MODELLING THE MEDIATION EFFECT OF MANAGEMENT SUPPORT ON THE RELATIONSHIP BETWEEN AI ADOPTION INNOVATION DIMENSIONS AND AI IMPLEMENTATION IN THE UAE TOURISM SECTOR

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ABSTRACT

Objective: This study aims to develop an empirical framework of the mediation effect of management support on the relationship between AI adoption innovation dimensions and the successful implementation of AI technologies within the UAE tourism sector

Research Method: Data to validate the theoretical framework was collected from 370 employees of the Dubai Tourism Authority using purposive sampling. The validation process employed SmartPLS software, utilizing PLS-SEM techniques to examine relationships between variables. PLS-SEM is particularly well-suited for validating theoretical models and ensuring analytical robustness in developing the empirical framework

Findings: The empirical framework indicates that Management Support significantly enhances AI adoption by amplifying the impact of Compatibility, Relative Advantage, and Trialability, while Low Complexity has an insignificant indirect effect. Additionally, the direct effects of these innovation dimensions on AI adoption vary in strength. This framework has several practical applications. From a strategic AI implementation perspective, organizations can prioritize AI innovations that demonstrate strong direct and indirect influences on adoption, particularly focusing on Compatibility and Relative Advantage

Originality: Through applying this framework, tourism businesses and policymakers can develop optimized AI adoption strategies, ultimately improving efficiency, customer experiences, and overall industry competitiveness

Keywords: Compatibility, Low Complexity, Observability, Relative Advantage, Trialability

1. INTRODUCTION

The rapid advancements in artificial intelligence technologies, automation, and robotics drove the Fourth Industrial Revolution, transforming industries such as hospitality and tourism (Syam & Sharma, 2018). AI was implemented at varying levels of sophistication, ranging from basic automated processes to advanced intelligent systems. Organizations adopted AI primarily to maintain a competitive edge (84%), expand into new markets (75%), and reduce costs (63%) (Ransbotham et al., 2017). Despite these strategic advantages, AI adoption remained inconsistent across industries due to challenges such as technological complexity, cybersecurity risks, human-AI interaction difficulties, and a lack of technical expertise (Cheatham et al., 2019).

In the hospitality and tourism sector, AI revolutionized operations by enhancing efficiency, personalization, and customer engagement. Hotels and travel service providers increasingly integrated AI-driven solutions such as virtual voice assistants, automated check-ins, concierge services, and robotic systems to streamline operations and improve guest experiences (Kuo, Chen, & Tseng, 2017). Airports also leveraged AI-powered robots to assist travelers, replacing traditional information centers. These innovations contributed to real-time responsiveness, data-driven decision-making, and service customization, aligning with the broader digital transformation in tourism (Buhalis & Sinarta, 2019). However, the industry faced significant hurdles in fully implementing AI, including high initial costs, a shortage of skilled professionals, data privacy concerns, and resistance to change (Dwivedi et al., 2024; Raina, 2023).

Beyond operational efficiency, AI adoption in tourism had far-reaching implications for safety, economic performance, and environmental sustainability. AI enhanced security through predictive analytics and real-time monitoring, creating safer travel environments (Dwivedi et al., 2024). Its economic benefits included cost savings, optimized pricing strategies, and improved resource management, strengthening business competitiveness and long-term growth (Gajić et al., 2024). AI also supported sustainability by minimizing waste, promoting eco-friendly travel choices, and encouraging ethical tourism practices (Majid et al., 2023). These advantages aligned with the UAE government's strategic vision of integrating AI across all sectors, including tourism, to drive innovation and automation. However, a critical gap remained in understanding the specific innovation dimensions that facilitated AI adoption and its effective implementation in the tourism sector.

While AI presented opportunities for growth, its successful implementation depended on several factors, particularly management support. Strong leadership commitment was essential for overcoming barriers such as financial constraints, employee resistance, and organizational inertia (Chan & Tung, 2019). The role of management support was critical in fostering an AI-ready culture, ensuring proper resource allocation, and facilitating training programs that enhanced AI competency within tourism businesses. Without clear strategic guidance and support from top management, AI initiatives faced implementation challenges despite their potential benefits (Nam et al., 2021).

This study aimed to develop a framework that examined the mediation effect of management support on the relationship between AI adoption innovation dimensions and AI implementation in the UAE tourism sector. By identifying key innovation dimensions that influenced AI adoption and assessing the extent to which management support facilitated successful implementation, this research provided valuable insights for policymakers, industry leaders, and tourism businesses. Understanding these dynamics helped create strategies that optimized AI-driven innovation, ensuring that the UAE tourism sector remained competitive in the evolving digital landscape.

2. UAE TOURISM AND AI ADOPTION

The UAE tourism sector is a key driver of economic growth, significantly contributing to the country's GDP. In 2024, its economic impact is projected to reach AED 236 billion ($64.2 billion), accounting for 12% of the nation's GDP (Economy Middle East, 2024). This growth is fueled by a continuous influx of international visitors, high hotel occupancy rates, and strategic investments in tourism infrastructure. Recognizing the sector's economic potential, the UAE government has introduced several initiatives, most notably the UAE Tourism Strategy 2031. This strategy aims to increase the sector's contribution to AED 450 billion, attract 40 million hotel guests annually, and secure AED 100 billion in additional tourism investments (UAE Government Tourism, 2024). It comprises 25 initiatives focused on strengthening the national tourism identity, diversifying tourism products, enhancing sector capabilities, and expanding investment opportunities. Additionally, the UAE Strategy for Domestic Tourism seeks to align federal and local efforts to maximize the country's tourism potential.

