., 2022)
12	E12	Competitive advantage	(Nam et al., 2021) (Hangl et al., 2022)
13	E13	Synergy between supply and demand	(Nam et al., 2021)
14	E14	Green house gas reduction	(El Bhilat et al., 2024)
15	E15	Top management leadership and support	(Pozzi et al., 2023)
16	E16	Organisation culture	(Radhakrishnan & Chattopadhyay, 2020)

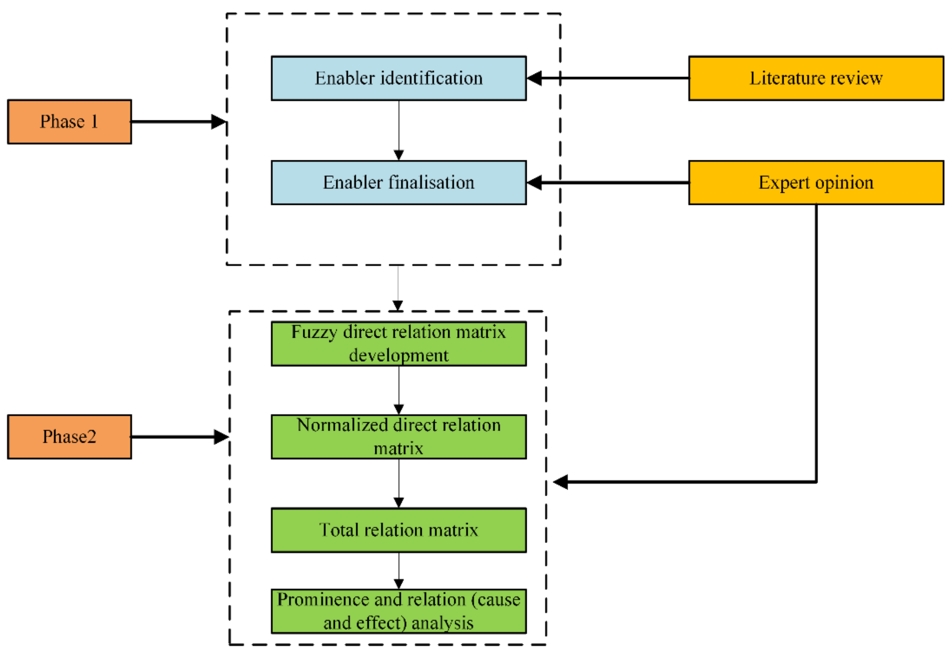

Figure 1. Proposed methodology

This method is particularly advantageous for addressing multi-criteria decision-making scenarios, especially in situations where factors are interdependent. FDEMATEL was instrumental in this study for analyzing the intricate relationships among the enablers, providing valuable insights into their mutual influences (Gupta & Rathore, 2024). Unlike traditional DEMATEL, FDEMATEL leverages fuzzy sets with values between 0 and 1 to accommodate partial truths, enhancing the precision of the analysis (Lin, 2013).

To facilitate the evaluation process, a five-point linguistic scale was adopted, as detailed in Table 3 (Chen & Hwang, 1992). Experts were tasked with assessing the direct impact of each enabler on all others, enabling the identification of causal links and their relative prominence within the network of enablers. Thus, a direct relation matrix A^k was obtained as shown in (1), where aij is the extent to which i affects j as per judgement of expert k where k ∈ {1, 2, …, p}, where p is the number of respondents. The number of enablers analyzed is denoted by n such that i,j ∈ {1, 2, …, n}

$$A^k = [a_{ij}^k]_{n \times n} \tag{1}$$

The matrix Ak comprises linguistic variables that are transformed into corresponding triangular fuzzy numbers (TFNs), as illustrated in the Table 3. The fuzzified matrix Ak is obtained which is represented in (2).

$$\tilde{A}\text{k} = [\ (l_{ij}^k), (m_{ij}^k), (r_{ij}^k)]\ \text{n x n} \tag{2}$$

Where l, m and r are fuzzy members.

