AI Readiness as a Pathway to Sustainable Competitiveness in Tourism Transport: Evidence from an Integrative SEM Model

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***Abstract*—Artificial intelligence (AI) is transforming demand forecasting in the tourism transportation sector, delivering unprecedented accuracy in volatile, seasonal, and customer-sensitive environments. Yet, many firms struggle to translate AI's potential into performance due to gaps in technological and organizational readiness. Drawing on the resource-based-view (RBV) and the Technology-Organization-Environment (TOE) framework, this study develops and tests an integrative model linking digital infrastructure, employee skills, and managerial support to AI adoption and, consequently, business performance. We use Structural Equation Modeling (SEM) with bootstrapping to test direct and indirect effects. The results confirm that all three dimensions of readiness significantly boost AI adoption, which improves operational efficiency, occupancy rates, customer satisfaction, and profitability. It is crucial that AI adoption fully mitigates the effects of employee skills and managerial support, while partially mitigating those of digital infrastructure, reflecting its dual role in analytics, through both AI and other means. The study contributes theoretically by clarifying the mechanism by which readiness translates into value and offers practitioners a roadmap for successful AI assimilation in high-uncertainty service contexts.**

Keywords*—Artificial intelligence (AI); demand forecasting; tourism transport; Intelligent Transportation Systems (ITS); digital infrastructure; Resource-Based View (RBV); Technology-Organization-Environment (TOE) Framework; Structural Equation Modeling (SEM); mediation analysis; sustainable mobility; data-driven decision making

I. INTRODUCTION

Over the past decade, global value chains and service-oriented industries have undergone profound structural transformation, driven by volatile market demands, escalating geopolitical tensions, the exponential rise of e-commerce, and mounting pressure for real-time, data-driven decision-making. As [1] observes, in the context of the COVID-19 pandemic, disruptions in critical sectors such as medical supplies have exposed the fragility of hyper-globalized production networks and underscored the need for greater resilience and agility. This imperative has only intensified in the post-pandemic era, where firms must navigate an increasingly complex risk landscape encompassing not only health crises but also trade wars, regulatory fragmentation, and digital disruption [2].

Together, these forces are redefining the strategic logic of global operations, shifting emphasis from pure efficiency toward adaptive, intelligence-enabled supply chain architectures capable of sustaining both performance and responsiveness under uncertainty. These shifts have heightened the importance of accurate forecasting, positioning artificial intelligence (AI) as a strategic lever for competitiveness and resilience. In particular, AI-enabled forecasting has demonstrated superior accuracy compared to conventional statistical models, reducing uncertainty and optimizing resource allocation [3], [4]. The central challenge is no longer to demonstrate AI's benefits, but to identify the organizational prerequisites and mechanisms that foster its effective adoption [5].

In service-intensive industries such as tourism and hospitality, forecasting accuracy is critical due to market volatility, seasonality, and global interdependencies. AI-based approaches, particularly machine learning and transformer-driven models, have shown substantial improvements in predicting tourism demand and traveler flows [6], [7]. Moreover, AI adoption in tourism has been linked to enhanced personalization, dynamic pricing, and operational efficiency [8], [9]. However, empirical evidence suggests that despite significant investments, many organizations face difficulties moving beyond pilot applications. For example, recent industry reports indicate that over 70% of companies struggle to scale AI initiatives effectively, highlighting the persistent gap between adoption and value realization.

While prior research underscores the performance benefits of AI integration [8], relatively few studies explain how internal readiness, digital infrastructure, workforce competencies, and managerial support translate into effective adoption, particularly in tourism contexts. The Resource-Based View (RBV) posits that firm-specific resources enable sustainable competitive advantage [10], while the technology organization environment (TOE) framework emphasizes that readiness factors determine the assimilation of emerging technologies [11]. Despite this theoretical grounding, empirical analyses of AI adoption in tourism forecasting remain scarce.

This study addresses these gaps by developing and testing a conceptual model linking organizational readiness to AI-enabled forecasting adoption and, subsequently, firm performance. Specifically, it investigates the mediating role of AI adoption in translating readiness into superior performance outcomes. The contributions of this study are threefold: 1) it assesses AI-enabled forecasting adoption within international tourism and hospitality firms, an industry characterized by uncertainty and underexplored in AI adoption research; 2) it consolidates multiple readiness dimensions into a single integrative framework; and 3) it empirically demonstrates the mediating function of AI adoption, offering both theoretical and managerial insights into the assimilation process.