Despite its rapid expansion, the UAE tourism sector faces several challenges. Over-tourism poses a significant risk, straining infrastructure, impacting the environment, and disrupting local communities. To address these concerns, the UAE is prioritizing sustainable tourism through eco-friendly initiatives such as renewable energy integration, water conservation, and waste management systems (Investopia, 2024). Additionally, evolving global tourism trends and increased competition require adaptive strategies to maintain the sector's competitive edge. The UAE's focus on sustainable and responsible tourism management is essential for ensuring long-term industry resilience (Kyriakidis et al., 2024).

As a premier global travel destination, the UAE thrives on a blend of cultural heritage, modern attractions, and luxury experiences. Cities like Dubai and Abu Dhabi lead the industry, offering diverse attractions that appeal to global travelers (Dubai Tourism, 2022; Abu Dhabi Tourism, 2024). Dubai, often referred to as the "City of Gold," is home to iconic landmarks such as the Burj Khalifa and Palm Jumeirah. It also hosts globally renowned events like the Dubai Shopping Festival and Dubai Food Festival, attracting millions of visitors annually (Dubai Tourism, 2022). Meanwhile, Abu Dhabi distinguishes itself with cultural and historical sites, including the Sheikh Zayed Grand Mosque and Louvre Abu Dhabi, while also championing sustainability initiatives such as Masdar City. The capital further enhances its global reputation by hosting major events like the Abu Dhabi Grand Prix and Abu Dhabi Film Festival, reinforcing its status as a cultural and entertainment hub (Abu Dhabi Events, 2025).

Beyond Dubai and Abu Dhabi, other emirates also contribute significantly to the UAE's tourism landscape. Sharjah, recognized by UNESCO as the "Cultural Capital of the Arab World," is known for its rich heritage and numerous museums. Ras Al Khaimah appeals to adventure enthusiasts with its diverse landscapes, including Jebel Jais, the UAE's highest peak. Meanwhile, Fujairah offers pristine beaches and historical sites, providing a tranquil retreat for visitors (UAE Government Tourism, 2024).

The success of the UAE's tourism sector is underpinned by world-class infrastructure, including modern airports, efficient transportation networks, and high-quality hospitality facilities. Government-led strategic initiatives, such as UAE Vision 2021 and the Dubai Tourism Strategy 2025, further enhance sector growth by promoting the country as a leading global destination, improving visitor experiences, and fostering innovation in tourism services (UAE Government Tourism, 2024). UAE tourism sector remains a cornerstone of economic diversification, supported by its exceptional infrastructure, strategic government initiatives, and commitment to sustainability. With its unique combination of cultural heritage, modern marvels, and luxury offerings, the UAE continues to attract millions of visitors, solidifying its position as one of the world's top travel destinations (Dubai Tourism, 2022).

2.1 ARTIFICIAL INTELLIGENCE IN TOURISM

Artificial Intelligence (AI) has become a game-changer across various industries, and the tourism sector is no exception. With rapid advancements in machine learning, big data analytics, and automation, AI is reshaping the way tourism businesses operate and how travellers experience destinations. From personalized recommendations to smart customer service, AI enhances efficiency, customer engagement, and revenue generation in the tourism industry (Dwivedi et al., 2021). One of the most significant contributions of AI to tourism is personalization. AI-powered recommendation engines analyse customer preferences, booking history, and online behaviour to offer tailored travel suggestions. Platforms like Expedia and Booking.com use AI to provide customized hotel, flight, and activity recommendations, improving user satisfaction (Tussyadiah, 2020). Similarly, AI chatbots integrated into travel agency websites assist travellers in planning their trips by offering real-time suggestions and personalized itineraries.

AI-driven virtual assistants and chatbots have revolutionized customer service in tourism. AI-powered chatbots like those used by airlines and hotel chains provide 24/7 customer support, answering inquiries related to flight schedules, hotel bookings, and travel policies. These chatbots enhance efficiency by reducing human workload and providing instant responses (Marin-Peñalver et al., 2022). For instance, Hilton Hotels' AI-powered concierge, "Connie," offers guests personalized recommendations on local attractions and dining options. AI has also improved travel planning by integrating predictive analytics. AI algorithms analyze past travel trends, seasonality, and customer demand to optimize pricing strategies. Airlines and hotels utilize AI-based dynamic pricing models to adjust prices in real-time based on demand fluctuations, maximizing revenue and occupancy rates (Kapoor et al., 2021). Moreover, AI-based platforms like Google Travel assist users in finding the best travel deals by predicting future price trends.

The COVID-19 pandemic accelerated the adoption of AI in contactless travel solutions. AI-powered facial recognition and biometric authentication systems are now widely used at airports and hotels to facilitate seamless check-ins, security screening, and border control (Zhu & Morosan, 2023). For example, Dubai International Airport has implemented AI-based smart gates that allow travelers to pass through immigration without human intervention, reducing waiting times and enhancing security. Tourism boards and city planners are leveraging AI for smart destination management. AI-powered data analytics help cities monitor tourist foot traffic, predict visitor trends, and optimize infrastructure. AI-driven sentiment analysis tools also analyse social media and online reviews to gauge tourist satisfaction, allowing businesses to improve services based on real-time feedback (Gretzel et al., 2020). For example, Amsterdam's smart tourism initiative uses AI to distribute tourist traffic efficiently and prevent overcrowding in popular areas.

Despite its numerous benefits, AI adoption in tourism faces several challenges, including high implementation costs, data privacy concerns, and the need for skilled AI professionals (Alnuaimi et al., 2022). However, continuous advancements in AI technology, combined with increasing investments in digital transformation, indicate a promising future for AI-driven tourism. Emerging technologies such as AI-driven augmented reality (AR) and virtual reality (VR) will further enhance tourist experiences by offering immersive travel previews and virtual guided tours. AI is revolutionizing the tourism industry by improving efficiency, personalization, security, and customer service. From AI-driven chatbots and predictive pricing models to smart destination management, AI enhances every aspect of the travel experience. While challenges remain, the continued evolution of AI technologies will further transform the tourism landscape, making travel more seamless, enjoyable, and innovative.