The fuzzy data in matrix Ak is transformed into crisp scores by the Fuzzy Data into Crisp Scores (CFCS) method proposed by (Opricovic & Tzeng, 2004). CFCS normalizes the fuzzy numbers by using (3)−(5).

$$xl_{ij}^k = \frac{\left(l_{ij}^k - minl_{ij}^k\right)}{\Delta_{min}^{max}} \tag{3}$$

$$xm_{ij}^k = \frac{(m_{ij}^k - minm_{ij}^k)}{\Delta_{min}^{max}} \tag{4}$$

$$xr_{ij}^k = \frac{(r_{ij}^k - minr_{ij}^k)}{\Delta_{min}^{max}} \tag{5}$$

Where xl, xm, xr are normalized fuzzy members and $\Delta_{min}^{max} = maxr_{ij}^n - minl_{ij}^n$

The left side normalized value (xls) and right-side normalized value (xrs) of each expert is calculated using (6) and (7).

$$xls_{ij}^k = xm_{ij}^k / (1 + xm_{ij}^k + xl_{ij}^k) \tag{6}$$

$$xrs_{ij}^k = xr_{ij}^k / (1 + xr_{ij}^k + xm_{ij)}^k) \tag{7}$$

The total normalized crisp value is obtained using (8).

$$x_{ij}^k = \left[xls_{ij}^k \left(1 - xls_{ij}^k\right) + xrs_{ij}^k \times xrs_{ij}^k\right] / [1 - xls_{ij}^k + xrs_{ij}^k] \tag{8}$$

Where x is the normalized crisp value.

The crisp value of the defuzzied numbers is calculated using (9).

$$\tilde{a}_{ij}^k = minl_{ij}^k + x_{ij}^k \times \Delta_{min}^{max} \tag{9}$$

The aggregate of the normalized crisp value for all the respondents is the arithmetic mean of the crisp values which results in the direct relation matrix using (10).

$$\bar{A} = [\bar{a}_{ij}]\text{n x n} = [(\textstyle\sum_{k=1}^{p} \hat{a}_{ij}^k)/p]\text{n x n} \tag{10}$$

Where $\bar{a}$ is consensus pairwise comparison.

Each element a_{ij} is normalized to the aggregated maximum causal influence i, which results in matrix B as shown is (11).

$$\text{B} = \left[b_{ij}\right]\text{n x n} = [\bar{a}_{ij} / \max_{1 \leq i \leq n} (\textstyle\sum_{j=1}^{n} \bar{a}_{ij})] \tag{11}$$

Where b is normalized pairwise comparison.

Then the total relational matrix T is obtained using (12) as given in Table 4, in which I is the identity matrix.

$$T = B \times (I - B)^{-1} \tag{12}$$

This results in the total relation matrix.

$$T = [t_{ij}]_{n \times n}, i, j = 1,2, \dots, n. \tag{13}$$

Vectors D and R is found out by summing up the rows and columns respectively using (14) and (15).

$$D = [\textstyle\sum_{j=1}^{n} t_{ij}]_{1 \times n} = [d_i]_{1 \times n} \tag{14}$$

$$R = [\textstyle\sum_{i=1}^{n} t_{ij}]_{1 \times n} = [r_i]_{1 \times n} \tag{15}$$

A threshold value α is found out using (16) where c is the total number of elements in matrix T.

$$\alpha = (\textstyle\sum_{j=1}^{n} \sum_{i=1}^{n} t_{ij}) / c^2 \tag{16}$$

Table 3. Triangular fuzzy scale (Chen & Hwang, 1992)

Linguistic Response	**Linguistic Scale**	**Fuzzy Members**
No influence (N)	0	(0.00,0.00,0.25)
Very low influence (VL)	1	(0.00,0.25,0.50)
Low influence (L)	2	(0.25,0.50,0.75)
High influence (H)	3	(0.50,0.75,1.00)
Very high influence (VH)	4	(0.75,1.00,1.00)