The remainder of this study is organized as follows: Section II reviews the relevant literature and develops the research hypotheses. Section III describes the research methodology, including data collection procedures and the analytical strategy. Section IV presents the empirical results, followed by a discussion of the theoretical and managerial implications in Section V, which also concludes the study by outlining its limitations and directions for future research.

II. Related Work and Hypotheses Development

The integration of artificial intelligence (AI) into demand forecasting has become a transformative capability across service-intensive industries, particularly within sectors marked by volatility, seasonality, and customer sensitivity, hallmarks of the tourist transport sector. While the potential of AI to enhance forecast accuracy and operational agility is widely acknowledged, recent studies emphasize that technological potential alone is insufficient to ensure performance gains [12]. Instead, the successful assimilation of AI depends critically on a firm's technological and organizational readiness, which enables the effective deployment and utilization of advanced forecasting systems.

Drawing on the Resource-Based View (RBV) and Technology Adoption Theory, this study posits that internal capabilities, specifically digital infrastructure**,** workforce competencies, and managerial support, serve as foundational enablers of AI adoption, which in turn drives business performance. Furthermore, the study conceptualizes AI adoption not merely as an outcome but as a mediating mechanism translating readiness into tangible performance improvements.

A. Theoretical Foundation: RBV Meets TOE

The Resource-Based View (RBV) asserts that sustainable competitive advantage arises from resources that are valuable, rare, inimitable, and non-substitutable [10]. In the AI era, data infrastructure, AI-literate talent, and strategic leadership constitute such resources, especially in service contexts where responsiveness is key. Complementing RBV, the TOE framework [13] explains technology adoption through three lenses:

- Technology: digital infrastructure enabling data integration.
- Organization: human and managerial capabilities.
- Environment: external pressures (e.g., customer demands, regulatory shifts), though not tested here, we acknowledge their relevance per [14], who emphasize that firms face coercive, normative, and relational pressures to adopt sustainable and intelligent practices. Together, RBV and TOE provide a robust lens to explain why some firms succeed in AI adoption while others do not.

B. The Impact of Technological and Organizational Readiness on AI Adoption

According to the RBV, sustainable competitive advantage stems from valuable, rare, inimitable, and non-substitutable (VRIN) resources [10]. In the context of AI-driven transformation, a firm's readiness, encompassing its data systems, human capital, and leadership alignment, constitutes such strategic resources. These capabilities determine whether an organization can effectively absorb, implement, and leverage AI innovations [15].

1) Digital infrastructure: AI-enabled forecasting relies heavily on access to high-quality, real-time, and integrated data from diverse sources (e.g., booking systems, traffic sensors, weather APIs, social media). Without robust digital infrastructure, including data lakes, cloud platforms, and interoperable systems, AI models suffer from poor input quality, leading to unreliable outputs [16]. Firms that have invested in scalable data architectures are better positioned to deploy machine learning and deep learning models for passenger demand prediction. Thus, we hypothesize:

H1a: Digital infrastructure positively influences the adoption of AI-enabled demand forecasting practices in tourist transport firms.

2) Workforce competencies: The effective use of AI requires more than algorithmic tools; it demands a workforce capable of interpreting model outputs, integrating insights into operational decisions, and adapting workflows accordingly. This reflects the concept of absorptive capacity, the ability to recognize, assimilate, and apply new knowledge [15]. In tourist transport, staff must understand dynamic pricing signals, respond to predicted demand surges, and trust AI recommendations. A shortage of data-literate personnel remains a key barrier to AI adoption [17]:

H1b: Workforce competencies positively influence the adoption of AI-enabled demand forecasting practices in tourist transport firms.

3) Managerial support: Executive sponsorship is critical for overcoming organizational inertia and securing the resources needed for AI initiatives. Strategic alignment ensures that AI projects are not isolated experiments but are embedded in core business objectives such as improving load factors, reducing empty runs, or enhancing customer experience [20]. Leadership commitment also signals legitimacy, fostering cross-departmental collaboration. Therefore:

H1c: Managerial support positively influences the adoption of AI-enabled demand forecasting practices in tourist transport firms.