2.2 AI ADOPTION INNOVATION DIMENSIONS IN TOURISM

The key AI adoption innovation dimensions in the tourism sector include Compatibility, Low Complexity, Observability, Relative Advantage, and Trialability (Rogers, 2003; Oliveira & Martins, 2011). These dimensions play a crucial role in determining how effectively AI technologies can be integrated into tourism operations, enhancing service quality, operational efficiency, and customer satisfaction. Compatibility refers to how well AI technologies align with the existing values, experiences, and needs of tourism organizations. In the tourism sector, this means that AI solutions, such as chatbots, personalized recommendation engines, and virtual tour guides, must seamlessly integrate with existing hospitality and customer service processes. For instance, AI-driven customer support systems must complement traditional concierge services rather than disrupt them. Additionally, AI-powered analytics tools should align with the decision-making processes of hotel managers, travel agencies, and tour operators to ensure smooth adoption.

Low Complexity indicates the ease of understanding and using AI technologies, making them more accessible for adoption (Venkatesh et al., 2012). Tourism professionals, including hotel staff, travel agents, and tour guides, often do not have advanced technical expertise. Therefore, AI tools should be user-friendly and require minimal training. For example, AI-powered booking platforms should feature intuitive interfaces that allow travel agents to use predictive analytics without needing extensive technical knowledge. Similarly, AI-driven translation tools should provide real-time language assistance without requiring complex setup or operation.

Observability measures the visibility of AI technology's results and benefits, which can influence the decision-making process. In tourism, AI applications such as dynamic pricing algorithms for hotel bookings, real-time sentiment analysis of customer reviews, and automated check-in systems provide tangible and observable benefits. When stakeholders see measurable improvements in customer satisfaction, operational efficiency, and revenue generation, they are more likely to adopt AI-driven solutions. For instance, AI-driven facial recognition technology for check-ins at hotels or airports becomes more widely accepted when management sees reduced wait times and enhanced security.

Relative Advantage assesses the perceived benefits of AI technologies compared to existing solutions, emphasizing the value addition brought by AI (Chong et al., 2009). In tourism, AI can significantly enhance guest experiences by offering hyper-personalized services. AI-powered recommendation engines, for example, analyze customer preferences to offer tailored travel itineraries, helping travel agencies provide better service than traditional static package deals. Similarly, AI-driven sentiment analysis helps hospitality businesses respond to guest feedback in real-time, providing a competitive edge over traditional customer service models. AI's ability to optimize pricing strategies, predict demand fluctuations, and streamline booking processes further reinforces its relative advantage.

Trialability allows organizations to experiment with AI technologies on a limited basis before full-scale implementation, reducing uncertainties and fostering adoption (Tornatzky & Klein, 1982). In tourism, businesses may be hesitant to fully implement AI due to concerns about costs, compatibility, and effectiveness. Trialability mitigates these concerns by allowing businesses to test AI-powered chatbots, automated check-in kiosks, or AI-driven customer service platforms on a smaller scale before committing to full integration. For example, a hotel chain might introduce AI-driven room service assistance in a few locations before rolling it out across all properties. Similarly, tour operators could pilot AI-powered virtual tour guides in select destinations to assess their impact on customer engagement before broader deployment. By understanding these AI adoption dimensions in the tourism sector, industry stakeholders can make informed decisions on integrating AI technologies to enhance efficiency, improve customer satisfaction, and drive competitive advantage.

2.3 MANAGEMENT SUPPORT ON AI ADOPTION INNOVATION AND IMPLEMENTATION IN THE UAE TOURISM SECTOR

Management support plays a pivotal role in the successful adoption and implementation of AI technologies in the UAE tourism sector by providing essential resources, strategic direction, and organizational commitment (Ifinedo, 2011). In an industry where customer experience, operational efficiency, and competitive differentiation are key priorities, strong leadership ensures that AI-driven innovations align with business objectives. Effective management backing facilitates seamless integration of AI technologies into tourism operations, ensuring compatibility with existing organizational workflows and service standards (Sun et al., 2020). For instance, AI-powered concierge services, smart room automation, and facial recognition check-in systems must be implemented in a way that complements traditional hospitality values. By prioritizing training and structured change management, leadership can help frontline employees adapt to AI tools, reducing resistance and improving usability (Cheng & Jin, 2019).

Furthermore, management support enhances the observability of AI innovations by demonstrating their impact through data-driven performance metrics, case studies, and real-world success stories. For example, a hotel chain utilizing AI-driven sentiment analysis to assess customer feedback can showcase measurable improvements in guest satisfaction scores, reinforcing confidence in AI solutions (Ivanov & Webster, 2019). Similarly, travel agencies adopting AI-based personalized itinerary recommendations can evaluate their effectiveness through increased conversion rates and customer engagement metrics (Tussyadiah, 2020). By highlighting these success stories, top executives create a compelling case for AI adoption, illustrating its advantages over traditional processes.

A critical challenge in AI adoption is the perceived financial and operational risks. Management plays a crucial role in fostering trialability, enabling businesses to experiment with AI solutions on a small scale before committing to full-scale implementation (Gangwar et al., 2015). For instance, a luxury resort in the UAE might pilot AI-powered voice assistants in select rooms before expanding across multiple properties (Morosan, 2021). Similarly, a national tourism board could test AI-driven virtual tour guides in a single emirate before a broader rollout (Gretzel et al., 2020). A restaurant chain may implement AI-based dynamic pricing algorithms in a limited number of locations to assess revenue impact before wider deployment (Li et al., 2021). By supporting controlled trials, management reduces uncertainty, builds stakeholder confidence, and minimizes resistance from employees and customers.