Table 4. Prominence and Relation

Enablers		**D + R**	**D - R**	**Rank**	**Cause/Effect**
Access to real time information	E1	4.819	1.897	**7**	Cause
Real time analytics	E2	5.327	1.032	**1**	Cause
Enhanced customer loyalty and satisfaction	E3	4.140	-0.108	**14**	Effect
Environmental sustainability improvement	E4	4.896	-0.248	**6**	Effect
Saves cost, waste and resources	E5	5.138	-0.745	**3**	Effect
Improved predictive maintenance	E6	3.929	0.850	**15**	Cause
Transparency and visibility	E7	4.545	0.134	**10**	Cause
Enhanced privacy and security	E8	3.325	0.276	**16**	Cause
Quick adaptation to changing market demand	E9	4.415	0.612	**11**	Cause
Knowledge sharing	E10	5.032	-0.752	**4**	Effect
Automation	E11	4.703	0.071	**9**	Cause
Competitive advantage	E12	5.025	-1.890	**5**	Effect
Synergy between supply and demand	E13	4.405	0.924	**12**	Cause
Greenhouse gas reduction	E14	5.168	-0.649	**2**	Effect
Top management leadership and support	E15	4.210	-0.279	**13**	Effect
Organization culture	E16	4.706	-1.125	**8**	Effect

4. Results

The FDEMATEL outcomes are presented in the complete relation matrix in Table 4. The threshold value is determined to be 0.144. Values below the threshold indicate enablers with insignificant or no effect. The elements in the matrix with values exceeding the threshold is classified into mild (red), moderate (yellow) and strong (green) interactions. These interaction ranges are obtained by subtracting the threshold value from the highest interaction effect and then dividing by three.

The row values of the total relation matrix for each driver are aggregated to obtain D, and the same procedure is applied to the columns for each driver to derive R. Table 5 illustrates the prominence and the cause/effect relationship. A higher (D + R) value confers prominence. In Table 5, E2 (Real time analytics) exhibits the highest prominence among all enablers, with a (D + R) value of 5.327. Likewise, E8 (Enhanced privacy and security) exhibits the lowest significance, with a (D + R) value of 3.322. A positive value in the (D – R) column indicates a causal relationship, while a negative value denotes an effect. E1, E2, E6, E7, E8, E9, E11 and E13 represent causes. These exert influence on other options rather than being influenced themselves. E3, E4, E5, E10, E12, E14, E15 and E16 and are effects that are influenced themselves. The cause-and-effect relation is better visualized in Figure 2.

5. Discussion

RQ1 is addressed by the expert survey's evaluation, which identified the top 16 enablers prior to doing the FDEMATEL analysis presented in Table 2. RQ2 is addressed using the quantification solution of the total relationship matrix presented in Table 4. RQ3 is addressed through the study and interpretation of the total relation matrix in Table 4 and the prominence/relation values in Table 5.

5.1 Interactions within Enablers

The total relation matrix of the 16 enablers influencing AI adoption in the air cargo sector provides insights into their interdependencies and the extent of their interactions. The matrix uses three interaction classifications. mild, moderate and strong.