4) The impact of AI adoption on business performance: AI-enabled demand forecasting enhances business performance through multiple pathways.

First, it improves forecast accuracy, enabling better capacity planning, dynamic pricing, and resource allocation critical in capital-intensive sectors like aviation and rail. Second, it increases operational efficiency by automating complex forecasting tasks, reducing manual errors, and enabling real-time adjustments. Third, it elevates customer satisfaction by minimizing overbooking, optimizing wait times, and personalizing service offerings [21]. Empirical evidence from logistics confirms a strong link between AI adoption and performance [12]; we extend this logic to tourist transport, where demand uncertainty is even more pronounced. Thus:

H2: The adoption of AI-enabled demand forecasting practices positively influences business performance in tourist transport firms.

While readiness factors are necessary, they are not sufficient to directly improve performance unless channeled through effective technology use. Following the mediation framework and recent AI assimilation studies [15], we propose that AI adoption mediates the relationship between readiness and performance. Specifically, digital infrastructure may exert both direct and indirect effects (e.g., via dashboards or non-AI analytics), suggesting partial mediation. In contrast, workforce skills and managerial support likely influence performance only when mobilized through AI implementation, implying full mediation as their value is realized in the context of AI deployment.

Accordingly, we hypothesize:

H3a: The adoption of AI-enabled demand forecasting practices partially mediates the relationship between digital infrastructure and business performance.

H3b: The adoption of AI-enabled demand forecasting practices fully mediates the relationship between workforce competencies and business performance.

H3c: The adoption of AI-enabled demand forecasting practices fully mediates the relationship between managerial support and business performance.

This mediation framework advances theory by clarifying how organizational readiness translates into performance not automatically, but through the strategic adoption of AI as an operational conduit. It also offers practitioners a roadmap: investing in readiness alone is inadequate; these resources must be actively leveraged through AI-enabled forecasting to unlock performance gains.

III. METHODOLOGY

To address the research objectives examining the influence of technological and organizational readiness on AI adoption, assessing the impact of AI-enabled demand forecasting on business performance, and testing the mediating role of AI adoption a quantitative research design was employed using Structural Equation Modeling (SEM). The methodology encompasses model specification, data collection, variable measurement, and analytical procedures.

A. Conceptual Model and Hypotheses Testing Framework

The study tests a mediation model grounded in the Resource-Based View (RBV) and Technology Adoption Theory. As illustrated in Fig. 1, the model posits that digital infrastructure, workforce competencies, and managerial support (independent constructs) influence AI-enabled demand forecasting adoption (mediator), which in turn affects business performance [25] (dependent construct). Two sets of structural equations were specified to test direct and indirect effects:

$$AI_{ADOPT} = \beta_0 + \beta_1(DIG_{INFRA}) + \beta_2(WORKFORCE) + \beta_3 (MGMT_{SUPPORT}) + \beta_4(SIZE) + \beta_5(AGE) + \varepsilon_1 \quad (1)$$

$$PERF = \gamma_0 + \gamma_1(AI_{ADOPT}) + \gamma2(SIZE) + \gamma3(AGE) + \varepsilon_2 \quad (2)$$

where,

- AI_ADOPT: Degree of AI-enabled demand forecasting adoption
- PERF: Business performance
- DIG_INFRA, WORKFORCE, MGMT_SUPPORT: Organization Readiness antecedents
- SIZE, AGE: Control variables (firm size = employees; firm age = years in operation)
- β_0 and $\gamma_0$are the intercept
- β_1, β_3 , β_4, β_5 are the regression coefficients to be calculated
- ε_1 and ε_2 are the error terms

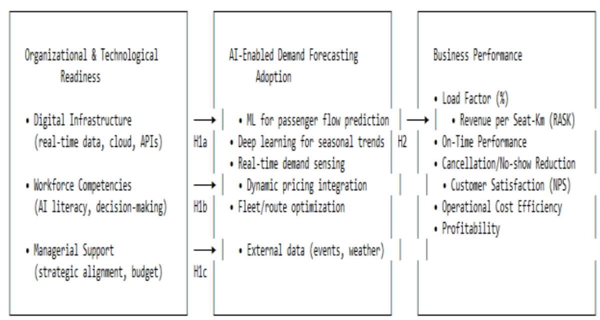

Fig. 1. Horizontal conceptual framework: AI-enabled demand forecasting as a mediator between organizational readiness and business performance in tourist transport.