In the UAE tourism sector, management support is not merely about approving budgets, it is about driving AI adoption strategically. Leadership must ensure that AI technologies align with existing operational frameworks, facilitate workforce adaptation through training, and emphasize measurable benefits. Additionally, by encouraging structured experimentation and iterative deployment, organizations can mitigate risks and enhance AI implementation success. A strong management commitment fosters an AI-driven culture that accelerates digital transformation, leading to improved guest experiences, optimized operations, and a sustained competitive advantage in the global tourism industry (Gursoy et al., 2019).

3 MODELLING OF FRAMEWORK

This study underscores the importance of AI in enhancing the UAE's tourism sector, aligning with Abu Dhabi's vision to become the world’s first fully AI-native government by 2027, as outlined in the Abu Dhabi Government Digital Strategy 2025-2027. In this context, a conceptual framework was developed to demonstrate the relationship between AI Adoption Innovation Dimensions and AI Implementation in the UAE tourism sector, with Management Support introduced as a mediating factor.

To validate the framework, data was collected from 370 employees of the Tourism Authority using purposive sampling, specifically targeting Dubai. This sampling strategy was chosen because it allows for easier generalizations about the sample compared to random sampling, where respondents might not share the same traits (Etikan, Musa, & Alkassim, 2016). The validation process was conducted using SmartPLS software, which applies PLS-SEM techniques to examine relationships between variables. PLS-SEM is particularly well-suited for validating theoretical models and ensuring analytical robustness (Hair et al., 2021). The modelling process follows a structured two-step validation approach: first, assessing the measurement model to ensure reliability and validity, and second, evaluating the structural model to test the hypothesized relationships (Hair et al., 2022). The developed PLS-SEM model is depicted in Figure 1.

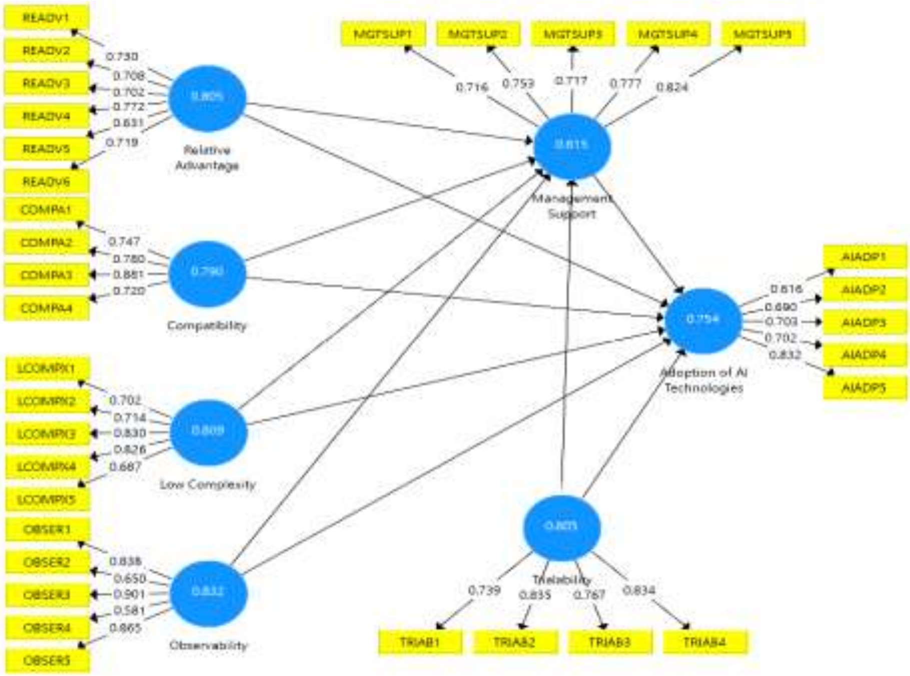

Figure 1: Final model

3.1 ASSESSMENT OF MEASUREMENT MODEL

The assessment of the measurement model involved two criteria: construct reliability and validity (CRV), and discriminant validity. For discriminant validity, both the Fornell-Larcker criterion and the cross loading were utilized, as these methods are deemed sufficient according to Henseler, Ringle, & Sarstedt (2015).

3.1.1 CONSTRUCT RELIABILITY AND VALIDITY

After constructing the model in SmartPLS, the PLS Algorithm function is applied to evaluate the measurement model. This step is essential because it assesses the reliability and validity of the constructs, thereby ensuring the model's robustness before proceeding with further analysis. Specifically, construct reliability refers to the consistency of a construct's measurement, ensuring it is free from random error. It is typically assessed using composite reliability and Cronbach's alpha. Moreover, construct validity determines the extent to which a construct accurately measures what it is intended to measure. In this regard, it includes two key aspects: convergent validity, which ensures that related constructs are strongly correlated, and discriminant validity, which confirms that unrelated constructs are weakly correlated (Hair et al., 2017). Consequently, after executing the PLS Algorithm, the results for construct reliability and validity are presented in Table 1.

Table 1: Results of Construct Reliability and Validity

Constructs	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Adoption of AI Technologies	0.754	0.836	0.507
Compatibility	0.790	0.864	0.616
Low Complexity	0.809	0.868	0.569
Management Support	0.815	0.871	0.576
Observability	0.832	0.881	0.604
Relative Advantage	0.805	0.86	0.506
Trialability	0.805	0.873	0.632

Table 1 demonstrates that the Cronbach's Alpha values for all constructs are above 0.7, indicating good internal consistency and reliable measurement of the underlying constructs. For Composite Reliability, each construct has values above 0.8, signifying strong reliability. Furthermore, most constructs have Average Variance Extracted (AVE) values above 0.5, suggesting good validity. In comparison, studies on AI adoption generally report Cronbach's Alpha values above 0.7, Composite Reliability values above 0.8, and AVE values above 0.5 as acceptable thresholds for reliability and validity. For instance, a study on the adoption of AI applications in online learning environments reported similar reliability values, with Cronbach's Alpha values ranging from 0.75 to 0.85 and Composite Reliability values above 0.8 (Almaiah et al., 2022).