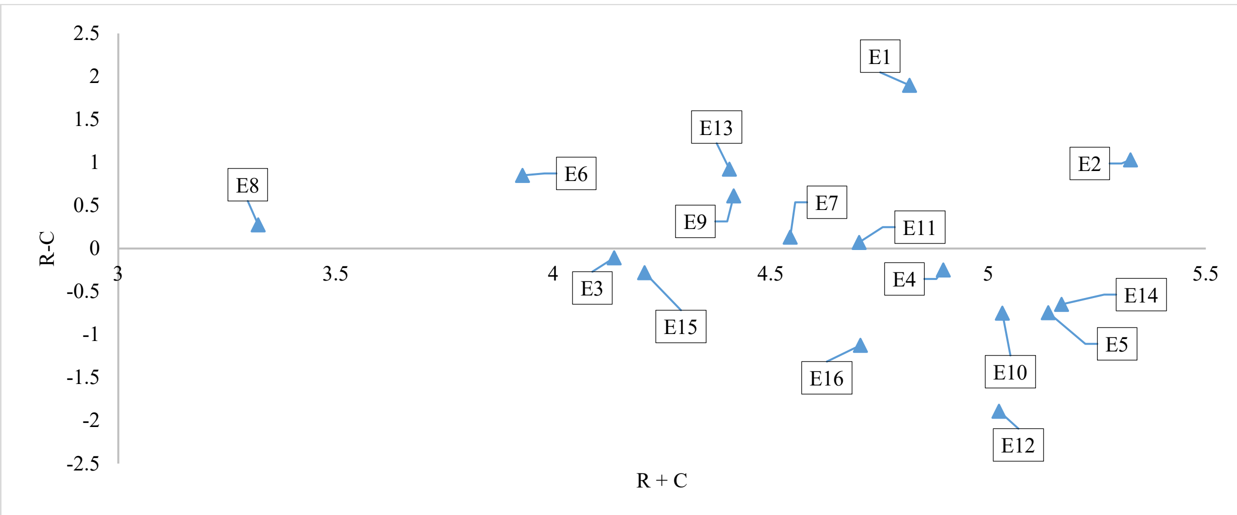

Figure 2. Cause and Effect relationship

Several enablers exhibit strong interaction values, emphasizing their foundational role in driving AI adoption. E1 (Access to Real-Time Information) demonstrates strong interactions with E2 (Real-Time Analytics) (0.293), E7 (Transparency and Visibility) (0.295), and E12 (Competitive Advantage) (0.304). These interactions highlight its critical role in enhancing analytics, transparency, and competitive positioning. Additionally, its strong relationship with E10 (Knowledge Sharing) (0.278) underscores its importance in fostering collaboration. E2 (Real-Time Analytics) strongly influences E5 (Saves cost, waste and resources) (0.299), E10 (Knowledge Sharing) (0.316), and E12 (Competitive Advantage) (0.299), emphasizing its role in driving resource optimization, decision-making, and competitiveness. E3 (Enhanced Customer Loyalty and Satisfaction) exhibits a strong relationship with E12 (Competitive advantage) (0.284), indicating how enhanced customer trust and satisfaction induces competitive advantage. Similarly, E4 (Environmental Sustainability Improvement) strongly interacts with E5 (Saves cost, waste, and resources) (0.292) and E14 (Greenhouse Gas Reduction) (0.264), highlighting the importance of sustainability in aligning operational goals with environmental objectives. E11 (Automation) strongly impacts E5 (Saves Cost, Waste, and Resources) (0.259) demonstrating its role in optimizing resources. E13 (Synergy Between Supply and Demand) shows strong interactions with E4 (Environmental Sustainability Improvement) (0.270), E14 (Greenhouse Gas Reduction) (0.278), and E15 (Top Management Leadership and Support) (0.243), underscoring its role in sustainability and strategic leadership. Finally, E15 (Top Management Leadership and Support) displays a strong relationship with E16 (Organizational Culture) (0.265), emphasizing its influence on shaping organizational values.

Moderate interactions further reveal the interconnected nature of the enablers. E1 (Access to Real-Time Information) moderately influences E4 (Environmental Sustainability Improvement) (0.175), E5 (Saves Cost, Waste, and Resources) (0.202), and E9 (Quick Adaptation to Changing Market Demand) (0.249), highlighting its role in cost optimization, sustainability, and agility. E5 (Saves Cost, Waste, and Resources) shows moderate influence on E12

(Competitive advantage) (0.223) and E14 (Greenhouse Gas Reduction) (0.243), confirming its role in reducing emissions and aligning cost-saving efforts with sustainability goals. Additionally, E7 (Transparency and Visibility) moderately impacts E3 (Enhanced customer loyalty) (0.245), E10 (Knowledge sharing) (0.217), E12 (Competitive advantage) (0.218) and E16 (Organizational culture), reflecting its role in enhancing and retaining competitive advantage and customer loyalty, and collaborative organizational culture. E10 (Knowledge Sharing) demonstrates moderate interactions with E16 (Organization culture) (0.246), highlighting the importance of collaboration in achieving organizational alignment.

Mild interactions provide insights into secondary or indirect relationships. E1 (Access to Real-Time Information) shows a mild influence on E8 (Enhanced Privacy and Security) (0.146), indicating its indirect role in strengthening security. E2 (Real-Time Analytics) interacts mildly with E13 (Synergy Between Supply and Demand) (0.153), reflecting its role in resource alignment.

E8 (Enhanced Privacy and Security) demonstrates mild interactions with E11 (Automation) (0.113) and E13 (Synergy Between Supply and Demand) (0.128), emphasizing its indirect contribution to secure operations. Lastly, E12 (Competitive Advantage) interacts mildly with E16 (Organizational Culture) (0.177), showcasing how culture supports competitiveness.

The enablers can be further sub divided into cause groups and effect groups based upon their positive or negative relation value (D-R).

5.2 Cause Group

Table 5 indicates that E1, E2, E6, E7, E8, E9, E11 and E13 are potential causes. These possess a positive (D – R) value, signifying their role as key drivers that influence other enablers.