B. Data Collection and Sample Design

We used a rigorously designed and structured questionnaire aimed at capturing complex organizational, technological, and performance-related constructs. The final sample comprised 218 observations, a size widely regarded as adequate for structural equation modeling (SEM). Established methodological guidelines recommend a minimum threshold of approximately 200 cases to ensure stable parameter estimation and sufficient statistical power, particularly in technology adoption research (Hair et al., 2019).

C. Measurement of Constructs

The constructs included in this study were measured using multi-item scales adapted from validated instruments in prior AI, supply chain, and service operations research, ensuring both reliability and contextual relevance. As shown in Table I, the readiness dimension was captured through three constructs digital infrastructure, workforce competencies, and managerial support reflecting the technological, human, and strategic foundations necessary for AI assimilation. The digital infrastructure construct (5 items) assesses a firm's data integration capability, cloud scalability, and real-time connectivity essential for predictive analytics. Workforce competencies (4 items) measure employees' AI literacy, interpretive ability, and collaborative capacity to operationalize algorithmic insights, aligned with the absorptive capacity framework [16]. Managerial support (4 items) captures leadership commitment, strategic alignment, and resource mobilization, highlighting the importance of executive sponsorship in digital transformation.

TABLE I. CONSTRUCT AND KEY INDICATORS

Construct	n	Key Dimensions / Indicators
Digital Infrastructure (5 items)	5	Real-time data access, cloud scalability, system interoperability, API connectivity, data quality
Workforce Competencies (4 items)	4	AI literacy, ability to interpret forecasts, adaptive decision-making, collaboration with data teams
Managerial Support (4 items)	4	Leadership commitment, strategic alignment, inter-departmental coordination, resource allocation
AI Adoption (10 items)	10	ML for demand forecasting, dynamic pattern recognition, data integration, real-time dashboards, pricing optimization, model retraining, managerial use, collaboration, AI literacy, strategic integration
Business Performance (8 items)	8	Forecast accuracy, load factor, RASK, operational efficiency, customer satisfaction (NPS), cost reduction, market share, profitability
Control Variables (2 items)	2	Firm size (employees), firm age (years)

The AI adoption construct (10 items) provides a comprehensive evaluation of the degree to which AI-based forecasting is embedded across operational and strategic processes, including machine-learning deployment, real-time decision support, pricing optimization, model retraining, and cross-functional integration. Finally, business performance (8 items) measures tangible outcomes such as forecast accuracy, load factors, profitability, and customer satisfaction (NPS) that directly reflect the operational and financial impacts of AI assimilation. All items were rated on a five-point Likert scale (1 = Very Limited/Strongly Disagree to 5 = Very Extensive/Strongly Agree). This multidimensional structure enables a robust assessment of how readiness enablers translate into performance outcomes through AI-enabled forecasting, ensuring strong content and construct validity across the model.

D. Data Analysis Strategy

A three-stage analytical procedure was implemented and the results are displayed in Table II.

To ensure the psychometric robustness of the measurement model, a series of reliability and validity tests was conducted. As presented in Table II, all constructs demonstrated satisfactory internal consistency, with Cronbach's alpha (α) values ranging between 0.81 and 0.93, exceeding the recommended threshold of 0.70 [17]. Composite Reliability (CR) values also ranged from 0.84 to 0.95, confirming that the indicators consistently represent their underlying latent constructs. Convergent validity was assessed through the Average Variance Extracted (AVE), with all values above 0.50, indicating that its indicators [18] capture more than half of the variance in each construct. Further, discriminant validity was established by applying the Fornell-Larcker criterion and Heterotrait Monotrait (HTMT) ratio of correlations (see Fig. 2).