3.1.2 DISCRIMINANT VALIDITY

Discriminant validity evaluates the extent to which a measurement model is distinct from other constructs in a study. It ensures that a given model is not excessively correlated with other models in the structural framework (Memon & Rahman, 2013). Traditionally, discriminant validity has been assessed using the Fornell and Larcker criterion and the cross-loading criterion.

According to Fornell and Larcker (1981), discriminant validity is established when the square root of a construct's average variance extracted (AVE) is greater than its correlation with any other construct in the model. This implies that each construct should share more variance with its own indicators than with other constructs in the structural model (Hair et al., 2014). In the current study, this criterion has been met, as demonstrated in the Fornell and Larcker test results presented in Table 2.

Table 2: Fornell Laker's test

	Adoption of AI Technologies	**Compatibility**	**Low Complexity**	**Management Support**	**Observability**	**Relative Advantage**	**Trialability**
Adoption of AI Technologies	**0.712**						
Compatibility	0.756	**0.785**					
Low Complexity	0.754	0.688	**0.924**				
Management Support	0.768	0.759	0.776	**0.919**			
Observability	0.785	0.628	0.777	0.668	**0.870**		
Relative Advantage	0.802	0.746	0.85	0.712	0.730	**0.851**	
Trialability	0.710	0.663	0.749	0.658	0.689	0.795	**0.915**

The Fornell and Larcker test results in table 2 confirm discriminant validity, as the square root of each construct's average variance extracted, represented by the diagonal values, is greater than its correlations with other constructs, represented by the off-diagonal values. This indicates that each construct in the study, including Adoption of AI Technologies, Compatibility, Low Complexity, Management Support, Observability, Relative Advantage, and Trialability, is distinct and shares more variance with its own indicators than with other constructs.

The cross-loading criterion serves as the second test for discriminant validity. According to Chin (1998), this method is a reliable approach for assessing discriminant validity. The criterion states that each item should load more strongly on its respective construct than on any other construct (Hair et al., 2014; Wong, 2016). As shown in Table 3, the results confirm that each factor in the current study exhibits higher loadings on its own construct than on others, thereby establishing discriminant validity

Table 3: Cross-loading assessment

	Adoption of AI Technologies	Compatibility	Low Complexity	Management Support	Observability	Relative Advantage	Trialability
AIADP1	**0.816**	0.72	0.428	0.537	0.352	0.449	0.379
AIADP2	**0.890**	0.283	0.561	0.319	0.542	0.427	0.413
AIADP3	**0.803**	0.341	0.702	0.512	0.531	0.517	0.321
AIADP4	**0.792**	0.596	0.714	0.529	0.642	0.633	0.702
AIADP5	**0.832**	0.676	0.83	0.757	0.692	0.759	0.647
COMPA1	0.449	**0.847**	0.482	0.717	0.424	0.587	0.514
COMPA2	0.582	**0.790**	0.598	0.777	0.544	0.636	0.577
COMPA3	0.709	**0.881**	0.627	0.824	0.614	0.651	0.589
COMPA4	0.616	**0.820**	0.428	0.537	0.352	0.449	0.379
LCOMPX1	0.703	0.341	**0.802**	0.512	0.531	0.517	0.321
LCOMPX2	0.702	0.596	**0.814**	0.529	0.642	0.633	0.702
LCOMPX3	0.732	0.676	**0.830**	0.757	0.692	0.759	0.647
LCOMPX4	0.63	0.512	**0.826**	0.613	0.693	0.714	0.644
LCOMPX5	0.578	0.423	**0.687**	0.46	0.742	0.548	0.486
MGTSUP1	0.471	0.509	0.521	**0.796**	0.387	0.631	0.356
MGTSUP2	0.663	0.553	0.692	**0.793**	0.535	0.719	0.448
MGTSUP3	0.449	0.747	0.482	**0.817**	0.424	0.587	0.514
MGTSUP4	0.582	0.78	0.598	**0.827**	0.544	0.636	0.577
MGTSUP5	0.709	0.681	0.627	**0.824**	0.614	0.651	0.589
OBSER1	0.641	0.546	0.724	0.541	**0.838**	0.65	0.697
OBSER2	0.541	0.516	0.57	0.528	**0.850**	0.34	0.226
OBSER3	0.68	0.501	0.796	0.587	**0.901**	0.729	0.672
OBSER4	0.396	0.116	0.388	0.112	**0.881**	0.205	0.254
OBSER5	0.716	0.598	0.787	0.641	**0.865**	0.721	0.673
READV1	0.554	0.397	0.608	0.479	0.553	**0.830**	0.739
READV2	0.665	0.582	0.658	0.501	0.566	**0.808**	0.635
READV3	0.483	0.548	0.558	0.546	0.555	**0.802**	0.667
READV4	0.548	0.572	0.555	0.569	0.518	**0.872**	0.634
READV5	0.471	0.509	0.521	0.716	0.387	**0.831**	0.356
READV6	0.663	0.553	0.692	0.753	0.535	**0.819**	0.448
TRIAB1	0.554	0.397	0.608	0.479	0.553	0.73	**0.839**
TRIAB2	0.665	0.582	0.658	0.501	0.566	0.708	**0.835**
TRIAB3	0.483	0.548	0.558	0.546	0.555	0.702	**0.867**
TRIAB4	0.548	0.572	0.555	0.569	0.518	0.772	**0.834**

Table 3 presents the results of the discriminant analysis using the cross-loading criterion. The bold values indicate the loadings of each item on its respective construct. The results show that all items load more strongly on their respective constructs than on any other construct, confirming that the measurement models achieve discriminant validity