The cause enablers play a critical role in driving AI adoption within the air cargo industry, influencing other enablers in the system. Real-Time Analytics (E2) emerges as the most prominent enabler with a D+R value of 5.327 and a D-R value of 1.032 (Rank 1), highlighting its strong influence on optimizing operational efficiency and data-driven decision-making. Similarly, Access to Real-Time Information (E1) (D+R = 4.819, D-R = 1.897, Rank 7) is a crucial factor in enhancing visibility, competitive advantage, and market adaptability. Improved Predictive Maintenance (E6) (D+R = 3.929, D-R = 0.850, Rank 15) strengthens operational efficiency by enabling proactive asset management, reducing downtime, and increasing reliability. Transparency and Visibility (E7) (D+R = 4.545, D-R = 0.134, Rank 10) further supports AI adoption by fostering trust and operational clarity across the supply chain. Additionally, Enhanced Privacy and Security (E8) (D+R = 3.321, D-R = 0.276, Rank 16) ensures robust cybersecurity frameworks, critical for AI-driven digital transformation. Quick Adaptation to Changing Market Demand (E9) (D+R = 4.415, D-R = 0.612, Rank 11) highlights AI’s ability to improve agility and responsiveness in dynamic market conditions. Automation (E11) (D+R = 4.703, D-R = 0.071, Rank 9) is another key driver, facilitating efficiency improvements, reducing human intervention, and streamlining operations. Lastly, Synergy Between Supply and Demand (E13) (D+R = 4.405, D-R = 0.924, Rank 12) underscores AI’s potential to optimize resource allocation and balance logistical demands, reinforcing the importance of seamless supply chain integration.

5.3 Effect Group

Table 5 indicates that E3, E4, E5, E10, E12, E14, E15 and E16 are potential effects. These possess a negative (D – R) value and are primarily influenced by other enablers.

The effect enablers represent the outcomes influenced by the cause enablers, illustrating how AI adoption leads to various strategic, operational, and environmental benefits. Saves Cost, Waste, and Resources (E5) is a highly prominent outcome with a D+R value of 5.138 and a D-R value of -0.745 (Rank 3), demonstrating that AI adoption significantly enhances cost efficiency and sustainability. Similarly, Knowledge Sharing (E10) (D+R = 5.032, D-R = -0.752, Rank 4) emphasizes AI’s role in fostering a collaborative, data-driven work environment. Competitive Advantage (E12) (D+R = 5.024, D-R = -1.890, Rank 5) highlights the long-term strategic benefits of AI adoption, as it strengthens market positioning, operational excellence, and service differentiation. AI’s contribution to environmental sustainability is evident in Greenhouse Gas Reduction (E14) (D+R = 5.168, D-R = -0.649, Rank 2) and Environmental Sustainability Improvement (E4) (D+R = 4.896, D-R = -0.248, Rank 6), reinforcing AI’s potential in achieving carbon footprint reduction and aligning industry goals with sustainability regulations. Furthermore,