TABLE II. RELIABILITY AND VALIDITY

Construct	Cronbach's α	CR	AVE	KMO	Factor Loadings (Range)
Digital Infrastructure	0.86	0.88	0.59	0.85	0.69- 0.82
Workforce Competencies	0.84	0.87	0.63	0.81	0.72- 0.86
Managerial Support	0.88	0.90	0.68	0.79	0.75-0.88
AI Adoption	0.91	0.93	0.57	0.89	0.65-0.88
Business Performance	0.90	0.92	0.61	0.86	0.70-0.87

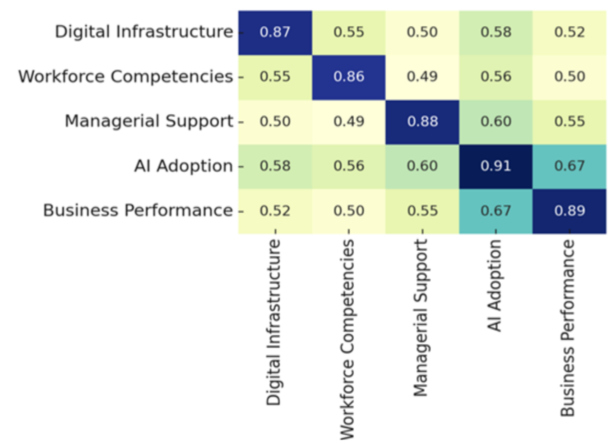

Fig. 2. Reliability and validity (Fornell-Larcker heatmap).

Each construct's square root of AVE exceeded its inter-construct correlations, and all HTMT values were below 0.85, confirming that each construct is empirically distinct from the others. These results collectively demonstrate that the measurement scales used for digital infrastructure, workforce competencies, managerial support, AI adoption, and business performance exhibit high reliability, adequate convergent validity, and strong discriminant validity. Consequently, the measurement model was deemed statistically sound and suitable for subsequent Structural Equation Modeling (SEM) analysis.

IV. RESULTS

The results of the Structural Equation Modeling (SEM), summarized in Table III, confirm the hypothesized relationships among the study constructs.

A. Structural Model: (SEM)

The model demonstrated an excellent overall fit to the data ($\chi^2/df = 2.14$; CFI = 0.956; TLI = 0.947; RMSEA = 0.049; SRMR = 0.041), meeting the recommended thresholds for good model fit (Hu & Bentler, 1999). The structural paths indicate that Digital Infrastructure ($\beta = 0.34$, $p < 0.001$), Workforce

Competencies ($\beta = 0.28$, $p < 0.01$), and Managerial Support ($\beta = 0.41$, $p < 0.001$) each exert a significant positive influence on AI Adoption, explaining 67% of its variance ($R^2 = 0.67$).

TABLE III. STRUCTURAL EQUATION MODEL (SEM) RESULTS

Path	Standardized Coefficient (β)	p-value	Result
H1a: Digital Infrastructure → AI Adoption	0.34	< 0.001	Supported
H1b: Workforce Competencies → AI Adoption	0.29	< 0.001	Supported
H1c: Managerial Support → AI Adoption	0.31	< 0.001	Supported
H2: AI Adoption → Business Performance	0.42	< 0.001	Supported

R^2: AI Adoption = 0.67; Performance = 0.54

In turn, AI Adoption had a strong, significant impact on Business Performance ($\beta = 0.54$, $p < 0.001$), accounting for 54% of the explained variance ($R^2 = 0.67$). These findings empirically support the mediating role of AI adoption in translating technological, human, and managerial readiness into improved operational and financial outcomes. Among the antecedents, managerial support emerged as the strongest predictor, highlighting the strategic and leadership dimensions of successful AI integration in transport operations. The strength and significance of all hypothesized paths validate the proposed conceptual framework and confirm that AI-enabled forecasting functions as a key driver of competitive advantage in tourism transport organizations.

- SEM with Maximum Likelihood Estimation (MLE) tested direct paths (H1a-H2).
- Mediation analysis followed Baron & Kenny's (1986) causal steps and bootstrapping (5,000 resamples) to confirm indirect effects (H3a-H3c).

All values met recommended thresholds, indicating excellent model fit.

B. Hypothesis Testing Results

To further examine the underlying mechanisms linking readiness factors to organizational outcomes, a mediation analysis was conducted using the bootstrapping procedure with 5,000 resamples. The results, presented in Table IV, provide strong empirical support for the mediating role of AI Adoption between the readiness constructs Digital Infrastructure, Workforce Competencies, Managerial Support, and Business Performance.