3.2 ASSESSMENT OF STRUCTURAL MODEL

This section evaluates model fit and quality using key metrics, including the coefficient of determination (R-square), effect size (f-square), predictive relevance (Q-square), and overall model fit indices. The R-square value measures the proportion of variance in the dependent variable explained by the predictor variables, reflecting the model's explanatory power (Hair, Black, Babin, & Anderson, 2019). Effect size (f^2)

quantifies the strength of the relationship between variables and is commonly used in multiple regression analysis to assess the proportion of variance explained by each predictor (Hair et al., 2019). Predictive relevance (Q-square) evaluates the model's ability to accurately reconstruct observed values, providing insight into its predictive accuracy (Chin, 1998). Finally, overall model fit is assessed using goodness-of-fit indices to ensure the model's robustness and validity (Byrne, 2016). Together, these metrics provide a comprehensive assessment of the model's performance, reliability, and predictive capability (Kline, 2016).

3.2.1 QUALITY OF THE STRUCTURAL MODEL (R-SQUARE)

R^2, or the coefficient of determination, measures the quality of a structural model by quantifying how well the exogenous constructs explain the variance of the endogenous construct. A higher R^2 value indicates better model quality. Scholars have different recommendations for acceptable R^2 values, which vary by discipline. For instance, R^2 values of 0.25, 0.50, and 0.75 are considered low, moderate, and strong, respectively (Hair et al., 2014; Wong, 2016). In consumer behaviour, an R^2 value of 0.2 is deemed high (Hair et al., 2014). These criteria were used to evaluate the R^2 levels in this study, as shown in Table 4.

Table 4: R^2 assessment

Endogenous constructs	R Square
Adoption of AI Technologies - DV	0.915
Management Support – Mediator	0.978

Table 4 outlines the coefficients of determination (R^2) for the study's structural model. The Adoption of AI Technologies as dependent construct achieved an R^2 value of 0.919, while the mediator construct, Management Support, achieved an R^2 value of 0.978. These high R^2 values indicate significant prediction accuracy according to the rule of thumb, which states that R^2 values greater than 0.75 are considered strong. Therefore, the models exhibit a high level of prediction accuracy (Hair et al., 2014)

3.2.2 EFFECT SIZE (F^2) EVALUATION

The f-square (f^2) statistic is used to evaluate the impact of a specific exogenous variable on an endogenous variable, helping to determine the contribution of each independent variable. This measure is essential for understanding the significance of individual paths in the model (Cohen, 1988). According to Chin (1998), effect size is determined by assessing changes in the R-squared (R^2) value, which represents the relative influence of specific exogenous constructs on endogenous constructs. Cohen's f^2 is specifically used to calculate the effect size of each construct within the structural model. This calculation involves removing a particular construct from the model and observing the resulting changes in R^2 (Hair, Hult, Ringle, & Sarstedt, 2014). Cohen (1988) established a criterion for evaluating effect sizes, defining a small effect size as f^2=0.02, a medium effect size as f^2=0.15, and a large effect size as f^2=0.35. Based on these benchmarks, the effect sizes of the research constructs were assessed, and the results are presented in Table 5.

Table 5: Effect Sizes (f^2)

Exogenous constructs	Dependent construct	Mediator
	Adoption of AI Technologies	Management Support
Compatibility	0.574	7.144
Low Complexity	1.285	0.008
Observability	0.017	0.118
Relative Advantage	0.201	4.101
Trialability	0.215	3.151

Table 5 presents the effect sizes (f^2) for the relationships between exogenous constructs and AI adoption, as well as the mediating role of Management Support. The results indicate that Compatibility and Low Complexity have the strongest influence on AI adoption, with large effect sizes of 0.574 and 1.285, respectively. In contrast, Observability has a negligible effect (f^2=0.017). Relative Advantage and Trialability demonstrate moderate effects on AI adoption, with values of 0.201 and 0.215, respectively. Regarding Management Support, Compatibility exerts the highest influence (f^2=7.144), followed by Relative Advantage (f^2=4.101) and Trialability (f^2=3.151), suggesting their strong role in fostering management support for AI adoption. Conversely, Low Complexity has an almost negligible impact (f^2=0.008), while Observability remains weak (f^2=0.118). Overall, these findings highlight that Compatibility and Low Complexity are key drivers of AI adoption, whereas Management Support is primarily influenced by Compatibility, Relative Advantage, and Trialability. Observability, on the other hand, plays a minimal role in both contexts

3.2.3 PREDICTIVE RELEVANCE (Q-SQUARE)

Cross-validated redundancy (CVR), assessed through Stone-Geisser's predictive relevance (Q^2), evaluates the predictive value of the structural model of endogenous constructs. This approach involves sample re-use, where a portion of the data is omitted, model parameters are estimated, and the omitted portion is predicted (Hair et al., 2011; Hair et al., 2014). For Q^2 to indicate effective predictive relevance, its values must be positive integers greater than 0 (Chin, 1998). The study's final models were assessed using the blindfolding technique and SmartPLS software (Ringle, Wende, & Becker, 2015), with results detailed in Table 6.

Table 6: Predictive relevance of CVR

Constructs	**SSO**	**SSE**	**Q^2 (=1-SSE/SSO)**
Adoption of AI Technologies - DV	1885	1042.668	0.447
Compatibility	1508	1508	
Low Complexity	1885	1885	
Management Support – Mediator	1885	834.916	0.557
Observability	1885	1885	
Relative Advantage	2262	2262	
Trialability	1508	1508	

Table 6 highlights the predictive relevance of Cross-validated Redundancy (CVR) among the endogenous constructs. The Adoption of AI Technologies, as the dependent variable, achieved a Q^2 value of 0.447, indicating moderate predictive relevance. In contrast, the mediator construct, Management Support, attained a Q^2 value of 0.557, demonstrating substantial predictive relevance. These results underscore the crucial role of Management Support in predicting the adoption of AI technologies, while also emphasizing the moderate relevance of the Adoption of AI Technologies construct itself (Chin, 1998).