Table 5. Total relation matrix

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14	E15	E16
E1	0.091	0.293	0.195	0.175	0.202	0.107	0.295	0.146	0.249	0.278	0.242	0.304	0.165	0.222	0.156	0.238
E2	0.107	0.127	0.177	0.196	0.299	0.113	0.211	0.132	0.195	0.316	0.257	0.299	0.128	0.222	0.173	0.229
E3	0.072	0.121	0.091	0.108	0.145	0.071	0.207	0.080	0.111	0.152	0.126	0.284	0.082	0.123	0.102	0.140
E4	0.109	0.113	0.107	0.132	0.292	0.096	0.107	0.079	0.094	0.158	0.139	0.167	0.114	0.292	0.180	0.145
E5	0.105	0.109	0.130	0.154	0.137	0.189	0.131	0.079	0.096	0.138	0.114	0.223	0.082	0.243	0.106	0.160
E6	0.113	0.143	0.111	0.129	0.258	0.079	0.114	0.108	0.175	0.250	0.191	0.204	0.102	0.152	0.112	0.150
E7	0.077	0.133	0.245	0.124	0.133	0.078	0.109	0.150	0.099	0.217	0.113	0.218	0.111	0.163	0.115	0.256
E8	0.063	0.084	0.089	0.132	0.111	0.094	0.153	0.056	0.076	0.145	0.087	0.142	0.070	0.138	0.200	0.159
E9	0.089	0.186	0.148	0.176	0.198	0.118	0.118	0.086	0.092	0.180	0.240	0.174	0.217	0.192	0.129	0.170
E10	0.102	0.130	0.098	0.145	0.129	0.073	0.101	0.076	0.159	0.121	0.113	0.294	0.087	0.159	0.108	0.246
E11	0.111	0.140	0.183	0.169	0.259	0.095	0.146	0.085	0.100	0.141	0.103	0.174	0.201	0.189	0.149	0.142
E12	0.085	0.077	0.075	0.121	0.099	0.059	0.080	0.088	0.068	0.104	0.081	0.110	0.063	0.128	0.152	0.177
E13	0.117	0.153	0.144	0.270	0.183	0.120	0.121	0.117	0.135	0.183	0.160	0.188	0.088	0.278	0.243	0.166
E14	0.081	0.169	0.131	0.264	0.271	0.090	0.109	0.076	0.092	0.137	0.142	0.165	0.087	0.145	0.139	0.161
E15	0.071	0.085	0.087	0.174	0.120	0.096	0.091	0.098	0.080	0.155	0.095	0.260	0.073	0.125	0.089	0.265
E16	0.067	0.086	0.113	0.102	0.107	0.062	0.113	0.067	0.080	0.217	0.114	0.252	0.071	0.137	0.092	0.112

Organizational Culture (E16) (D+R = 4.705, D-R = -1.125, Rank 8) is significantly shaped by AI-driven transformation, promoting a technology-first mindset and adaptability within organizations. Enhanced Customer Loyalty and Satisfaction (E3) (D+R = 4.140, D-R = -0.108, Rank 14) also benefits from AI adoption, as improved analytics and transparency foster stronger customer relationships. Finally, Top Management Leadership and Support (E15) (D+R = 4.209, D-R = -0.279, Rank 13) demonstrates that AI-driven decision-making influences leadership strategies and executive buy-in, crucial for seamless AI integration across the air cargo ecosystem.

5.4 Managerial Inference

The FDEMATEL analysis provides actionable insights into the interdependencies among enablers influencing AI adoption in the air cargo sector. The findings emphasize the need for managers and decision-makers to strategically prioritize and leverage the identified cause group enablers as they act as key drivers for other factors. Simultaneously, focusing on the effect group enablers is crucial for achieving targeted outcomes.

Focus on Core Drivers (Cause Group)

To facilitate AI adoption in the air cargo industry, managers and decision-makers must prioritize key drivers that serve as enablers for transformation. Among these, Real-Time Analytics (E2) (D+R = 5.327, D-R = 1.032, Rank 1) and Access to Real-Time Information (E1) (D+R = 4.819, D-R = 1.897, Rank 7) emerge as the most critical enablers, emphasizing the need for robust data infrastructures and AI-driven analytics capabilities. Investing in advanced AI-powered systems that enable real-time data processing and predictive analytics will enhance operational decision-making, improve forecasting accuracy, and ensure seamless logistics management. Additionally, Automation (E11) (D+R = 4.703, D-R = 0.071, Rank 9) should be strategically implemented to optimize cost efficiency, reduce human intervention, and enhance workflow efficiencies, ensuring smoother AI integration across key operational areas. Transparency and Visibility (E7) (D+R = 4.545, D-R = 0.134, Rank 10) further underscore the need for open AI ecosystems, regulatory compliance, and stakeholder trust, enabling seamless AI adoption in complex cargo networks. Furthermore, fostering Quick Adaptation to Changing Market Demand (E9) (D+R = 4.415, D-R = 0.612, Rank 11) is essential to maintain resilience in a rapidly evolving market, making AI-enabled adaptability a strategic imperative. Organizations should also prioritize Synergy Between Supply and Demand (E13) (D+R = 4.405, D-R = 0.924, Rank 12) to improve resource allocation, dynamic pricing models, and demand forecasting accuracy. Finally, enhancing Privacy and Security (E8) (D+R = 3.321, D-R = 0.276, Rank 16) will reinforce trust in AI adoption, ensuring compliance with data protection regulations and safeguarding critical business operations.