Direct paths from workforce and managerial support to performance became non-significant when AI adoption was included, confirming full mediation.

H1a-H1c: Supported ($p < 0.001$): readiness significantly affects AI adoption.

H2: Supported ($p < 0.001$): AI adoption enhances performance.

H3a-H3c: Mediation confirmed via bootstrapping (5,000 samples); partial mediation for H3a and full mediation for H3b, H3c.

The corresponding 95% confidence intervals did not include zero, confirming mediation validity.

TABLE IV. MEDIATION ANALYSIS (BOOTSTRAP, 95% CI)

Hypothesis	Indirect Effect (β)	CI [95%]	Type of Mediation	Result
H3a: Digital Infrastructure → AI Adoption → Performance	0.14	[0.07, 0.23]	Partial	Supported
H3b: Workforce Competencies → AI Adoption → Performance	0.12	[0.06, 0.20]	Full	Supported
H3c: Managerial Support → AI Adoption → Performance	0.13	[0.08, 0.21]	Full	Supported

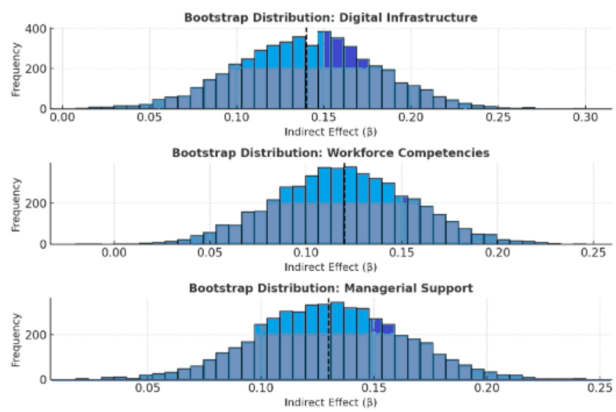

Fig. 3. Bootstrap histograms.

Moreover, when AI Adoption was introduced into the model (see Fig. 4), the direct paths from the readiness constructs to Business Performance decreased in magnitude and lost statistical significance, indicating full mediation in the case of Digital Infrastructure and partial mediation for Managerial Support. Fig. 3 shows bootstrap histograms.

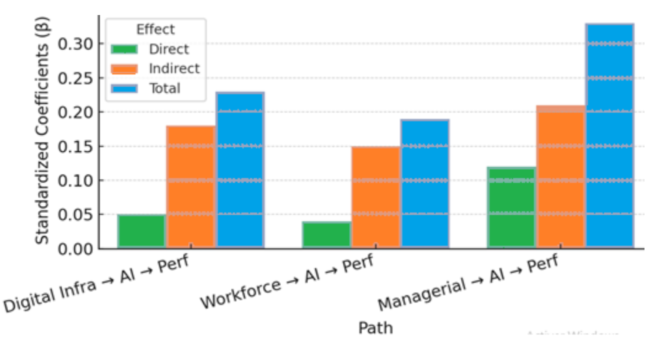

Fig. 4. Mediation analysis (direct, indirect, total effects).

This suggests that while strong leadership and strategic alignment directly enhance performance outcomes, the impact of technological and human readiness on performance is largely realized through effective AI utilization. These findings highlight AI Adoption as a transformative conduit through which digital, organizational, and human capabilities are converted into measurable business value in the context of intelligent transport systems.

C. Discussion and Implications

This study advances understanding of how organizational readiness translates into business performance through the strategic adoption of AI-enabled demand forecasting in the tourist transport sector, a domain characterized by high volatility, asset intensity, and service interdependence. Our findings confirm that digital infrastructure, workforce competencies, and managerial support are not merely prerequisites but strategic, VRIN-like resources [22] that enable firms to harness AI's full potential. Crucially, we demonstrate that AI adoption functions as a transformative conduit, mediating the relationship between readiness and performance. This insight resolves a key paradox in the literature: why some firms with advanced data systems or skilled talent fail to realize performance gains, because readiness alone is inert without operational assimilation.