3.2.4 GOODNESS-OF-FIT (GOF) ASSESSMENT

Unlike covariance-based structural equation modeling (CB-SEM), PLS-SEM does not have a widely accepted global goodness-of-fit (GoF) metric (Vinzi et al., 2010). To address this limitation, Tenenhaus et al. (2005) introduced the GoF index, a global criterion for evaluating model fit. This index is calculated as the geometric mean of the average communality (AVE) and the average coefficient of determination (R^2), providing an overall measure of model performance. The GoF index can be computed using the following formula:

$$GoF = \sqrt{\overline{AVE^2}\ X\ \overline{R^2}}$$

Where,

$\overline{AVE^2}$ is mean of Average Variance Extracted of the model

$\overline{R^2}$ is mean of coefficient of determination of the model

The Goodness-of-Fit (GoF) index is designed to assess the overall performance of a PLS model by evaluating both the measurement model and the structural model, with a focus on its predictive capability (Memon & Rahman, 2013). In this context, R^2 represents the explanatory power of the structural model, while AVE^2 reflects the accuracy of the measurement model. According to Akter et al. (2011), GoF values of 0.1, 0.25, and 0.36 indicate small, medium, and large model fit, respectively. The mean values of R^2 and AVE^2 used in the GoF calculation are presented in Table 7.

Table 7: Mean Values of R2 and AVE2

Constructs	**Average Variance Extracted (AVE)**	**R-square**
Adoption of AI Technologies	0.507	0.915
Compatibility	0.616	
Low Complexity	0.569	
Management Support	0.576	0.978
Observability	0.604	
Relative Advantage	0.506	
Trialability	0.632	
Average	0.573	0.947

Based on the results from table 7, the GoF index for the model is presented below.

$$GoF = \sqrt{0.573 \; x \; 0.947}$$

$$GoF = \sqrt{0.542}$$

$$GoF = 0.736$$

The formula for calculating the Goodness-of-Fit (GoF) index is provided above. In this study, the model achieved a GoF value of 0.736. According to Akter et al. (2011), this value is considered high, indicating that the research model demonstrates strong predictive power and overall quality.

3.2.5 HYPOTHESIS TESTING OF PATH

PLS-SEM aims to predict causal relationships between exogenous and endogenous constructs, often stated as hypotheses. After running the model, hypotheses are tested using path coefficients, which quantify the strength of relationships between constructs. Values near one indicate a significant positive link (Hair et al., 2014). The significance of paths is determined using t-statistics or p-values from the bootstrapping technique (Kock, 2014). Significant path coefficients demonstrate internal consistency and high-quality models (Hair et al., 2011; Wong, 2016).

Table 8: Hypothesis testing [IV to DV]

Direct relationship [IV to DV]	**Path strength**	**P Values (<0.05)**	**Remark**
Compatibility -> Adoption of AI Technologies	0.965	0.000	Significant
Low Complexity -> Adoption of AI Technologies	0.901	0.000	Significant
Observability -> Adoption of AI Technologies	-0.080	0.016	Significant
Relative Advantage -> Adoption of AI Technologies	1.001	0.000	Significant
Trialability -> Adoption of AI Technologies	-0.709	0.000	Significant

The results from Table 8 reveal the direct relationships between various independent variables and the dependent variable, Adoption of AI Technologies. The findings show that Compatibility has a strong positive relationship with the adoption of AI technologies, with a path strength of 0.965 and a P-value of 0.000, indicating a significant influence. Similarly, Low Complexity also exhibits a strong positive relationship (path strength: 0.901, P-value: 0.000), signifying its significant impact.

On the other hand, Observability shows a negative relationship with the adoption of AI technologies, with a path strength of -0.080 and a P-value of 0.016, but it remains significant. This negative relationship suggests that as observability, or the degree to which the benefits of AI technologies are visible and noticeable, decreases, the likelihood of adopting AI technologies increases. It could imply that when AI technologies are less observable, there might be a higher tendency to adopt them due to factors like perceived privacy or competitive advantage.

Relative Advantage demonstrates a very strong positive relationship, with a path strength of 1.001 and a P-value of 0.000, indicating a significant influence. However, Trialability reveals a significant negative relationship (path strength: -0.709, P-value: 0.000). The negative relationship here indicates that as the ease of trialing AI technologies decreases, the adoption increases. This might suggest that the adoption of AI technologies is driven by the recognition of their advantages without the need for extensive trial periods, perhaps due to strong endorsements or urgent needs in the sector.

Table 9: Indirect effect relationship

Indirect relationship [IV to Mediator to DV]	**Path strength**	**P Values (<0.05)**	**Remark**
Relative Advantage -> Management Support -> Adoption of AI Technologies	-1.171	0.000	Significant
Compatibility -> Management Support -> Adoption of AI Technologies	-0.697	0.000	Significant
Low Complexity -> Management Support -> Adoption of AI Technologies	0.041	0.077	Not Significant
Observability -> Management Support -> Adoption of AI Technologies	-0.048	0.006	Significant
Trialability -> Management Support -> Adoption of AI Technologies	0.779	0.000	Significant

The results from Table 9 reveal the indirect effects of various independent variables on the Adoption of AI Technologies, mediated by Management Support. The relationships between Relative Advantage, Compatibility, and Observability through Management Support to Adoption of AI Technologies are significant, with path coefficients of -1.171, -0.697, and -0.048, respectively, and all have P-values less than 0.05. Trialability also shows a significant indirect effect through Management Support, with a path coefficient of 0.779 and a P-value of 0.000. However, Low Complexity does not have a significant indirect effect, as indicated by a path coefficient of 0.041 and a P-value of 0.077.