Strengthen Collaborative and Competitive Outcomes (Effect Group)

The impact of AI adoption extends beyond operational efficiency to strategic business growth and collaboration, shaping competitive advantages within the air cargo industry. Cost Savings, Waste Reduction, and Resource Optimization (E5) (D+R = 5.138, D-R = -0.745, Rank 3) indicate that AI-enabled efficiencies directly translate into profitability, sustainable resource management, and waste minimization, making AI a key enabler for financial and environmental sustainability goals. Additionally, fostering a knowledge-sharing culture through AI-driven collaboration tools (E10) (D+R = 5.032, D-R = -0.752, Rank 4) will accelerate innovation, improve cross-functional teamwork, and enable continuous learning within organizations. The significant role of Competitive Advantage (E12) (D+R = 5.024, D-R = -1.890, Rank 5) highlights that AI adoption should be aligned with long-term business strategy, enabling companies to enhance market positioning, differentiate their services, and capitalize on AI-driven operational intelligence. Sustainability-driven outcomes, including Greenhouse Gas Reduction (E14) (D+R = 5.168, D-R = -0.649, Rank 2) and Environmental Sustainability Improvement (E4) (D+R = 4.896, D-R = -0.248, Rank 6), underscore AI's critical role in achieving regulatory compliance, minimizing carbon footprints, and driving sustainable logistics strategies. Furthermore, strengthening Organizational Culture (E16) (D+R = 4.705, D-R = -1.125, Rank 8) will be essential in ensuring that AI adoption is not only a technological shift but also an organizational transformation, requiring leadership support, change management strategies, and employee engagement initiatives. Lastly, Top Management Leadership and Support (E15) (D+R = 4.209, D-R = -0.279, Rank 13) must actively drive AI adoption by aligning corporate strategies with AI capabilities, securing investments, and fostering a culture of digital transformation across the organization.

6. Conclusion

The adoption of AI in the air cargo industry is driven by a set of key enablers that influence both technological integration and strategic outcomes. This study highlights the core drivers (cause enablers) that serve as the foundation for AI adoption, including Real-Time Analytics (E2), Access to Real-Time Information (E1), Automation (E11), Transparency and Visibility (E7), and Quick Adaptation to Changing Market Demand (E9). These enablers emphasize the importance of data-driven decision-making, predictive capabilities, operational efficiency, and organizational adaptability. To maximize AI's potential, air cargo firms must invest in advanced analytics, automation, and privacy-enhancing technologies, while fostering leadership engagement and agile decision-making frameworks.

On the other hand, the collaborative and competitive outcomes (effect enablers) represent the long-term benefits AI adoption brings to organizations, such as Cost Savings (E5), Knowledge Sharing (E10), Competitive Advantage (E12), and Environmental Sustainability (E4, E14). These findings suggest that AI not only enhances operational performance but also drives customer satisfaction, strategic differentiation, and sustainability compliance. Organizations must ensure that AI integration aligns with corporate goals, regulatory requirements, and cultural transformation efforts to fully realize its benefits.

Ultimately, successful AI adoption in the air cargo industry requires a systematic approach that prioritizes core drivers and strengthens competitive advantages.

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Biographies

Arnab Chakraborty is a PhD scholar at the Indian Institute of Technology Kharagpur, India. His research focuses on the adoption of Artificial Intelligence (AI) within the air cargo industry, particularly the transition from Industry 4.0 to Industry 5.0. Passionate about innovation, Arnab is dedicated to exploring transformative solutions to advance the global air cargo sector.

Prof. (Dr.) M. Vimala Rani obtained her Ph.D. degree in Operations Management from the Indian Institute of Science (IISc), Bangalore. She has received a Gold medal and the Best Ph.D. thesis award from the council of IISc. After her Ph.D., she worked as IISc Research Associate at the Department of Management Studies, IISc. She also worked as an Assistant Professor at Amrita School of Business, Bangalore. She has offered Production and Operation Management, Supply Chain Management, Quantitative Techniques-1, Spreadsheet Modelling and Programming for Business to Master Students. Her research interest pertains to developing mathematical and heuristic optimization for the problems related to Management; IoT and blockchain in Port logistics and supply chain management; Humanitarian supply chain optimization; Clinical decision support system in Mental healthcare.