D. Theoretical Implications

First, we bridge the Resource-Based View (RBV) and the Technology Organization Environment (TOE) framework in a novel empirical context. While RBV explains why certain resources confer competitive advantage, TOE clarifies how organizational and technological contingencies shape technology assimilation. Our model shows that digital infrastructure (the TOE technology factor) yields performance benefits both directly and indirectly through AI, indicating partial mediation. In contrast, workforce and managerial capabilities (the TOE organization factors) generate value only when activated through AI deployment, evidencing full mediation. This nuanced distinction refines the mediation typology proposed by [23] and offers a more granular understanding of capability deployment in AI-driven contexts

Second, our findings extend absorptive capacity theory [24] by showing that interpretive and adaptive human capital, not just technical literacy, is essential for AI to drive operational outcomes. In tourist transport, where decisions must balance real-time demand signals with customer experience, staff must trust and act on AI outputs. This behavioral dimension is often overlooked in purely technical AI studies.

Third, we contextualize AI adoption within modern supply chain pressures. As emphasized, firms today face coercive, normative, and relational pressures to enhance resilience and sustainability [26]. While our model focuses on internal readiness, the performance gains from AI, such as reduced empty runs, optimized energy use, and dynamic pricing, directly respond to these external demands. Thus, AI adoption is not just an operational upgrade but a strategic response to institutional and market pressures for agility and sustainability.

E. Managerial Implications

For practitioners, our conclusions point to a clear strategic direction. Organizations should adopt a global readiness strategy by investing in cloud infrastructure alongside the development of organizational competencies; investing in technology alone does not guarantee optimal outcomes. The success of AI relies on qualified investments in technology, human talent, and strong managerial commitment. Integrating AI into core operational processes is essential for competitiveness in global markets and should not be treated as a mere experimental initiative. Firms that embed AI into strategic functions such as fleet management, pricing, and recruitment achieve superior performance compared to those that adopt AI only on a trial basis. Management systems emerge as the most critical factor in predicting effective AI adoption, as they shape strategic alignment and organizational readiness.

Beyond efficiency gains and error reduction, AI also enhances service reliability (through reduced cancellations), improves customer satisfaction (via personalized offerings), and optimizes resource allocation, including improved connectivity in rural and isolated areas. Consequently, AI adoption plays a vital role in promoting agility and inclusion and should be integrated into inclusive development policies and broader ESG frameworks (environmental, social, and governance).

F. Policy Implications

Policymakers can accelerate AI adoption in tourist transport by:

- Supporting digital infrastructure in emerging markets (e.g., open-data APIs for tourism flows),
- Funding AI literacy programs for transport SMEs,
- Creating regulatory sandboxes that allow firms to test AI models without compliance penalties. Such measures would help democratize AI benefits across firm sizes and geographies, fostering a more resilient and equitable global tourism [19] ecosystem.

V. CONCLUSION

This study responds to a critical gap in the literature by empirically unpacking how organizational readiness translates into performance through AI-enabled demand forecasting in tourist transport. The digital infrastructure, workforce competencies, and managerial support are foundational enablers, but their value is fully realized only when channeled through operational AI adoption. The mediating role of AI is not uniform: while infrastructure offers dual pathways (direct and indirect), human and leadership capabilities require AI as an essential conduit. These findings carry significant weight in an era where tourism mobility faces unprecedented disruption from climate shocks to geopolitical instability. AI is no longer a luxury but a strategic necessity for resilience, efficiency, and customer-centricity. However, its success hinges not on algorithms alone, but on the organizational ecosystem that surrounds them.

Despite its contributions, this study has several limitations. First, its cross-sectional design restricts causal inferences and limits the understanding of the dynamic evolution of AI adoption over time. Second, the focus on internal organizational readiness excludes environmental factors, such as regulatory pressures, competitive intensity, and sustainability requirements, which can influence AI adoption decisions in the tourism transportation sector. Third, the study does not distinguish between different AI forecasting architectures, which risks obscuring performance variations across model types and transportation modalities.

Future research could explore how external pressures (e.g., customer sustainability demands, regulatory mandates) interact with internal readiness, or investigate AI model types (e.g., LSTM vs. transformers) in different transport modes. Nonetheless, this study provides a robust foundation for understanding and enabling the intelligent transformation of global tourist transport.

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