The negative relationships for Relative Advantage, Compatibility, and Observability through Management Support indicate that as these variables increase, the influence of Management Support on the adoption of AI technologies decreases. This could imply that when Relative Advantage and Compatibility are high, there is less reliance on Management Support to drive AI adoption, possibly because the advantages and compatibility are already well recognized. Similarly, lower Observability may reduce the perceived need for strong Management Support.

Finally, the indirect effects reveal that Management Support significantly mediates the relationships for most variables, except for Low Complexity, which does not show significant mediation. The negative relationships suggest a nuanced dynamic where higher values in certain variables reduce dependence on Management Support.

3.3 EMPIRICAL FRAMEWORK

An empirically validated framework is a structured model that has been rigorously tested and confirmed through real-world data, ensuring its reliability and practical applicability across various fields (Smart, Maddern, and Maull, 2009; Aristovnik, Ravšelj, and Murko, 2024; Tudose, Rusu, and Avasilcai, 2021). In this study, the conceptual framework was validated using the PLS-SEM approach in SmartPLS software, with data collected from tourism department employees. The PLS-SEM method is particularly effective for evaluating complex relationships between latent variables, making it well suited for models with multiple constructs and small to medium sample sizes. This approach enhances the accuracy of the framework by capturing underlying relationships with precision, offering valuable insights into the factors influencing AI adoption. The empirical evidence gathered from employees further supports the framework's validity and relevance, reinforcing its robustness and applicability in organizational studies.

The validated framework, as illustrated in Figure 2, highlights the mediation effect of Management Support on the relationship between AI Innovation Dimensions and AI Adoption in the UAE tourism sector. It examines how five key AI innovation factors, namely Compatibility, Low Complexity, Observability, Relative Advantage, and Trialability, influence AI adoption both directly and indirectly through Management Support. This comprehensive validation underscores the importance of organizational backing in driving AI adoption and provides a structured approach for policymakers and industry leaders to optimize AI implementation strategies.

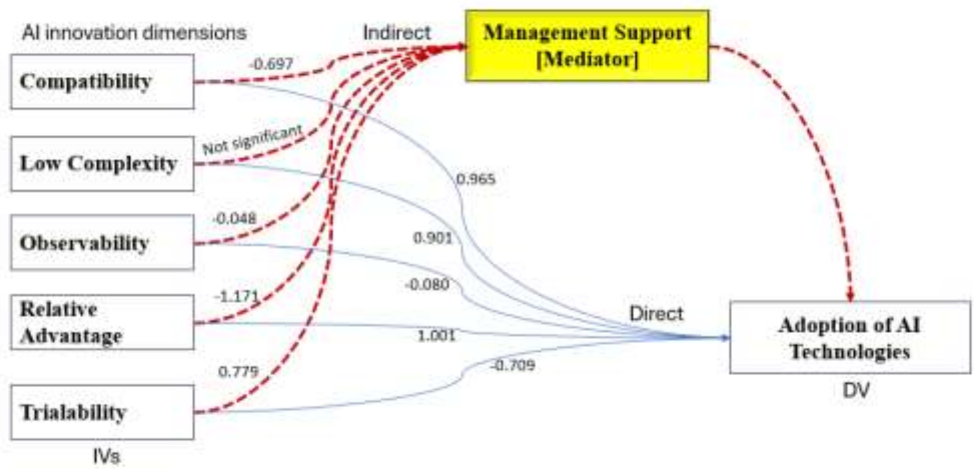

Figure 2: Empirical Framework

The empirical framework indicates that Management Support significantly enhances AI adoption by strengthening the impact of Compatibility, Relative Advantage, and Trialability, while Low Complexity has an insignificant indirect effect. Additionally, the direct effects of these innovation dimensions on AI adoption vary in strength. This framework has several practical applications. From a strategic AI implementation perspective, organizations can prioritize AI innovations that demonstrate strong direct and indirect influences on adoption, particularly Compatibility and Relative Advantage.

In terms of policy development, government and tourism authorities can design initiatives that enhance management support to ensure seamless AI integration. Moreover, businesses can leverage these insights for organizational decision-making, emphasizing training and leadership support to strengthen the mediating role of Management Support. The framework also contributes to technology adoption models, offering a structured approach to understanding how innovation dimensions interact with organizational factors, making it applicable across various industries beyond tourism. Through applying this framework, tourism businesses and policymakers can develop optimized AI adoption strategies, ultimately improving efficiency, customer experiences, and overall industry competitiveness.

4 CONCLUSIONS

This study has successfully developed and validated an empirical framework that elucidates the mediation effect of Management Support on the relationship between AI adoption innovation dimensions and the successful implementation of AI technologies within the UAE tourism sector. The findings highlight that Management Support significantly enhances AI adoption by amplifying the impact of Compatibility, Relative Advantage, and Trialability, while Low Complexity shows an insignificant indirect effect. The direct effects of these innovation dimensions on AI adoption also exhibit varying strengths.

From a practical standpoint, this framework offers valuable insights for organizations and policymakers in the tourism sector. By prioritizing AI innovations that demonstrate strong direct and indirect influences on adoption, particularly focusing on Compatibility and Relative Advantage, tourism businesses can develop optimized AI adoption strategies. These strategies can ultimately improve operational efficiency, enhance customer experiences, and bolster overall industry competitiveness.

Through the application of this framework, tourism businesses and policymakers can strategically leverage AI technologies to align with Abu Dhabi's vision of becoming the world's first fully AI-native government by 2027. The robust analytical approach employed in this study, including the use of SmartPLS software and PLS-SEM techniques, ensures the reliability and validity of the findings, providing a solid foundation for future research and practical applications in AI adoption within the tourism sector.

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